

CRANFIELD UNIVERSITY

JAKUB DEJA

**ENERGY RECOVERY FOR COMMERCIAL AIRCRAFT
DURING LANDING**

FACULTY OF ENGINEERING AND APPLIED
SCIENCES

Doctor of Philosophy
Academic Year: 2025

Supervisor: Martin Skote and Iman Dayyani
May 2025

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Abstract

This project explores advanced technologies for kinetic energy recovery in aviation, focusing on sustainable and efficient solutions for short-range aircraft operations. Given that such aircraft may perform up to thirteen flights per day, spending significant time taxiing, climbing, and descending, there is substantial potential to recover energy typically lost during braking on landing. A novel system coupling arresting gear with electrical generators was developed to recover this kinetic energy, demonstrating scalability across aircraft sizes and addressing integration challenges such as energy storage, safety, and passenger comfort.

The research begins with the development of a sustainable arresting gear energy recovery system that captures kinetic energy during aircraft landing through coupling with electrical generators. This system demonstrates approximately 60% energy conversion efficiency with scalability across aircraft sizes from Airbus A319 to A380. Applied at a major hub like Heathrow Airport, such technology could generate approximately 17 GWh of electrical energy annually, equivalent to offsetting 6,367 metric tons of coal or 5,667 m of diesel fuel consumed in conventional power generation.

Building on this foundation, a battery-powered landing gear drive system is designed to enable all-electric ground operations for narrowbody aircraft. Through integration of regenerative braking recovering 10% of landing energy, the system supports up to 26 minutes of electric taxiing via a 200 kWh modular battery architecture. Implementation analysis demonstrates 7% fuel consumption reduction for short-haul flights, with projections indicating potential savings of 500 kg fuel per flight by 2050 as component efficiencies improve.

To facilitate efficient design optimization of these complex systems, the SPCrane framework is developed, introducing a pointwise ensemble surrogate modeling methodology that enhances prediction accuracy compared to traditional approaches. This computational innovation employs spatial adaptive weighting and sigmoid-based transition logic to improve boundary prediction stability, enabling more robust optimization of energy recovery systems.

The research culminates in an electric machine braking system to replace conventional carbon-carbon composite brakes, utilizing a yokeless and segmented armature topology that achieves 120 Nm/kg torque density while enabling regenerative deceleration. Through electromagnetic-thermal co-design incorporating novel cooling strategies, the system meets performance requirements equivalent to commercial autobrake settings while withstanding extreme thermal gradients encountered during flight operations.

Collectively, these innovations enable harvesting of wasted kinetic energy during typical short-haul operations while providing practical solutions toward more sustainable aviation within existing operational frameworks. The integrated technological solutions represent a comprehensive approach to reducing aviation's environmental

ABSTRACT

impact while maintaining performance and safety requirements essential for commercial aircraft operations.

Keywords

Energy recovery; Energy harvesting; Landing gear; Electric taxiing; Ground operations; Brake system; Arresting gear

Acknowledgements

This thesis has been written precisely ten years after I decided to pursue higher education. Back in 2015, I packed my belongings and landed in the UK, a day before enrolling in the BEng course. In retrospect, the boldness (or maybe recklessness) of my younger self with the plan for full-time education in a foreign country while self-sustaining was not going to be easy. But it actually was much easier thanks to some individuals I was gifted to cross paths with.

Fast forward to the end of PhD, I am deeply grateful to my advisers, Prof. Martin Skote and Dr Iman Dayyani, for their true leadership and guidance throughout this project. Their office doors were always open and I received generous amounts of time, patience, and encouragement. I am also grateful to the academics and friends from Cranfield University, McGill University, and University of Strathclyde who made this project more enjoyable. I acknowledge financial support from EPSRC, Airbus, UKRI, and Mitacs which enabled me to prioritize academic tasks.

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Table of Contents

ABSTRACT	I
ACKNOWLEDGEMENTS	III
LIST OF FIGURES	IX
LIST OF TABLES	XV
ABBREVIATIONS	XVII
NOMENCLATURE	XXI
PUBLICATIONS	XXVII
1 INTRODUCTION	3
1.1 Background and Context	3
1.2 Current State of Energy Recovery in Aviation	4
1.3 Research Gaps and Opportunities	5
1.4 Research Aim and Objectives	6
1.5 Methodological Approach	7
1.5.1 Energy Conversion and Recovery Principles	9
1.5.2 Electromechanical Systems Design	10
1.5.3 Optimization Theory and Surrogate Modeling	10
1.5.4 Methodological Approaches	11
1.6 Overview of Research Contributions	11
1.6.1 Sustainable Arresting Gear Energy Recovery System	11
1.6.2 Landing Gear Drive System for All-Electric Ground Operations	12
1.6.3 SPCrane Optimization Framework	13
1.6.4 Electric Machine Braking System	13
1.7 Thesis Structure	14
1.8 Significance and Innovation	15
2 SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT	19
2.1 Introduction	19
2.2 Standard Landing Procedure Review	20
2.3 Idealized Arresting Gear Cable System	24
2.3.1 Arresting Gear Cable	26
2.3.2 Coupling Between Aircraft and Winding Drum Subsystem	28
2.3.3 Electric Machines	31

TABLE OF CONTENTS

2.3.4	System Moment of Inertia	32
2.3.5	Winding Process	33
2.3.6	Energy Storage	34
2.4	Simulation and Results	35
2.5	System Optimization Based on Parametric Study for Airbus A320 . . .	43
2.6	Arresting Gear Energy Recovery System in Practice	46
2.7	Conclusions	51
3	MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LAND- ING GEAR DRIVE SYSTEM	53
3.1	Introduction	54
3.2	Landing Gear Drive System and Impact on Aircraft	57
3.2.1	Dynamic Model	60
3.2.2	Initialization Parameters	63
3.2.3	Drive Cycles	66
3.3	Electric Power Demand of More Electric Aircraft	68
3.4	Landing Gear Drive System Components Sizing and Optimization . .	70
3.5	Internal Combustion Engines Usage	73
3.6	Net Fuel Savings	76
3.7	Parametric Study for Fuel Savings	79
3.7.1	Modular Batteries	81
3.8	Landing Gear Drive System in Future	82
3.9	Conclusions	85
4	SPCRANE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE EN- SEMBLE OF SURROGATES	87
4.1	Introduction	88
4.2	SPCrane Engineering Optimization Framework	92
4.2.1	Individual Surrogate Modeling Techniques and Methodological Implementations	99
4.2.2	Benchmarking Problems for Validation and Performance Veri- fication	104
4.3	Results	108
4.4	Case Study for Brake Sizing Optimization	117
4.5	Conclusions	122
4.5.1	Ensemble of Surrogates Future Work Recommendations . . .	124
5	SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXI- MIZED IMPACT OF LANDING GEAR DRIVE SYSTEM	133
5.1	Introduction	134
5.2	Application constraints and drive cycle	135
5.2.1	Electric machine and design requirements	140
5.3	Electromagnetic design and optimization of yokeless axial-flux machine	143

5.4	Thermal considerations	151
5.5	Frictionless brakes emergency backup device	156
5.6	Material Characterization: Literature Review	161
5.7	Preliminary Calculus for Mechanical And Thermal Loads	167
5.8	Experimental Nd ₂ Fe ₁₄ B and 49Co49Fe2V material characterization .	170
5.8.1	Thermal Characterization via Laser Flash Analysis, Differential Scanning Calorimetry and Thermomechanical Analyzer	174
5.8.2	Mechanical Characterization via Servohydraulic Testing	183
5.9	Revised Analytical Models for Fuel Savings and Heat Distribution . . .	191
5.10	Conclusions	197
6	CONCLUSIONS	199
6.1	Future Work	202
A	ILLUSTRATION OF THE WINDING SUBSYSTEM	227
B	PARAMETERS OF THE ROPE	229
C	ROPE FRICTION INDUCED BY CONTACT WITH RUNWAY	231
D	TOP-LEVEL ENERGY TRANSFER	233
D.0.1		233
D.0.2		234
E	PRODUCTION SOURCE CODE FOR SPCRANE	235
F	REDUNDANT THERMAL MEASUREMENT THROUGHOUT MECHANICAL CHARACTERIZATION	245
G	MECHANICAL CHARACTERIZATION PROCEDURE AND SAMPLES	247
H	FECOV PROCUREMENT: LCD-LASERCUT AG	251
I	JIGS PROCUREMENT: METALCUBE SP. Z O.O. AND XOMETRY	253
J	LUMPED THERMAL NETWORK: MATLAB/SIMULINK IMPLEMENTATION	263
K	CRANFIELD UNIVERSITY ETHICAL APPROVAL EVIDENCE	265

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List of Figures

1.1	V-diagram explaining progress of the PhD in relation to the abstraction level of each topic.	9
2.1	Arresting gear system demonstration showing arresting process, cross-section of underground installation and related degrees of freedom used in dynamic simulation. a) Arresting process graphic demonstrator b) Winding drum and steel wire rope cross-section	24
2.2	Split view between free body diagram and winding drum aircraft coupling kinematics annotated with dimensions	29
2.3	Motor-generator efficiency map against different torque and angular velocity values	32
2.4	Top-Level simulation flowchart logic explaining runout breakpoints . .	36
2.5	Arresting gear subsystem flowchart logic showing a coupling between aircraft and winding drum and energy loss factors	37
2.6	Winding flowchart logic showing energy transfer to wind up each subsystem	38
2.7	Airbus A320 results showing motion of aircraft along with all involved arresting subsystems and forces acting on a rope during landing. a) Aircraft acceleration, b) Aircraft position , c) Rope tension, d) Subsystems angular velocity, e) Energy transfer during landing	40
2.8	Gear ratio optimization results performed for Airbus A320. a) Optimization of first subsystem, b) Optimization of second subsystem, c) Optimization of third subsystem, d) Optimization of all subsystems combined, e) Aircraft response at final setup	45
3.1	Demonstrator of the landing gear drive system. (a) System-level presentation among with impact on aircraft, (b) Free-body diagram of the aircraft.	59
3.2	Dynamic model shown as block diagram disclosing the relation between multiple systems and the validation algorithm.	61
3.3	The ground velocity data recorded for two missions ((a) to (f)) and quasi-realistic model for the third ((g) to (i)) . The vertical intermittent lines are the separators for mission phases. Taxi cycles were magnified within each graph: (a) Luton (LTN) taxi-out and takeoff, (b) Krakow (KRK) landing and taxi-in, (c) map for LTN-KRK flight W65002 (d) Athens (ATH) taxi-out and takeoff, (e) Luton (LTN) landing and taxi-in, (f) map for ATH-LTN flight FR7806 (g) Toronto (YYZ) taxi-out and takeoff, (h) Calgary landing and taxi-in, and landing (i) map for YYZ-YYC flight TS682 [1].	67

LIST OF FIGURES

3.4	The graphs of power usage against time for the multiple systems during very long ground operations.[2, 3, 4, 5] (a) Longest outbound cycle with respective main engines warmup. (b) Longest inbound with respective main engines cooldown. (c) Longest outbound cycle without warmup (d) Longest inbound cycle without cooldown.	69
3.5	Scaling and optimization of the landing gear drive system. (a) Optimization algorithm, (b) Combined efficiency of electric machines, power converters and drivetrain, (c) gear ratio optimization for taxiing, (d) gear ratio optimization for landing and takeoff.	71
3.6	ICE usage during ground and transition phases of mission.	74
3.7	Fuel saving simulation results for technology level from 2022. Negative values indicate the excessive fuel consumed due to weight penalty. The first row assumes that all battery modules are present whereas the second row reflects the module removal for shorter taxiing cycles (indicated by the dashed lines) . The landing gear drive system was benchmarked with: (a,d) Twin-engine taxiing (TET), (b,e) Single-engine taxiing (SET) , (c,f) EGTS and tugs.	80
3.8	Simulation results of fuel and energy saving for future technology. Negative values indicate the excessive fuel consumed due to weight penalty. (a) 2030 performance metrics against single-engine taxiing (SET), (b) 2040 performance metrics against SET, (c) 2050 performance metrics against SET, (d) 2050 performance metrics combined with the neglected warmup and cooldown cycles against SET, (e) 2050 performance metrics combined with the battery weight, warmup and cooldown cycles neglected. (f) Energy recovery during W65002 landing for present and future performance metrics.	84
4.1	SPCrane optimization flowchart and its description in context of the Mixture of Ensembles of Experts (MOEOE)	96
4.2	Combination of the Mixture of Experts (MOE) logic and the SPCrane ensemble of surrogates modelling technique. (a) demonstration of single-dimensional problem with three clusters visible and (b), fitness curve for each model	113
4.3	Cantilever beam function-based boxplots for sample size n=100 showing the performance metrics for the Gaussian Process Regression models, including: (a) MAE, (b) RMSE, (c) MAPE and (d) R^2	115
4.4	Cantilever beam function-based boxplots for sample size n=100 showing the performance metrics for the low-computational cost models models, including: (a) MAE, (b) RMSE, (c) MAPE and (d) R^2	116
4.5	Design variables for mechanical-thermal optimization of the automotive friction brake: x_1 (outer diameter), x_2 (inner diameter), x_3 (thickness) [6].	118

4.6	Boundary conditions and sample results for (a,b) thermal and (c,d) structural optimization [6]	120
4.7	Surrogate modelling and ensembling results for the mechanical-thermal friction brake optimization dataset; (a) one-dimensional disc thickness feature optimization vs peak temperature target, (b) two-dimensional surrogate R2 performance, (c) two-dimensional surrogate RMSE, (d) three-dimensional models R2 performance, (e) three-dimensional models RMSE performance	121
4.8	SPCrane sigmoid-based approach demonstrating how the offset would be calculated based on error metrics for competing surrogate models across the parameter space.	126
4.9	Operational workflow of the SPCrane framework implementing the Mixture of Ensembles of Experts (MOEOE) methodology. The top section illustrates the high-level process from clustering through local expert training (SP1-CRANE) to final recombination using the Surrogate Modeling Toolbox. The detailed implementation of SP1-CRANE is shown in the lower section, demonstrating the complete surrogate ensemble construction process from initialization to output generation.	130
5.1	Design requirements formulation for electric machine: Airbus (a) and Boeing (b) autobrake panels together with given deceleration rates, (c) example runway lengths in Europe, (d) example runway lengths in the US and (e) drive cycles for both landing and taxiing.	139
5.2	Electric machine for the landing gear drive system; (a) demonstrator of assembled electric machine, (b) volumetric constraints associated with a short-haul aircraft landing gear.	142
5.3	Optimization algorithm for the present work, including the optimization objectives, variables, validation and correction factor.	145
5.4	Electromagnetic FEA for the proposed electric machine: (a) quasi 3D and (b) 3D model magnetic flux paths and distribution of flux density; intermittent lines indicate the symmetry planes, (c) validation according to flux linkage, (d) Performance benchmark of all iterations showing the peak current density against the torque density.	149
5.5	Magnetic flux density for nine steps of quasi 3D transient simulation at 1000 rpm.	152
5.6	Thermal modelling of the electric machine: (a) Example short-haul flights that potentially permit cruise altitude cooling, (b) thermal simulation geometry initialization, (c) temperature shaded results for the highest current density simulated in Simcenter MAGNET Thermal, (d) Plot of temperature of winding against the current density at 15s, 20s, 25s, and 30s.	154

LIST OF FIGURES

5.7	Hybrid electromagnetic-friction brake demonstrator: (a) 2x3 design configuration, (b) 1x6 hybrid design configuration, (c) shear pin concept and (d) autobrake settings	159
5.8	Preliminary material benchmark featuring conventional brake and magnetic materials: (a) Fracture toughness vs compressive strength, (b) Tensile strength vs Young's modulus, (c) Thermal conductivity vs specific heat capacity and (d) Hardness-Vickers vs density	162
5.9	Dynamic compression testing of Nd ₂ Fe ₁₄ B [[7, 8], C/C [9] and C/SiC [10] materials at varying strain rates	165
5.10	Nd ₂ Fe ₁₄ B and 49Co49Fe2V characteristics at elevated temperatures: (a) specific heat capacity of Nd ₂ Fe ₁₄ B [11], (b) 49Co49Fe2V's Young's modulus [12], (c) 49Co49Fe2V yield strength [12] (c) tensile testing at 0.83 %/min strain rate of 49Co49Fe2V [12] and (d) tensile testing at 5%/min strain rate of 49Co49Fe2V [12]	166
5.11	Loads applied to the stator's core during friction braking: (a) compressive load exerted by hydraulic cylinders and (b) compressive load at the contact with housing.	168
5.12	lumped-parameter thermal network for the single stator and the single PM: (a) sketch of the network, (b) temperature gradient between the first two nodes in the PM, (c) temperature of the first node in the PM during landing, (d) temperature gradient between the first two nodes in the core and (e) temperature of the first core's node during landing.	171
5.13	Laboratory instruments used for thermal characterization of NdFeB and FeCoV: (a)TA Instruments; DLF 1200; THERMMAT (b) TA Instruments; DSC 2500; THERMMAT, (c) Netzsch; LFA 427; AMRL and (d) TA Instruments; TMA 450; THERMMAT	175
5.14	Samples used in thermal characterization: (a) the DSC pan filled with NdFeB sample, (b) LFA samples and the tray allowing to test three samples at once (c) the TMA sample made of stacked FeCoV sheets, (d) the TMA sample of NdFeB materials and (e) the stack FeCoV sheets for the LFA	177
5.15	The LFA results displaying thermal conductivity for: (a) FeCoV samples and (b) NdFeB samples.	178
5.16	The DSC results displaying specific heat capacity for: (a) FeCoV samples and (b) NdFeB samples	181
5.17	The TMA results displaying coefficient of thermal expansion as a function of temperature for: (a) FeCoV samples and (b) NdFeB samples.	182
5.18	Servohydraulic machinery used during the mechanical characterization with environmental chambers fitted: (a) Instron 5959 50 kN and (b) Instron 8801 100 kN	184

5.19	Design of the jigs enabling compressive testing of the materials according to ASTM E209-18: (a) ISO view of the assembly, (b) exploded and annotated view of the assembly and (c) the picture of manufactured and assembled parts.	185
5.20	Video extensometer measurement system: (a) the annotated view of Instron 5959 pointing the video extensometer, environmental chamber and sample fixtures, (b) the speckled compression sample inside the jigs, (c) the speckled tensile sample, (d) the speckled compression NdFeB sample and (e) video extensometer interface in the GUI. . . .	187
5.21	Stress vs strain of the NdFeB samples at elevated temperature. The strength of material remained constant over the temperature envelope, the stiffness reduced as temperature risen.	188
5.22	Stress vs strain curves (a) of the NdFeB samples at elevated temperature. (b) FeCoV samples; the strength of material remained constant over the temperature envelope, the stiffness reduced as temperature risen.	189
5.23	The macrograph illustrating the type of fracture for (a) FeCoV at room temperature, (b) FeCoV at 200 degree Celsius, (c) NdFeB at room temperature and (d) NdFeB at 200 degree Celsius.	190
5.24	The 49Fe49Co2V samples after characterization showing (a) smooth surface prior to characterization, (b) the grain structure on the surface nevertheless, no necking at the fracture and (c) buckling mode in the compressive testing.	191
5.25	Revised fuel savings results for the Landing Gear Drive System that substitutes the friction brakes completely.	193
5.26	Revised lumped thermal network based on experimental data for Fe-CoV and NdFeB materials: (a) the temperature gradient between first and second node of the PM, (b) the temperature rise in the first node of the PM, (c) the temperature gradient between first and the second node of the stator and (d) the temperature rise in the first node of the stator.	195
F.1	Environmental Chamber Temperature control (a) Default thermocouple, (b) backup thermocouple	246
G.1	Environmental Chamber Temperature control (a) Default thermocouple, (b) backup thermocouple	249
H.1	FeCoV procurement drawings for external communication with LCD LaserCut AG	252
I.1	Drawing of the part A01	254
I.2	Drawing of the part B01	255
I.3	Drawing of the part B02	256

LIST OF FIGURES

I.4	Drawing of the part B03	257
I.5	Drawing of the part C01	258
I.6	Drawing of the part C02	259
I.7	Drawing of the part C03	260
I.8	AISI 316L Material Certificate from Xometry	261
I.9	AISI 316L Material Certificate from MetalCube	262
J.1	Lumped Thermal Network: MATLAB/Simulink implementation	264
K.1	Ethical Approval letter	266

List of Tables

2.1	Experimental rolling resistance coefficient for Boeing 737 tyres [13] . .	22
2.2	Aircraft parameters used as initial conditions in dynamic simulation, nominal landing distance provided for reference [14, 15, 16, 17, 18] . .	23
2.3	Moments of inertia of each subsystem	33
2.4	Simulation results for aircraft ranging from Airbus A318 to A380	41
3.1	Dynamic and fuel saving simulation initialization parameters for the narrowbody aircraft.	64
3.2	System-level performance metrics.	72
3.3	Simulation results for the ground movement data of three different mis- sions	79
4.1	Performance assessment for two-dimensional cantilever beam function.	109
4.2	SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Rosenbrock function compared against the single surrogate models.	110
4.3	SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Branin function compared against the single surro- gate models.	110
4.4	SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Sphere function compared against the single surro- gate models.	111
4.5	SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Tensor Product function compared against the single surrogate models.	112
5.1	Reference distances from quick references handbook for both, an A320 [19] and B737-800 [20].	137
5.2	Braking modes for both proposed design configurations	160
5.3	Properties comparison between the magnetic materials and the con- ventional brake unit materials	163
5.4	Heatsink material available per single friction gap	169
5.5	Unknown properties and the corresponding characterization process .	173

LIST OF TABLES

G.1	FeCoV testing procedure	248
G.2	NdFeB testing procedure	250
H.1	Bill of Materials: LCD LaserCut AG procurement	251

Abbreviations

AMSL	Above Mean Sea Level
APU	Auxiliary Power Unit
CAD	Computer-Aided Design
DSC	Differential Scanning Calorimetry
ECS	Environmental control system
EDS	Electric drive system
EGTS	Electric green taxi system
EMF	Electromotive Force
EoS	Ensemble of Surrogates
ETOPS	Extended-range twin-engine operations performance standards
ETS	Electric taxi system
FEA	Finite Element Analysis
FOD	Foreign object damage
GATOR	Gear assisted takeoff run
GEKPLS	Gradient-Enhanced KPLS
GENN	Gradient-Enhanced Neural Networks
GPR	Gaussian Process Regression

LIST OF TABLES

GPX	Rust implementation of KRG and KPLS
HW	Headwind
ICAO	International Civil Aviation Organization
ICE	Internal combustion engine
IDW	Inverse Distance Weighting
ISA	International Standard Atmosphere
KERS	Kinetic energy recovery system
KPLS	Kriging with Partial Least Squares
KPLSK	Enhanced version of KPLS with optimization in original space
KRG	Kriging
LFA	Laser Flash Analysis
LHS	Latin Hypercube Sampling
LOOCV	Leave-One-Out Cross-Validation
LS	Least Squares
LSE	Least Squares Estimator
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MEA	More Electric Aircraft
MGP	Model with Bayesian perspective on GPR

MLG	Main landing gear
MOE	Mixture of Experts
MOEOE	Mixture of Ensemble of Experts
MoES	Mixture of Ensemble of Surrogates
MSE	Mean Squared Error
NACA	National Advisory Committee for Aeronautics
NLG	Nose landing gear
OLD	Operational Landing Distance
OTL-PEM	Optimization-based Two-Layer Pointwise Ensemble of surrogate Models
PM	Permanent Magnet
POEM	Pointwise-optimal Ensemble of Surrogate Models
PyDoE	Python Design of Experiments
RBF	Radial Basis Functions
REF DIST	Reference Distance
RMS	Root Mean Square
RMSE	Root Mean Squared Error
RMTB	RMTS with B-splines
RMTC	RMTS with Cubic Hermite splines

LIST OF TABLES

RMTS	Recursive Multi-Tensor Splines
R	Coefficient of Determination
SET	Single-engine taxi
SGP	Sparse approximation of GPR
SMT	Surrogate Modeling Toolbox
SP1	Acar's first pointwise weighing approach (spatial)
SP2	Acar's second pointwise weighing approach
SPCrane	Novel surrogate pointwise ensemble algorithm
SVR	Support Vector Regression
TMA	Thermomechanical Analyzer
TW	Tailwind
YASA	Yokeless and Segmented Armature

Nomenclature

ω_{em}	Angular velocity of electric machine.
ρ	Density of air.
A_s	Specific electric loading.
A	Reference area for drag equation; A320 wing area.
B_g	Air gap flux density.
B_r	Residual flux density of PMs.
C_φ	PM concentration factor.
C_d	Coefficient of drag.
C_{rr}	Coefficient of rolling resistance.
D_o	Outer diameter.
E_{dem}	Total energy demand of MEA for ground operations.
E_d	Energy transfer balance for drag.
E_{em}	Energy transfer balance for the landing gear drive system.
E_{met}	Energy transfer balance for main engines thrust.
E_{rr}	Energy transfer balance for rolling resistance.
E_{sds}	Energy transfer balance for the standard deceleration systems.
E	Energy transfer balance.
FC_{APU}	Average fuel consumption of auxiliary power unit per time unit.
FC_{me}	Average fuel consumption of single main engine per time unit.
FC_{pp}	In-flight fuel consumption per kilogram of payload-kilometer.

LIST OF TABLES

FP_{EGTS}	Fuel penalty incurred by electric green taxi and tug system ground operation mode.
FP_{oe}	Fuel penalty incurred by single-engine ground operation mode.
FP_{te}	Fuel penalty incurred by twin-engine ground operation mode.
FS_{EGTS}	Net fuel saving of landing gear drive system against electric green taxi and tug systems.
FS_{oe}	Net fuel saving of landing gear drive system against single-engine taxi.
FS_{te}	Net fuel saving of landing gear drive system against twin-engine taxi.
FU_{cd}	Fuel consumed during cooldown of main engines only.
FU_{iEGTS}	Fuel consumed during inbound electric green taxi or tug systems taxi.
FU_{ioe}	Fuel consumed during inbound single-engine taxi.
FU_{ite}	Fuel consumed during inbound twin-engine taxi.
FU_{oEGTS}	Fuel consumed during outbound electric green taxi or tug systems taxi.
FU_{ooe}	Fuel consumed during outbound single-engine taxi.
FU_{ote}	Fuel consumed during outbound twin-engine taxi.
FU_{toff}	Fuel saving during takeoff.
FU_{wup}	Fuel consumed during warmup of main engines only.
F_d	Force applied to longitudinal aircraft model due to drag.
F_{em}	Force applied to longitudinal aircraft model due to landing gear drive system.

F_{met}	Force applied to longitudinal aircraft model due to main engines thrust.
F_{rr}	Force applied to longitudinal aircraft model due to rolling resistance.
F_{sds}	Force applied to longitudinal aircraft model due to standard deceleration systems.
F	Force applied to longitudinal aircraft model.
$I_k(x)$	Function derived from inverse squared distance.
KE_{ac}	Kinetic energy of aircraft longitudinal body.
K_{met}	Proportional gain of main engines thrust.
K_{pem}	Proportional gain of landing gear drive system controller.
K_{sds}	Proportional gain of standard deceleration systems controller.
N_M	Number of metamodels.
P_{dem}	Power demand (0.96 MW).
P_{dem}	Peak power of landing gear drive system .
P_{out}	Power output.
R_{txi}	Taxiing-in proportion to overall taxiing time.
R_{txo}	Taxiing-out proportion to overall taxiing time.
SE_{bat}	Specific energy of battery at given battery technology level.
SP_{dr}	Specific power of drivetrain at given technology level .
SP_{em}	Specific power of electric machines at given technology level .
SP_{pcon}	Specific power of power converter at given technology level.

LIST OF TABLES

S_f	Flight distance.
TSFC	Thrust specific fuel consumption for static conditions.
T_{em}	Torque produced by electric machine.
T_{em}	Torque produced by electric machine.
$W_i(x)$	Unnormalized weight for metamodel i.
W_{APU}	Weight of auxiliary power unit and corresponding components.
W_{EGTS}	Weight of electric green taxi system and corresponding components.
W_{bat}	Total weight of battery of landing gear drive system.
W_{ik}	Weight factor for metamodel i at data point k.
W_{pow}	Total weight of powetrain and electric machines.
W_{tot}	Total weight of landing gear drive system.
$\cos \varphi$	Generator power factor.
η_s	Efficiency.
$\hat{y}_i(k)$	Predicted value by metamodel i at data point k.
$\hat{y}_{ens}(x)$	Ensemble surrogate model prediction.
μ_r	Recoil permeability.
$c_i(x)$	Correction terms for weights.
$d_k(x)$	Distance between prediction point and k-th data point.
e_{ik}	Cross-validation error for metamodel i at data point k.
f_{sat}	Function of electric machine saturation with respect to maximum torque and power.
g	gravitational acceleration, 9.81m/s^2 .
i_{taxi}	Gear ratio for taxi.
i_{tl}	Gear ratio for takeoff and landing.

i	Gear ratio.
k_d	Aspect ratio of outer diameter to axial length.
k_r	Reluctance factor of the steel path ($1 < k_r \leq 1.2$).
k_{rm}	Reluctance factor for Halbach magnet arrangement.
k_{w1}	Fundamental winding factor.
l_{pm}	PM thickness.
m_a	Mass of aircraft.
n_s	Rotational speed in rev/s.
r_w	Wheel radius of main landing gear.
t_{CD}	Time length of main engines cooldown.
t_{ILAP}	Time length of overlap between auxiliary power unit and main engines in inbound phase.
t_{OLAP}	Time length of overlap between auxiliary power unit and main engines in outbound phase.
t_{PAR}	Time length of post-arrival.
t_{PD}	Time length of pre-departure.
t_{TXI}	Time length of taxi-in.
t_{TXO}	Time length of taxi-out.
t_{WUP}	Time length of main engines warmup.
t	Time.
v_a	Actual ground speed of aircraft in longitudinal frame.
v_{dem}	Aircraft ground speed demand set by drive cycle in longitudinal frame.
v_{dem}	Aircraft ground speed demand set by drive cycle in longitudinal frame.
$w_i(x)$	Weight factors for each metamodel at prediction location.

LIST OF TABLES

$y(k)$	Actual value at data point k .
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Publications

Conferences

Corresponding to Chapter 5; Deja J, Akbari A, Dayyani I, Stote M & Lowther D, “**Energy harvesting frictionless brakes for short-haul aircraft: thermal and electromagnetic feasibility of an axial-flux machine for a landing gear drive system**”, *AIAA 2023-4153 Session: Electrified Aircraft Design & Mission Operation II*, 2023, <https://doi.org/10.2514/6.2023-4153>

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To Be Published

Corresponding to Chapter 4; Deja J, Rogers D, Asif S, Dayyani I, & Skote M, **SPCrane Optimization Framework Relying on Pointwise Ensemble of Surrogates: A Python Implementation**, 2025

Corresponding to Chapter 5; Deja J, Dayyani I, & Skote M, “**Joint Cranfield-Airbus Patent Application**”, 2025

Corresponding to Chapter 5; Deja J, Dayyani I, & Skote M, **Substituting A320 Brakes With Electric Machines for Maximized Impact of Landing Gear Drive System**, 2025

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Chapter 1

Introduction

This thesis presents comprehensive research on advanced technologies for sustainable aviation, focusing on energy recovery systems, electrification of ground operations, and optimization methodologies that collectively address the pressing environmental challenges that the aerospace industry faces. The research contributes novel engineering solutions for kinetic energy recovery during landing, all-electric taxiing capabilities, efficient optimization frameworks, and regenerative electric braking systems that demonstrate significant potential for reducing the environmental impact of commercial aircraft operations. Through a combination of innovative mechanical designs, electrification approaches, and computational methodologies, this work establishes practical pathways toward more sustainable aviation while maintaining operational performance and safety requirements.

1.1 Background and Context

The aviation industry faces mounting pressure to reduce its environmental footprint amid growing concerns about climate change and resource depletion. Commercial aviation accounts for approximately 2.5% of global carbon dioxide emissions, with this figure projected to rise significantly in the coming decades despite efficiency improvements [21]. While long-term solutions like hydrogen and fully electric propulsion continue to develop, there remains a critical need for intermediate technologies that can be implemented within existing aircraft architectures to improve energy efficiency and reduce emissions.

Short-range commercial aircraft present unique opportunities for energy recov-

ery and efficiency improvements due to their operational profiles. These aircraft typically perform multiple flight cycles daily, with a significant portion of operational time spent in ground movements, landings, and takeoffs. During these phases, substantial amounts of energy are currently wasted, particularly during braking operations where kinetic energy is dissipated as heat through conventional friction braking systems.

The concept of More Electric Aircraft (MEA) has gained traction in recent years as a path toward greater efficiency and reduced environmental impact. This approach involves progressively replacing hydraulic and pneumatic systems with electrical alternatives, offering potential benefits in terms of weight reduction, maintenance requirements, and energy efficiency. However, the implementation of MEA concepts faces significant challenges, particularly regarding energy storage limitations and the need to maintain compatibility with existing airport infrastructure.

1.2 Current State of Energy Recovery in Aviation

Traditional commercial aircraft operations involve substantial energy waste, particularly during landing and ground operations. When an aircraft lands, the kinetic energy is typically converted to heat through friction braking, representing a missed opportunity for energy recovery. Similarly, during taxiing operations, aircraft rely on their main engines operating at inefficient low-power settings, consuming significant amounts of fuel while producing disproportionate emissions and noise.

Previous research has explored various approaches to address these inefficiencies, including electric taxiing systems and regenerative braking concepts. Electric taxiing solutions such as the WheelTug system and the EGTS (Electric Green Taxiing System) developed by Safran and Honeywell [22] have demonstrated the potential for fuel savings during ground operations. However, these systems have faced challenges regarding weight penalties, integration complexities, and limitations in energy storage capacity that have hindered widespread adoption.

The concept of energy recovery during landing has received less attention, with most research focusing on military applications through arresting gear systems designed for carrier landings or emergency situations. The adaptation of such systems for commercial aviation with an emphasis on energy recovery represents a relatively unexplored area with significant potential.

1.3 Research Gaps and Opportunities

The identification of research gaps in this study is grounded in a systematic review of recent academic literature, industry white papers, and sustainability roadmaps issued by organizations such as ICAO, EASA, and major aerospace manufacturers. This analysis revealed that although significant progress has been made in electrification and fuel efficiency, several areas related to onboard energy recovery and sustainable ground operations remain underexplored. The selection of focus technologieskinetic energy recovery systems, electric ground propulsion integration, and regenerative brakingwas guided by their high potential impact on fuel savings, feasibility of near-term implementation, and alignment with current certification and retrofit solutions in commercial aviation.

Despite growing interest in sustainable aviation technologies, several critical gaps remain in the current research landscape:

1. Limited exploration of kinetic energy recovery systems for commercial aircraft landings that can effectively capture and repurpose energy otherwise lost as heat.
2. Insufficient integration of electric ground propulsion systems with energy recovery mechanisms to enable truly sustainable ground operations.
3. Inadequate optimization methodologies that can efficiently handle the complex multidisciplinary design challenges associated with integrating novel systems into existing aircraft architectures.

4. Lack of comprehensive approaches to replace conventional aircraft braking systems with regenerative alternatives that maintain safety requirements.

These research gaps were prioritized based on their potential to deliver measurable reductions in emissions and fuel consumption without requiring disruptive redesigns of current aircraft platforms. Collectively, they present opportunities for innovative engineering solutions that can contribute to more sustainable aviation practices. By addressing these challenges through a coordinated research program, there is potential to significantly reduce the environmental impact of aircraft operations while maintaining or improving operational efficiency.

1.4 Research Aim and Objectives

The overarching aim of this thesis is to develop and evaluate novel technologies for improving energy efficiency and sustainability in commercial aviation, with a particular focus on energy recovery systems and electrification strategies for short-range aircraft operations. This aim is pursued through four interconnected research objectives:

1. To design and analyze an arresting gear energy recovery system capable of capturing kinetic energy during aircraft landing and converting it to usable electrical energy
2. To develop and evaluate a landing gear drive system that enables all-electric ground operations for narrow-body aircraft, utilizing recovered energy to eliminate engine use during taxiing
3. To create an advanced optimization framework that facilitates more effective integration and design of complex aerospace systems through improved surrogate modeling techniques

4. To investigate the feasibility of replacing conventional aircraft braking systems with electric machines that provide regenerative braking capabilities while maintaining safety requirements

These objectives address complementary aspects of sustainable aviation technology development, from specific mechanical systems for energy recovery to broader computational frameworks that enable more efficient design optimization. Together, they form a cohesive research program aimed at advancing the state of the art in sustainable aviation technologies.

1.5 Methodological Approach

This research is grounded in a systems engineering approach that recognizes the complex interdependencies between aircraft subsystems and the need for integrated solutions that address multiple aspects of sustainability simultaneously. The research methodology follows a V-model development paradigm, as illustrated in Figure 1, which depicts the progression from high-level conceptual design to detailed implementation and back to system-level evaluation.

The proposed approach to regenerative braking differs fundamentally from previous efforts in both conceptual integration and practical feasibility for aerospace applications. Earlier research in regenerative braking primarily focused on automotive systems, where weight, safety certification, and thermal constraints differ significantly from those in aviation. In contrast, this thesis introduces a unified systems engineering framework that integrates regenerative braking within the aircrafts overall electrification and sustainability architecture.

The V-diagram captures the dual nature of this research: descending from abstract concepts to concrete technical implementation (left side), and then ascending toward broader impact analysis and system integration (right side). Each chapter of this thesis corresponds to a distinct stage of the V-diagram, establishing a direct link between conceptual investigation, detailed implementation, and system-level as-

essment:

- Chapter 2 Conceptual Foundation: Establishes the theoretical basis for regenerative energy recovery through dynamic modeling of the Sustainable Arresting Gear Energy Recovery System. This stage represents the high-level conceptual design phase of the V-diagram, where energy conversion principles and feasibility boundaries were defined.

- Chapter 3 System Implementation: Translates conceptual findings into applied design through development of the Battery-Powered Landing Gear Drive System. This phase focuses on subsystem-level design, simulation of realistic taxi cycles, and gear ratio optimization aligning with the detailed implementation phase of the V-diagram.

- Chapter 4 Computational Integration (Bottom Center and Linking Phase): Serves as the methodological bridge by introducing the SPCrane optimization framework and ensemble surrogate modeling. This chapter connects top-down design requirements to bottom-up component analyses by enabling efficient optimization across interacting parameters.

- Chapter 5 Component Realization and Validation (Lower Right Quadrant): Applies the developed methods to the design of the Electric Machine Braking System. This corresponds to the technical realization stage, integrating electromagnetic-thermal co-design, material characterization, and validation of regenerative braking feasibility.

- Chapter 5 continued. System Evaluation and Sustainability Integration (Upper Right Quadrant): Synthesizes outcomes from all lower-level studies to evaluate environmental, operational, and economic impacts. This stage completes the upward path of the V-diagram by translating technical detail into system-level sustainability insights and practical integration strategies.

This explicit alignment ensures that each research stage contributes coherently to the overarching systems engineering framework, maintaining methodological traceability across abstraction levels.

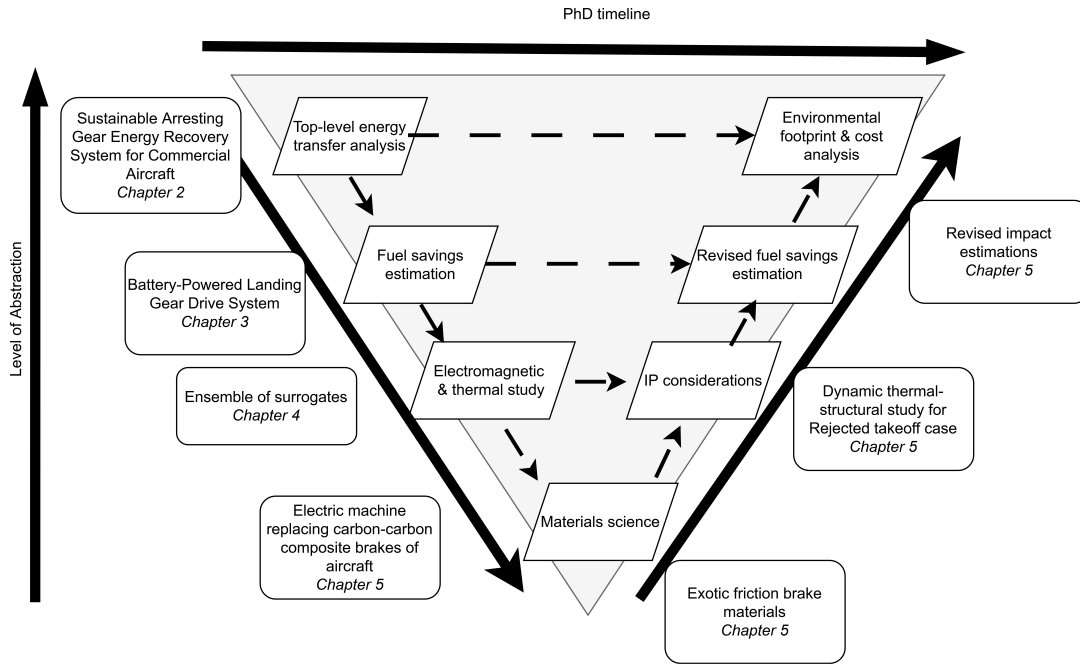


Figure 1.1: V-diagram explaining progress of the PhD in relation to the abstraction level of each topic.

1.5.1 Energy Conversion and Recovery Principles

The energy recovery systems developed in this thesis are based on the fundamental principle of energy conservation, with a focus on converting kinetic energy that would otherwise be dissipated as heat into usable electrical energy. As shown in the upper left quadrant of the V-diagram, this research began with top-level energy transfer analysis for the Sustainable Arresting Gear Energy Recovery System (Chapter 2). This conceptual framework established the theoretical foundation for subsequent developments, addressing mechanical coupling mechanisms, generator dynamics, and electrical storage considerations. The theoretical models developed account for energy losses at each conversion stage, providing realistic assessments of system efficiency and performance that later informed the environmental footprint and cost analyses shown on the right side of the V-diagram.

1.5.2 Electromechanical Systems Design

The design of electrified landing gear and braking systems draws upon advanced concepts in electric machine design, power electronics, and mechanical integration. Following the V-diagram progression, the research moved from initial fuel savings estimation to detailed electromagnetic and thermal studies. The Battery-Powered Landing Gear Drive System (Chapter 3) and electric machine braking system (Chapter 5) represent the application of these principles to specific aircraft subsystems. The research applies electromagnetic-thermal co-design approaches to develop high-performance electric machines suitable for aerospace applications, addressing the unique constraints of aircraft integration including weight limitations, thermal management challenges, and safety requirements. These detailed investigations later supported the revised fuel savings estimations and dynamic thermal-structural studies for rejected takeoff scenarios shown on the ascending side of the V-diagram.

1.5.3 Optimization Theory and Surrogate Modeling

The computational frameworks developed in this research build upon advanced concepts in optimization theory, particularly surrogate modeling techniques that enable efficient exploration of complex design spaces. As illustrated in the V-diagram, the Ensemble of Surrogates approach (Chapter 4) bridges higher-level fuel savings estimation and detailed electromagnetic studies by providing efficient optimization methodologies. The theoretical foundation includes pointwise ensemble methodologies, adaptive weighting schemes, and space-filling experimental design approaches that collectively enhance the robustness and accuracy of optimization processes for aerospace applications. This methodological contribution supports both detailed materials science investigations and intellectual property considerations shown on the right side of the V-diagram.

1.5.4 Methodological Approaches

The methodological structure of this research follows the V-model framework, guiding a progressive refinement from conceptual analysis to detailed technical investigation and, finally, system-level assessment. Rather than treating energy recovery, system design, and optimization as isolated studies, this approach integrates them into a continuous process linking theory to implementation.

The descending phase of the V-diagram addresses the analytical and modeling foundations of energy conversion, electromechanical integration, and surrogate-based optimization. During this stage, parametric models and co-design techniques established the theoretical and computational tools needed to evaluate feasibility and performance under realistic aircraft constraints.

At the ascending stage, these results were synthesized into system-level analyses that assessed environmental, economic, and operational impacts. This included integration of component-level results into broader sustainability metrics, evaluation of safety and regulatory compliance, and examination of potential intellectual property.

By structuring the research according to the V-model, each stage informed the next from conceptual principles to validated applications ensuring coherence between detailed technical insights and strategic sustainability objectives.

1.6 Overview of Research Contributions

This thesis makes several significant contributions to the field of sustainable aviation technologies, each addressing specific aspects of energy efficiency and environmental impact reduction.

1.6.1 Sustainable Arresting Gear Energy Recovery System

The first major contribution is the development of a novel arresting gear energy recovery system for commercial aircraft landings. This system couples traditional

arresting gear mechanisms with electrical generators to convert kinetic energy into electrical energy rather than dissipating it as heat. Key innovations include:

- A scalable design applicable to aircraft sizes ranging from Airbus A319 to A380
- A force-based dynamic model incorporating energy dissipation factors such as drag and rolling resistance
- An optimization approach achieving approximately 60% energy conversion efficiency
- Analysis demonstrating potential generation of 17 GWh of electrical energy annually at an airport like Heathrow

This research demonstrates that significant energy recovery is possible during aircraft landings, providing a new source of sustainable electrical energy that can be integrated into airport infrastructure or used to power aircraft systems.

1.6.2 Landing Gear Drive System for All-Electric Ground Operations

The second major contribution is the design and evaluation of a landing gear drive system that enables narrow-body aircraft to operate entirely on electric power during ground movements. This system addresses a critical gap in sustainable airport operations by eliminating the need for engine use during taxiing. Key innovations include:

- Integration of regenerative braking during landing to maximize energy efficiency
- Battery storage system capable of supporting up to 26 minutes of all-electric taxi operations
- Optimization of two-speed gear ratios to maximize performance

- Demonstration of 7% fuel cost reduction for short-haul flights based on current fuel and electricity prices.

This research overcomes a primary obstacle to electrified aircraft operations by demonstrating that the specific energy limitations of batteries can be addressed through efficient system design and energy recovery strategies.

1.6.3 SPCrane Optimization Framework

The third major contribution is the development of the SPCrane framework, a Python-based pointwise ensemble methodology for engineering optimization that supports more efficient design of complex aerospace systems. Key innovations include:

- Correction factors that reduce single-model biases by up to 18.5% in Mean Absolute Error
- A Mixture of Ensemble of Experts architecture that preserves discontinuities in optimization functions

This framework bridges the gap between theoretical ensemble research and practical engineering applications, providing an accessible implementation that enables more effective optimization of computationally expensive design problems in aerospace engineering.

1.6.4 Electric Machine Braking System

The fourth major contribution is the design and analysis of an electric machine braking system to replace conventional friction brakes on commercial aircraft. This system not only provides braking functionality but also enables regenerative energy recovery during deceleration. Key innovations include:

- A multistage yokeless and segmented armature (YASA) topology optimized for aerospace applications

- Electromagnetic-thermal co-design approach accounting for cruise altitude conditions
- Achievement of 120 Nm/kg active material torque density at approximately 50 A/mm RMS current density
- Integration of a mechanical backup system to ensure safety compliance

This research demonstrates the viability of replacing traditional aircraft braking systems with regenerative electric alternatives, further advancing the electrification of aircraft systems and enabling additional energy recovery during landing operations.

1.7 Thesis Structure

This thesis is organized into six chapters that collectively present a comprehensive examination of sustainable aviation technologies focused on energy recovery and system optimization.

This thesis relies on multiple first-authored scientific publications made by the PhD candidate. Thus, unlike traditional thesis formats where a dedicated literature review chapter is presented at the beginning, this work integrates the literature review within the early sections of each chapter. This structure allows the contextual discussion and critical review of previous research to be presented alongside the corresponding technical developments, ensuring clearer continuity between theoretical background and the specific contributions of each chapter.

Chapter 1 (Introduction) establishes the research context, identifies key challenges in sustainable aviation, presents the research objectives, and outlines the thesis structure.

Chapter 2 (Sustainable Arresting Gear Energy Recovery System for Commercial Aircraft) presents the design, analysis, and evaluation of a novel arresting gear system capable of recovering kinetic energy during aircraft landing. The chapter explores

system performance across different aircraft sizes and discusses integration challenges related to grid connection, energy storage, safety, and passenger comfort.

Chapter 3 (More Electric Aircraft Conversion to All-Electric: Landing Gear Drive System) details the development of an electric landing gear drive system that enables all-electric ground operations for narrow-body aircraft. The chapter analyzes system performance under various operational scenarios and quantifies potential fuel savings and environmental benefits.

Chapter 4 (SPCrane Optimization Framework Relying on Pointwise Ensemble of Surrogates) introduces a new computational framework for engineering optimization based on pointwise ensemble surrogate modeling. The chapter presents the theoretical foundations, implementation details, and performance evaluation of the framework across various benchmark problems and engineering applications.

Chapter 5 (Substituting A320 Brakes With Electric Machines for Maximized Impact of Landing Gear Drive System) explores the feasibility of replacing conventional aircraft braking systems with electric machines that provide regenerative capabilities. The chapter details the electromagnetic-thermal co-design process, material selection considerations, and performance evaluation against existing autobrake systems.

Chapter 6 (Conclusion) synthesizes the key findings across all research components, discusses their implications for sustainable aviation, identifies limitations, and suggests directions for future research.

1.8 Significance and Innovation

This thesis presents several significant innovations that collectively advance the state of the art in sustainable aviation technologies:

For the first time, this thesis demonstrates feasibility of large-scale kinetic energy recovery during commercial aircraft landings through arresting gear systems, quantifying potential energy generation and efficiency metrics.

It presents a comprehensive solution for all-electric ground operations that over-

comes battery energy density limitations through efficient system design and energy recovery integration.

It develops a novel optimization framework that enhances the accuracy and robustness of surrogate modeling for complex aerospace system design.

It establishes the viability of regenerative electric braking systems for commercial aircraft that meet performance and safety requirements while enabling additional energy recovery.

These innovations address critical challenges in sustainable aviation from complementary perspectives, providing a comprehensive approach to reducing the environmental impact of aircraft operations. The research has significant implications for aircraft manufacturers, airlines, airports, and regulatory bodies seeking practical solutions toward more sustainable aviation practices.

The Technology Readiness Level (TRL) of the developed concepts varies across the investigated systems. Overall, this research contributes to advancing technologies in the sustainable aviation domain from TRL 1 towards TRL 4.

For the sustainable arresting gear and the landing gear drive system concepts, the conducted studies primarily represent feasibility assessments, supported by analytical modeling and simulation results. These efforts establish the foundational understanding required for subsequent experimental validation, corresponding approximately to TRL 3.

In contrast, the exploration of regenerative electromagnetic braking mechanisms is positioned at an earlier stage, focusing on the observation of material properties and the formulation of a novel application concept. This corresponds to TRL 12, where the primary outcome is proof of principle rather than system-level demonstration.

To progress these concepts toward industrial applicability and certification, future work should prioritize detailed prototyping, comprehensive hardware-in-the-loop testing, and integration trials within representative aircraft systems. Close collaboration with regulatory bodies and industry partners will be essential to align perfor-

mance verification with certification frameworks and operational safety standards.

By focusing on technologies that can be implemented within existing aircraft architectures and airport infrastructure, this research offers retrofitting possibility that can contribute to quicker emissions reduction goals while longer-term transformative technologies continue to develop. The systems-level approach ensures that the proposed solutions address multiple aspects of sustainability simultaneously, maximizing their potential impact on the environmental footprint of commercial aviation.

While this research advances several promising concepts for sustainable aviation, certain limitations must be acknowledged. Due to the time constraints and available resources inherent to doctoral research, the development and validation of the proposed technologies, particularly in the areas of landing gear brake units and aircraft landing procedures have been limited to simulation, preliminary prototyping, and theoretical analysis. Both landing gear systems and landing procedures are crucial for flight safety and are subject to strict regulations and certification standards, which means that moving from research to real-world application will require much more extensive testing and validation.

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Chapter 2

Sustainable Arresting Gear Energy Recovery System for Commercial Aircraft

A significant amount of kinetic energy is dissipated during each commercial aircraft landing. To improve energy efficiency and environmental sustainability, the kinetic energy can instead be converted to electricity by utilizing the arresting gear systems. this chapter presents a novel design that couples an arresting gear system to electrical generators. The results show that the system can successfully recover aircraft kinetic energy and is applicable to different aircraft sizes ranging from Airbus A319 up to A380. Beyond system performance, wider context technical aspects including system integration into grid with multiple energy storage possibilities, safety and passenger comfort are discussed.

2.1 Introduction

A landing aircraft holds a significant amount of kinetic energy due to its mass and velocity. Currently, most of this energy is dissipated as heat whereas, if captured, it can be converted into electrical energy and used for airport operations. Therefore, the requirement is set for an additional deceleration system producing enough power to decelerate an aircraft at standard rate and harvest as much energy as possible during an operation. The military arresting gear technology is proven to work

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

on aircraft carrier decks and in emergency situations but is used only for stopping an aircraft without recovering kinetic energy [23]. The USS Navy aircraft carriers have had the Mark 7 Mod 3 arresting gear system installed [24], which is capable of stopping a fighter jet at a distance of up to 105 m.

An arresting cable is subjected to the toughest operating conditions due to high impact during contact with an arresting hook and dragging on runway. The military system utilizes two types of cables. The 'deck pendant' is a smaller diameter steel wire rope which catches the arresting hook while the 'purchase cable' is a bigger diameter rope and is used to translate the force from deck pendant to arresting engine. Alternatively to steel wire ropes, the BAK-12 military arresting gear system utilizes tape in place of the 'purchase cable' [25].

This section proposes a similar system to that used in the military, but one augmented with powerful motor-generators to enable the production of electricity. The large power generator applications include hydroelectric and wind turbines. The largest dam on earth, Three Gorges Dam, utilizes the electric machines capable of producing 700 MW rated power each [26]. One of the largest offshore wind turbines, Vestas V236, has a rated power equal to 15 MW [27]. Commercial aircraft vary by size depending on the application but the rated power of hydropower generator is much greater than that needed to stop even the largest aircraft, Antonov AN-225, at a standard landing distance. The demonstrator design incorporates a gear reducer which is used for energy efficiency optimization. A dynamic model was used to simulate the energy transfer between the system and the airline aircraft. The results allow for investigation of the forces acting during operation and estimation of the electrical energy produced from each landing.

2.2 Standard Landing Procedure Review

Implementation of the new system requires an understanding of standard landing procedure for all aircraft that are involved in an arresting process. The system

proposed in this chapter suits various commercial aircraft sizes, from Airbus A319 to Airbus A380. The stopping distance and deceleration are safety critical parameters due to runway excursion risk and additionally, severe deceleration may cause passenger and flight personnel discomfort. Hence, the objective has been set to maintain similar values to those during a normal landing. Rustenburg et al. [14] gathered telemetric data for Airbus A320 with a statistical sample equal to 10066 flights where landing gross mass varied between 47 and 65 metric tons and touchdown airspeed remained in the envelope between 56 and 78 m/s. The maximum velocity during a touchdown is limited by the tyre certification. An overhaul specialist company, RotableRepairs [28], stated that maximum Airbus A320 tyre speed equals approximately 100 m/s. Aircraft braking during a landing roll is nonlinear and dependent on multiple parameters. The highest deceleration value occurs when the thrust reverses are engaged and equals on average to 1.962 and 5.40 m/s² maximum [14]. Airbus A320 Flight Crew Operating Manual [29] provides the stopping distance values between 679 and 4742 m. The exact value is influenced by aircraft gross weight, airfield elevation as well as wind and weather conditions. Furthermore, Airbus Aircraft Characteristics for Airport and Maintenance Planning [15, 16] provide dry runway condition airfield length ranging from 914 m for Airbus A319-100 to 2700 m for Airbus A380-800.

The total kinetic energy of aircraft during landing roll available to recover is given by:

$$\Sigma KE = \frac{1}{2}mv^2 + \Sigma \frac{1}{2}I\omega^2 \quad (2.1)$$

where m is the mass of the aircraft, v is the resultant ground speed of an aircraft, I is the moment of inertia and ω is the angular velocity of landing gear rotary components. During a landing roll, the aircraft is continuously subjected to drag which can be divided into parasitic and induced drag. Induced drag is assumed to be negligible

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

whereas parasitic drag equation formula is given as:

$$F_D(t) = C_D \times A \times \frac{\rho v_a(t)^2}{2} \quad (2.2)$$

where F_D is the drag force, C_D is the drag coefficient, A is the reference area, ρ is the air density and v_a is the relative airspeed. The drag coefficient values are sourced from Sun et al. [30] who developed a stochastic hierarchical model in order to provide aerodynamic coefficients reflecting landing gear and flaps extension for multiple aircraft.

The rolling resistance has been modelled as:

$$F_{rr}(v) = \mu(v) \times mg \quad (2.3)$$

where F_{rr} is a force acting opposite to aircraft moving direction, μ is a coefficient of rolling resistance, m is an aircraft mass and g is a gravitational acceleration. Yager et al. [13] gathered experimental data for 40x14-19 tyres dedicated to similar aircraft such as Boeing 737. Table 2.1 shows μ values which were captured at 2.6, 51.4 and 82.3 m/s.

Table 2.1: *Experimental rolling resistance coefficient for Boeing 737 tyres [13]*

Velocity [m/s]	Rolling resistance coefficient
3	0.01
51	0.014
82	0.025

The rolling resistance coefficient values were used as breakpoints that were later linearly interpolated to match exact aircraft velocity at given time increment.

None of the landings are exactly the same due to varying aircraft landing gross weight and ground speed during touchdown. An aircraft manufacturer always pro-

2.2. STANDARD LANDING PROCEDURE REVIEW

vides the acceptable range for the landing parameters. Table 2 shows the exact initialization parameters values used in simulation iterations, which are in the standard landing procedure interval.

Table 2.2: Aircraft parameters used as initial conditions in dynamic simulation, nominal landing distance provided for reference [14, 15, 16, 17, 18]

Airbus aircraft for reference	Landing Gross Weight (metric tons)	Approximate total wing area (m ²) [31, 32]	Drag Coefficient	Arresting Ground Speed ($\frac{m}{s}$)	Landing Distance (sea-level, International Standard Atmosphere) (m)
A318	57	122.4	0.116	68 for all	1200
A319	61	122.4	0.116		1300
A320	64.5	122.4	0.12		1400
A321	77.8	122.4	0.133		1600
A332	180	362	0.118		1800
A333	182	362	0.12		1800
A340	192	430	0.12		1900
A350	205	440	0.12		1900
A359	233	443	0.12		1900
A380	386	845	0.104		2200

2.3 Idealized Arresting Gear Cable System

The proposed design is fitted onto a runway with footprint dimensions similar to London Heathrow southern runway [33]. The arresting process visualization, and winding drum assembly cross-section view are available in Figure 2.1.

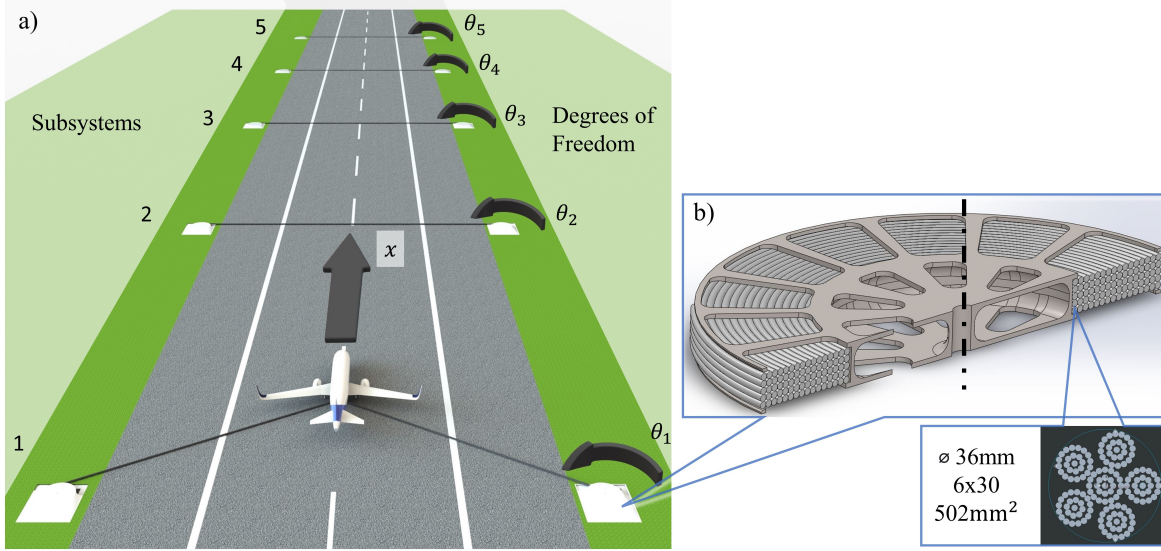


Figure 2.1: Arresting gear system demonstration showing arresting process, cross-section of underground installation and related degrees of freedom used in dynamic simulation. a) Arresting process graphic demonstrator b) Winding drum and steel wire rope cross-section

Unlike military applications where a single cable is used for the short distance landing on a flight deck, the landing of civil aircraft at the size of the Airbus A380 and standard deceleration and distance requires the sequential cables coupled to generators. Figure 2.1(a) shows that the whole arresting gear system fitted on the runway consists of five arresting cables where each is wound onto two drums located at each side of the runway. When the aircraft rolls over a cable, the arresting hook catches it and pulls the winding drum inducing a generator rotor angular motion. As soon as the aircraft passes 30 m distance from the arresting point, a generator control system applies counteracting torque that slows down the aircraft.

A critical distinction exists between military carrier arresting systems and the proposed arresting gear system designed for commercial aircraft application, primarily

2.3. IDEALIZED ARRESTING GEAR CABLE SYSTEM

driven by their differing operational requirements and constraints. Military arresting systems, such as the Mark 7 Mod 3 installed on aircraft carriers, are engineered to rapidly decelerate fighter jets within very short distances typically under 110 meters resulting in extremely high deceleration forces often exceeding 23 g. These systems dissipate the aircraft's kinetic energy mainly as heat through hydraulic or frictional means, focusing solely on abrupt stopping capability to accommodate the limited deck space and emergency nature of carrier operations. Passenger comfort is not a consideration due to the small crew size and the mission-specific environment.

In contrast, the commercial arresting gear system proposed here addresses the need for safe and efficient deceleration of large commercial aircraft over significantly longer distances on the order of 1 to 2.5 kilometers while enabling the recovery of kinetic energy as electrical power. The dynamic behavior of this system involves controlled deceleration rates aligned with standard landing procedures (approximately 1.2 to 2.8 m / s²) to prioritize passenger comfort and structural integrity. Unlike military systems, the proposed design integrates multiple sequential arresting cables coupled with motor-generators, allowing energy conversion with typical system efficiencies around 44 to 62%. Additionally, commercial aircraft retain conventional deceleration methods, providing redundancy and enhanced safety margins. The arresting system thus acts as a supplementary deceleration device rather than the sole means of stopping, incorporating features such as rapid hook release to mitigate emergency situations, differentiating its dynamic response from military systems fundamentally.

The selection of pulley (sheave) configurations and their quantities in the proposed arresting gear system conceptual layout is driven by several engineering requirements to balance mechanical strength, cable durability, system efficiency, and operational safety. Each arresting cable is wound onto a pair of winding drums located on either side of the runway, with the number of arresting subsystems increasing with aircraft size from three for smaller aircraft like the Airbus A320 to five for the largest, the A380. The cables are routed via pulleys sized with diameters at least

40 times greater than the cable diameter to minimize bending stresses and preserve cable mechanical strength, as bending on smaller sheaves significantly degrades wire rope integrity. Thus, the minimum sheave diameter is set to 1440 mm, matching guidelines to maintain approximately 95% of the cable's nominal strength under repeated bending loads.

Most components remain underground to maximize safety in case of runway excursion by allowing aircraft to roll over the enclosure without any damage. The system protrudes above soil by less than one meter and the safety enclosure separates the wheels from all the sharp components. The detailed cross-section view of each subsystem presenting the components under enclosure is available in Appendix A.

2.3.1 Arresting Gear Cable

Knowing that the Mark 7 Mod 3 system was suited for the F-14D Tomcat [24], it is possible to estimate how much force was applied to the cable. The aircraft maximum allowable gross landing weight equals approximately 20 metric tonnes and short-field landing maximum speed equals to 82 m/s [34]. Assuming linear deceleration, the cable in the Mark 7 Mod 3 arresting system is subjected to a force described by the following kinematic equation:

$$F_{\text{rope}} = m \times \frac{v^2 - u^2}{2s} \quad (2.4)$$

where m is mass of aircraft, v is initial velocity, u is final velocity and s is a path travelled. After substituting variables with values for the F-14D Tomcat, there is 640 kN tension applied to the cable.

Each winding drum can allocate up to 500 m of arresting cable raising the concern about corresponding mass and moment of inertia. Approximate mass for 36 mm diameter steel wire rope used in Mark 7 Mod 3 was estimated at 5.3 kg/m [35]. In dynamic model, the cable acts as a spring and its cross-sectional area and length affects spring stiffness. As presented in Figure 2.1 (b), the cross-section area esti-

2.3. IDEALIZED ARRESTING GEAR CABLE SYSTEM

mate has been made in CAD software and is equal to 502.55 mm^2 for 6x30, 36 mm diameter steel wire rope. The detailed arresting cable parameters are available in Appendix B. The steel wire rope loses its mechanical strength when bent. Group [36] provided data where they state that bending a rope on sheave with diameter 40 times greater than a rope diameter results in 95% of nominal rope strength. Hence, the minimum diameter for all sheaves and winding drums used in the proposed system is equal to 1440 mm.

The energy recovery requirements of the proposed arresting gear system are fundamentally based on achieving deceleration rates that align with standard commercial aircraft landing procedures while maximizing the capture of kinetic energy. Typical deceleration rates for large commercial aircraft, such as the Airbus A380, range between 1.2 and 2.8 m/s, corresponding to smooth and safe stopping distances usually exceeding 1 km. The kinetic energy available for recovery during landing is directly proportional to the aircraft's mass and the square of its landing speed, as expressed by the classical kinetic energy relation. For simulation and design, assumptions regarding the distribution of landing weights have been made based on certified aircraft maximum landing weights and statistical telemetric data from actual landing operations, ranging from minimum operational weights to maximum landing mass values. This approach provides a realistic envelope capturing the variability in aircraft landing conditions.

Sensitivity analyses demonstrate that variations in actual landing mass significantly affect the total recoverable energy and peak deceleration forces. Heavier aircraft generate proportionally higher kinetic energy but benefit from increased stopping distances and engagement of multiple sequential arresting subsystems, distributing the load and controlling deceleration smoothly. Conversely, lighter aircraft yield lower kinetic energy recovery with potentially higher peak deceleration rates due to lower inertia effects interacting with the system's moment of inertia. The system design accounts for this sensitivity by selecting appropriate generator power ratings and control algorithms that modulate torque to maintain deceleration within

safe limits across the range of expected landing masses. These considerations ensure the system's robustness and adaptability to real-world operational variability, as reflected in the dynamic simulation results.

2.3.2 Coupling Between Aircraft and Winding Drum Subsystem

The arresting process is idealized and consequently limits aircraft motion to only one axis. The aircraft kinematics are described by:

$$\ddot{x}(t) = \frac{\sum \vec{F}(t)}{m} \quad (2.5)$$

where x is the aircraft position, $\sum \vec{F}$ is the resultant force acting in x -axis and m is the mass of aircraft. Similarly, the angular drum kinematics are described by:

$$\ddot{\vartheta}(t) = \frac{\sum \vec{M}(t)}{I} \quad (2.6)$$

where ϑ is the drum angular position, $\sum \vec{M}$ is the resultant momentum and I is the moment of inertia for each sub-system. The dynamic model has six degrees of freedom where the first one is a moving aircraft and the rest are winding drums. Since the model is symmetrical, only one side is considered in simulation with doubled moment of inertia. An arresting cable acts as a spring where the strain is calculated by subtracting a length released from the winding drum from a cable length projection driven by an aircraft position. Figure 2.2 shows the kinematic coupling between the arresting gear system and constrained motion of aircraft. All variables are presented graphically in this figure.

where ω is the angular velocity of winding drum, τ_b is the negative torque due to bearing friction, F_{rope} is the force translated through the cable, F_{ag} is the force projected on the aircraft, V is the aircraft velocity, w is the distance from sheave to centre of runway, w' is the w corrected with tangential point displacement, x is the distance passed by aircraft from arresting point and x' is x corrected with tangential displacement.

2.3. IDEALIZED ARRESTING GEAR CABLE SYSTEM

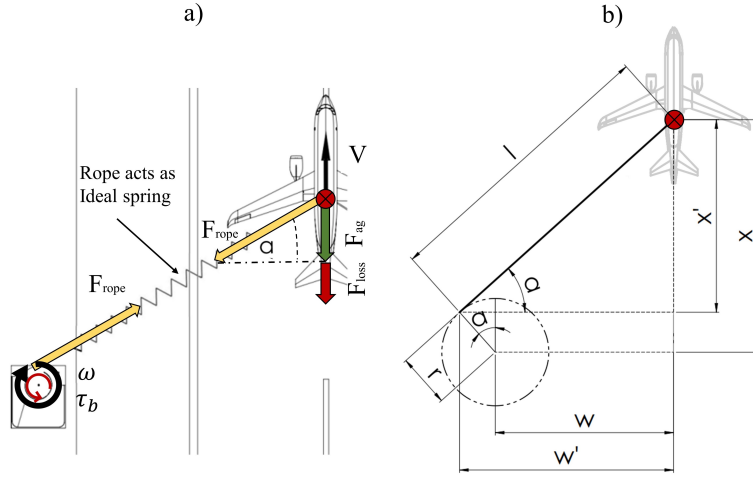


Figure 2.2: Split view between free body diagram and winding drum aircraft coupling kinematics annotated with dimensions

ment, l is the length of free cable, α is the angle between a cable and a runway axis.

Assuming that x and w are known at each time step, $\alpha(t)$ can be found by the following kinematic relations:

$$\begin{cases} w'(t) = w + r \times \sin \alpha(t) \\ x'(t) = x(t) + r \times \cos \alpha(x) \\ \tan \alpha(t) = \frac{x'(t)}{w'(t)} \end{cases} \quad (2.7)$$

The system has multiple real solutions but knowing that $\alpha \in [0, 90^\circ)$, there is only one solution in given quadrant. Thus, the system can be re-written as an angle function of x travel, where the only variable is aircraft travel in x -axis:

$$\alpha(x) = -2 \times \arctan \frac{w - \sqrt{-r^2 + w^2 + (x(t) + r)^2}}{x(t) + 2r} \quad (2.8)$$

Once the angle is known, the distance from winding drum tangential point to aircraft

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

hook can be estimated as:

$$\delta l_a(t) = (w + r \sin \alpha(t)) \times \cos \alpha(t) \quad (2.9)$$

while length of cable released from the sheave described is by:

$$l_r(t) = \sum^t \delta \vartheta(t) \times r(t) \quad (2.10)$$

The spring strain at each time increment is:

$$l_s(t) = \delta l_a(t) - l_r(t) \quad (2.11)$$

Hence, the force can be estimated according to Hooke's law:

$$F(t) = -k(t)x(t) \quad (2.12)$$

where spring constant is derived from Young's Modulus and can be calculated from:

$$k(t) = \frac{\Delta F(t)}{\Delta A} = \frac{EA}{L(t)} \quad (2.13)$$

Coupling the mechanical arresting system to the electrical generator during transient dynamic conditions introduces several engineering challenges that must be carefully addressed to ensure stable and efficient energy transfer. One primary challenge arises from the highly variable and impulsive forces transmitted through the cable as the aircraft engages and decelerates, which create non-smooth torque inputs on the winding drum and subsequently on the generator shaft. These transient loads can induce torsional vibrations and resonance phenomena within the cable-drum-generator assembly, potentially leading to mechanical fatigue or instability in the electrical machine control. Additionally, the moment of inertia mismatch between the generator rotor and the cable system complicates the dynamic response; too

large an inertia can cause excessive peak deceleration forces on the aircraft, while too low an inertia risks generator overspeed or control inaccuracies.

2.3.3 Electric Machines

The system requires powerful generators producing enough torque to slow down an aircraft at a demanded deceleration rate. The peak generator power is required for the heaviest aircraft during the initial arresting stage. Airbus A380 at maximum landing weight is equal to 386 metric tons and rolling at 68 m/s. The aircraft has to decelerate at approximately 1.3 m/s^2 and that power in simplified cases equals to force times velocity, Airbus A380 requires as much as 34 MW of power to slow down at given deceleration rate. There are two generators for each subsystem. Hence, the power required for each generator should be halved and consequently is equal to 17 MW.

The generator was chosen regarding this demand for peak power and also regarding maximum angular velocity which was driven by an aircraft landing speed, a winding drum radius and a gear reduced gear ratio. [37] offers large size industrial motors and provides a datasheet with efficiency for four power loads. Nonetheless, this analysis requires accuracy higher than four power breakpoints while the whole efficiency map is commercially sensitive. Theoretically, each motor can work as a generator with similar performance and therefore, assumption is made that efficiency curve is symmetrical for negative and positive torque. Figure 2.3 shows the efficiency estimates for whole torque and angular velocity envelope. The approximation was made by scaling the values from Kumar [38] and Badain et al. [39]. They provided the motor-generator data for their energy recovery applications.

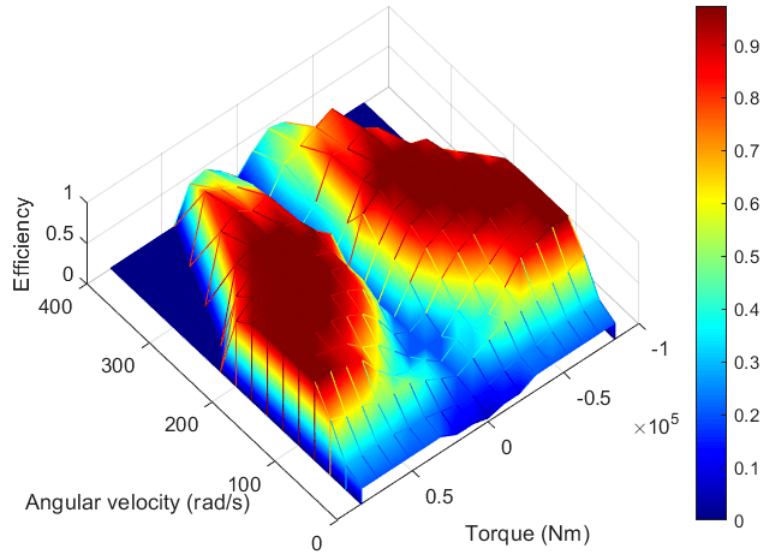


Figure 2.3: Motor-generator efficiency map against different torque and angular velocity values

The parallel gear reducer was selected rather than a right-angled alternative because of the higher efficiency at a price of the greater geometric footprint corresponding to parallel coupling. The off the shelf gearbox that matches the load requirements was found [40]. According to the datasheet, the proposed gear reducer has 97% efficiency. The control architecture for motor-generator was designed with the assumption that aircraft longitudinal deceleration is known. The feedback can be captured either by remote connection to an aircraft's inertial measurement unit (IMU) or by ranging devices.

2.3.4 System Moment of Inertia

During the initial stage of the arresting process, the aircraft translates its momentum via a cable to the stationary arresting gear system. The system resists due to the rotary components moment of inertia and is reflected to aircraft as slowing down force. If torque becomes excessive, the resultant aircraft deceleration will be too high. One way of reducing this issue is to use a motor-generator to induce rotation. However, there is a risk of motor-generator failure which may lead to excessive loads

2.3. IDEALIZED ARRESTING GEAR CABLE SYSTEM

on both the system and the aircraft. Instead, the problem was resolved by keeping the moment of inertia value small enough. Once the maximum value was known, the suitable components were selected. Table 2.3 shows the major components contributing to overall moment of inertia.

Table 2.3: *Moments of inertia of each subsystem*

Component	Moment of Inertia reflected to aircraft (kgm ²)	Quantity
Motor-Generator	1900 [37]	2
Gear Reducer	96 [40]	2
Winding drum	1490	2
Winded cable	768	2
Total for a subsystem	8508	

The span between drums equal approximately 120 m and the cable laying on the runway weighs 630 kg which equals to approximately 1 % of an Airbus A320 aircraft gross landing weight. Hence, the inertia of the cable across the runway at an initial stage of arresting process was neglected. The moment of inertia for most components is provided in suppliers' datasheets. Nevertheless, the design assumes a bespoke winding drum with moment of inertia estimated in CAD environment including the winding drum itself and approximately 500 m of winded cable. Figure 2.1(b) presents the winding drum cross-section view across centreline with rope winded onto it.

2.3.5 Winding Process

Aircraft land or take-off every forty five seconds on busy airports such as London Heathrow [41] requiring the arresting gear system to offer an efficient and automated cable winding system. The major energy loss factor during the winding process are

motor efficiency and cable dragging along the runway represented by

$$F_{\text{friction}}(t, v) = m_r \times l(t) \times g \times C_f(v) \quad (2.14)$$

where m_r is mass of cable per metre, g is gravitational force and C_f is coefficient of friction between runway and cable. The friction model is dependent on dragging velocity and combines Coulomb friction, Stribeck effect and Viscous Friction [42]. The friction occurs between steel and concrete where static and dynamic coefficients equal 0.57 [43] and 0.38 [44] accordingly. The graph showing coefficient of friction against a dragging velocity is available in Appendix B.

2.3.6 Energy Storage

Similarly to photovoltaic and wind farms, there is a problem of high intermittent power that is difficult to integrate with the grid [45, 46]. An aircraft decelerates within less than a minute while generating up to 140 kWh of energy. Thus, an energy storage system must be implemented wherein batteries and supercapacitors are considered. Steilen and Jrisen [47] stated that a round conversion efficiency for a battery remains between 70 % and 95 % while Barrade and Rufer [48] defined the efficiency of a supercapacitor reaching nearly 100 %. The supercapacitors are more appropriate for the arresting gear system because energy has to be stored only for a short period of time between aircraft landings, downsizing the self-discharge issue. Furthermore, the charge rate would be sufficient unlike with the Li-Ion batteries which are subjected to degradation processes at higher rates [49]. A major drawback is the cost of installation which is equal to approximately \$10,000 per kWh [50]. Nevertheless, it is suggested that the new technologies utilizing graphene and carbon nanotubes will reduce unit price in the future [51]. Finally, Song et al. [52] proposed a battery-supercapacitor hybrid solution for electric vehicles that sums up functionalities of both and result in reduced overall costs of implementation.

The hydro pumped storage may be considered as an alternative solution. Anag-

nostopoulos and Papantonis [53] proposed a wind-hydro design that can be altered so a pump would be connected directly to the arresting gear generators and work at a high power for a limited time. This solution could be particularly feasible for London Heathrow airport due to its close proximity to Staines reservoir.

2.4 Simulation and Results

To validate the arresting gear concept, a simulation was initialized with parameters given in Section 2.2 and the set of differential equations was analysed in time domain using MATLAB/ Simulink software. The idealized dynamic model assumes (a) a rigid airframe with the weightless rotational components, (b) a rigid winding drum, (c) an arresting cable acting as a spring, (d) idealized generator dynamics, (e) six degrees of freedom, (f) degrees of freedom consisting of aircraft linear motion and five subsystems angular motion, (g) an aircraft aligned perfectly with centreline, (h) aerodynamics accounting to drag only (neither lift nor downforce) and (i) International Standard Atmosphere (ISA) flight condition at sea level. Figure 2.4 presents The top-level simulation logic flowchart.

If velocity of an aircraft achieves the demanded taxi velocity v_{taxi} , the simulation ends. Otherwise, the process runs until the aircraft travels 2500 m from the beginning of the arresting process while changing the arresting subsystem at 500 m aircraft travel distance increment. The control logic was set to reduce the cable tension after 430 m aircraft travel distance within each subsystem in order to safely release a cable. The motion data from each subsystem is saved and later used as initialization for winding logic. Figure 2.5 presents the subsystem flowchart and details a coupling between an aircraft and a winding drum.

The yellow coloured area corresponds to two degrees of freedom, aircraft linear motion and winding drum angular motion, which are coupled with a spring that translates forces only due to tension. If compression occurs, there is no force acting between two degrees of freedom because the cable will bend sideways. There are five en-

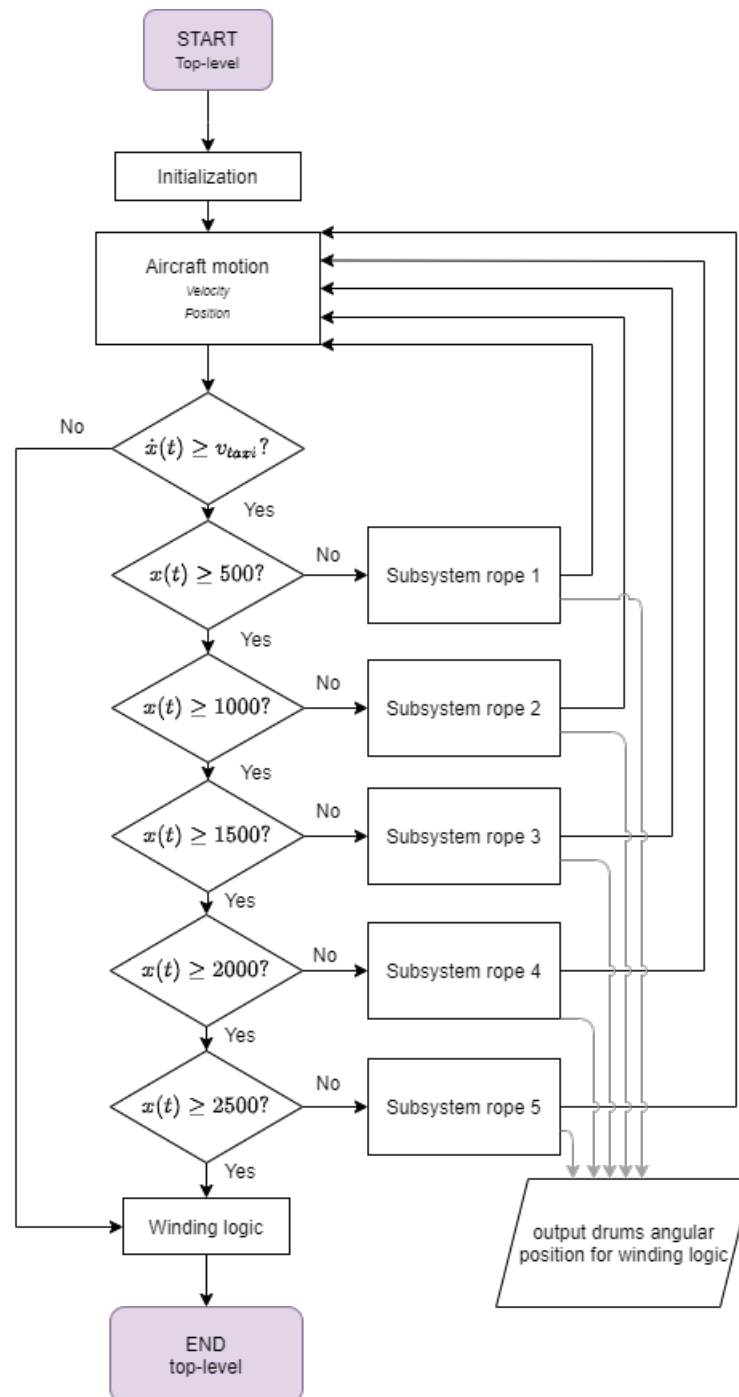


Figure 2.4: Top-Level simulation flowchart logic explaining runout breakpoints

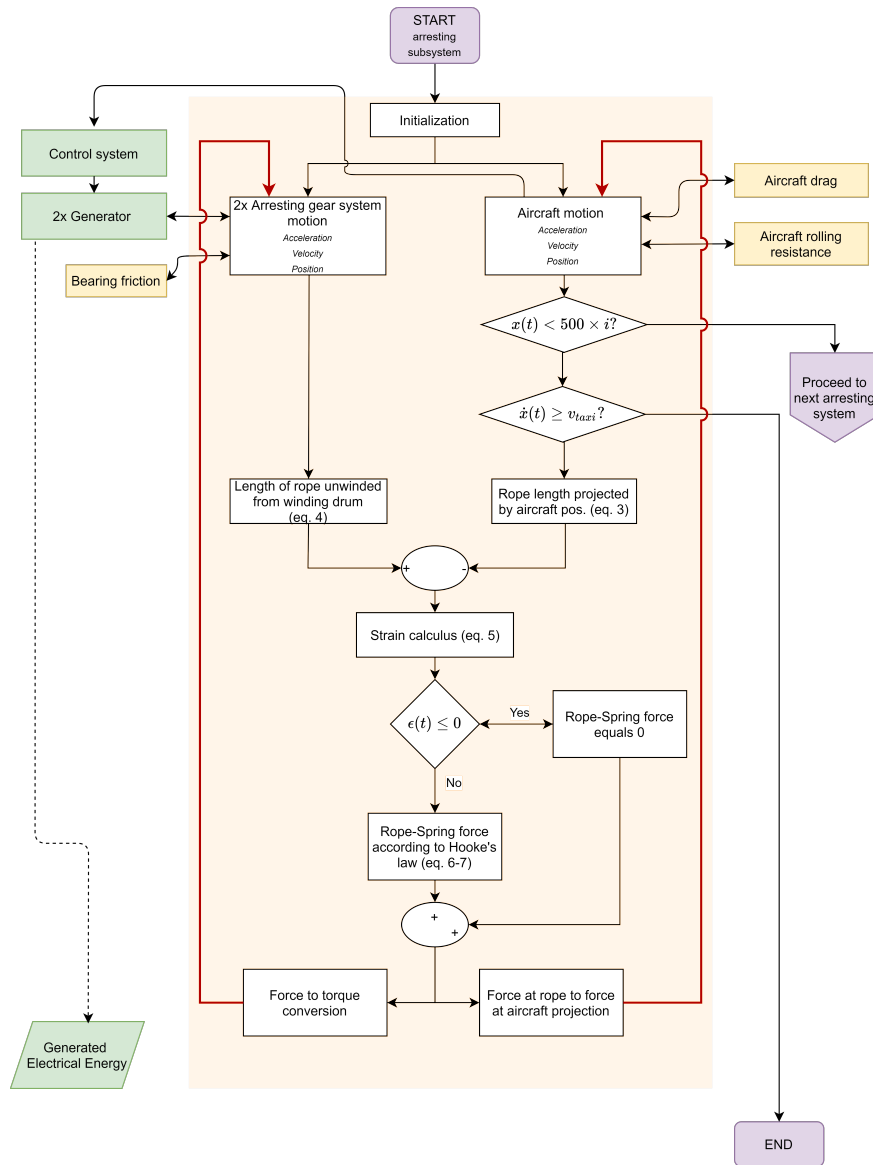


Figure 2.5: Arresting gear subsystem flowchart logic showing a coupling between aircraft and winding drum and energy loss factors

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

ergy loss factors. The winding drums lose energy due to bearing friction, while the aircraft itself dissipates kinetic energy due to drag and rolling resistance. The generator efficiency is affected by mechanical (friction), hysteresis, eddy current and ohmic phenomena, while the gear reducer is subjected to mechanical losses only [54]. Finally, most of the energy is converted to electricity through generators that apply torque corresponding to aircraft deceleration feedback. The winding process uses the generated electrical energy to wind back the rope and make the system available for the next aircraft. Figure 2.6 presents the winding simulation flowchart which consists of one degree of freedom.

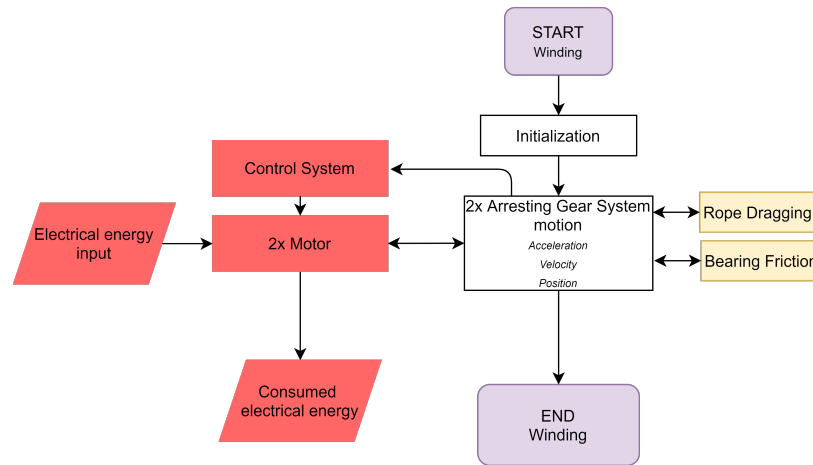


Figure 2.6: Winding flowchart logic showing energy transfer to wind up each subsystem

An additional energy dissipation factor, a rope dragging on runway, is simulated by estimating the cable on runway mass multiplied by coefficient of friction with regards to dragging velocity given in Appendix C. The simulation results show that the proposed large motor-generator has very low efficiency equal to approximately 20 % during the winding process due to the application of negligible loads. Hence, the alternative solution consisting of another, smaller motor coupled to each winding drum with a mean efficiency equal to 85 % is proposed. Figure 2.7 shows motion, forces and energy transfer during arresting of Airbus A320.

As can be seen in Figure 2.7(a), the actual aircraft deceleration matches the demanded signal (R1 dem, R2 dem, R3 dem) due to the idealized control architecture

with an instantaneous response. There is a small disturbance within all subsystems caused by a variable radius logic. The system response indicates that generators produce enough power to meet the application requirements. Figure 2.7(b) shows that the aircraft stops in approximately 32 seconds after passing 1100 m. The distance matches the aircraft manufacturer data specification [16]. The force translated through the first cable in Figure 2.7(c) reaches 40 metric tons, which fits the rope tensile strength envelope and remains lower than during an F14-D Tomcat landing on an aircraft carrier. The first and second system presented in Figure 2.7(d) works at nearly constant angular velocity due to variable radius of a released rope. The winding drums angular velocity varies between 45 and 0 rad/s. As presented in Figure 2.7(e), the system generates approximately 27 kWh of energy but uses 2 kWh for winding the rope back. Thus, the energy efficiency equals approximately 60 %. Other iterations were conducted according to the initial conditions from Table 2.2 and are presented in Table 2.4.

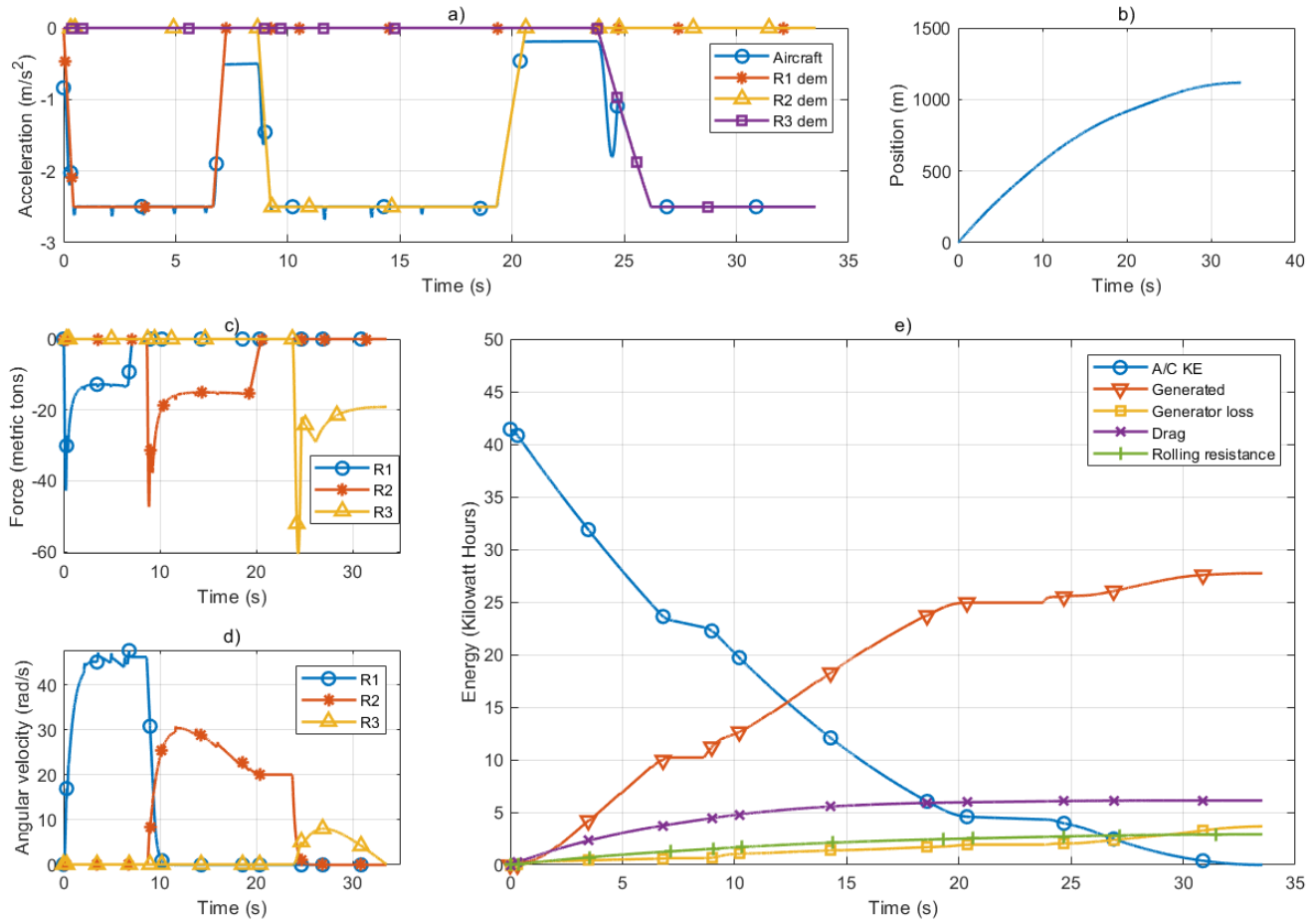


Figure 2.7: Airbus A320 results showing motion of aircraft along with all involved arresting subsystems and forces acting on a rope during landing. a) Aircraft acceleration, b) Aircraft position, c) Rope tension, d) Subsystems angular velocity, e) Energy transfer during landing

2.4. SIMULATION AND RESULTS

Table 2.4: *Simulation results for aircraft ranging from Airbus A318 to A380*

Aircraft for reference (IATA code)	Kinetic energy available [kWh]	Amount of energy stored in supercapacitors [kWh]	System efficiency %	Stopping distance [m]	Peak deceleration [$\frac{m}{s^2}$]	Number of arresting gear subsystems engaged
A318	37	21	57	1050	2.8	3
A319	39	24	62	1070	2.7	3
A320	41	25	61	1100	2.6	3
A321	50	34	68	1150	2.6	3
A332	116	67	58	1350	2.1	3
A333	117	67	57	1400	2.0	3
A340	123	64	52	1600	1.7	4
A350	132	67	51	1700	1.6	4
A359	150	75	50	1850	1.4	4
A380	248	110	44	2200	1.2	5

The efficiency varies between different aircraft where the highest is achieved with medium weight aircraft and tends to drop for heavier and lighter aircraft. The stopping distance for all remains within the standard landing envelope so is the peak deceleration. Deceleration for the smallest aircraft is driven by system moment of inertia. As the aircraft mass increases, the peak deceleration reduces. The number of subsystems engaged is increasing with the weight of aircraft due to limited generator power and runout distance. The graphs related to data from Table 2.4 are available in Appendix D.0.1 showing the energy transfer and in Appendix D.0.2 providing the stopping distance for all iterations.

While runway length influences the available distance over which deceleration occurs and thus the duration of the energy recovery process, the total kinetic energy itself is governed more prominently by aircraft mass and velocity. The drum radius

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

affects the mechanical advantage and angular velocity relationship of the winding drums to the motor-generators, thereby influencing system efficiency and torque requirements, but its impact on total recovered energy is secondary to the fundamental energy available from aircraft mass. The study also showed that the number of sequential arresting subsystems engaged increases with aircraft weight to safely distribute loads and maintain controlled deceleration, further coupling recovered energy with aircraft size. This rationale supports focusing design optimizations on accommodating variations in aircraft weight to maximize the energy recovery potential while respecting safety and operational constraints.

In both the dynamic and electromagnetic subsystem numerical models, ensuring stability and convergence of simulations was a key focus to guarantee accurate and reliable results. The dynamic simulations were implemented using fixed-step solvers in MATLAB Simulink with sufficiently small time increments to capture transient behaviors without inducing numerical instabilities. Stability was assessed by monitoring the conservation of energy throughout the simulations; the total energy variance remained below 0.1% of the total kinetic energy, indicating negligible numerical dissipation or artificial energy gain. Convergence was further validated by running simulations with progressively finer time steps and confirming that key outputs such as deceleration profiles, cable tensions, and generated electrical power remained consistent. For the electromagnetic models, the transfer functions of the motor-generators were verified against manufacturer data, and iterative solver tolerances were set to prevent oscillatory divergence during transient loading. These combined assessments ensured that the coupled dynamic-electric system simulation provides an accurate representation of the arresting gears transient behavior under variable loading conditions.

The simulation results were validated according to the law of conservation of energy. The aircraft kinetic energy and all energy dissipation factors were summed up and investigated throughout the simulation time. The results shown that the total energy variance of the dynamic model equals 0.1 % of the total energy. This negligible

error is caused by the multiple logical operators, the variable winding drum radii and the numerical inaccuracy. Furthermore, the kinematic coupling between the system and a landing aircraft has been validated with the hand calculus at several different angles.

2.5 System Optimization Based on Parametric Study for Airbus A320

The proposed system consists of multiple components that affect the overall energy transfer efficiency. Better performance can be achieved by optimising factors such as a radius of winding drum, where the adjustment allows to use the highest-efficiency torque and angular velocity ranges of generator. The solution is mostly applicable if direct drive design is chosen, but the adjustability is limited by bending radius of a cable and a system moment of inertia reflected to the rope. If a gear reducer is present in a system, optimization of gear ratio will have exactly the same effect as adjustment of a winding drum radius. Nevertheless, a generator moment of inertia reflected to the cable increases proportionally to the gear ratio squared. The generator efficiency can be adjusted by selecting a different design comprising the generator and the related inverter or controller. The main limitations are maximum power and moment of inertia. The elastic coupling between winding drum and aircraft affects the system dynamics. This phenomenon should be further evaluated in frequency domain to rule out the resonance phenomenon during the arresting process. Figure 2.8 presents the graphs of recovered energy against gear ratio and final setup response.

The management of generator thermal constraints and inertial characteristics during scaling across different aircraft classes was critical to maintaining system performance and safety. The generator selection process accounted for peak power demands corresponding to the heaviest aircraft (e.g., Airbus A380) to ensure adequate torque and energy conversion capacity, while thermal limits were evaluated

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

through thermal modeling to prevent overheating under peak loads. To address inertial mismatches that could lead to excessive peak deceleration or control instability, the moment of inertia of the motor-generator system was carefully optimized and kept sufficiently low by selecting lightweight components and limiting gear ratios. This approach ensured scalable performance across a range of aircraft masses by balancing generator inertia with robust control algorithms that modulate torque based on real-time landing deceleration feedback. The modular system design additionally allowed adjusting the number of active subsystems and generator sizes to accommodate specific aircraft classes, ensuring safe and efficient operation without compromising passenger comfort or structural integrity.

The results presented in this chapter represent a parametric study focused on a single design variable the gear ratio. The intent of this analysis is to understand how changes in gear ratio influence the energy recovery performance and system dynamics without simultaneously optimizing other parameters such as generator characteristics, cable geometry, or control strategies. Treating this as a parametric study allows clearer interpretation of individual parameter sensitivity, while acknowledging that a full system optimization would require multi-variable coupling, cross-parameter constraints, and trade-off assessments. The presented findings should therefore be viewed as an intermediate step toward broader optimization rather than as a final configuration of the system.

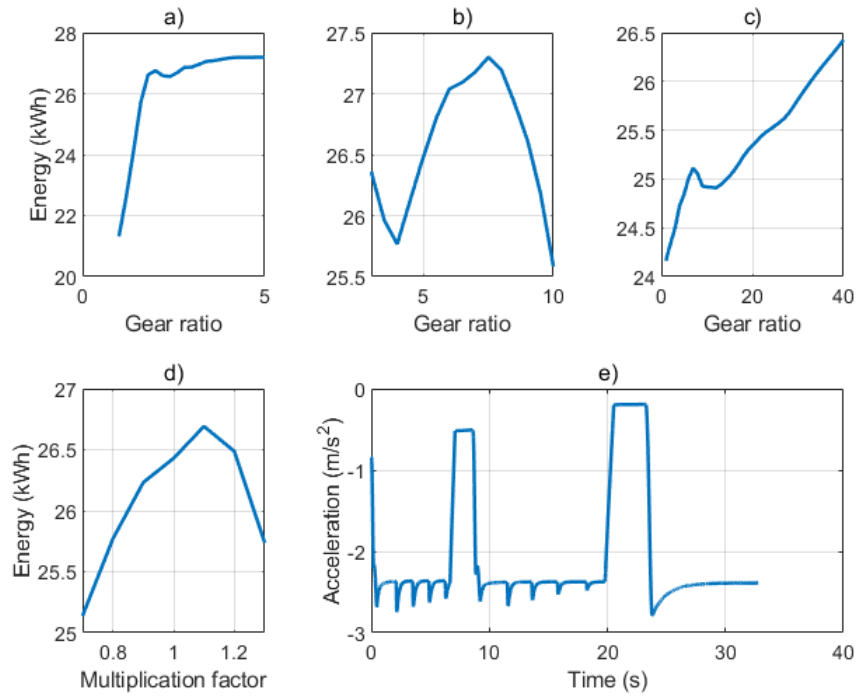


Figure 2.8: Gear ratio optimization results performed for Airbus A320. a) Optimization of first subsystem, b) Optimization of second subsystem, c) Optimization of third subsystem, d) Optimization of all subsystems combined, e) Aircraft response at final setup

Initially, the gear ratio for all subsystems was set to 3. Then, the optimization was performed for the first subsystem shown in Figure 2.8(a). Multiple iterations were conducted with varying gear ratios. The higher gear ratio resulted in more recovered energy but increased initial deceleration caused by initial mismatch between aircraft and subsystems velocity. Hence, the gear ratio of 3.4 was chosen. Next, a similar procedure was applied for the second subsystem given in Figure 2.8(b) and third presented in Figure 2.8(c) with corresponding gear ratios of 8.4 and 20. Finally, the iterations were made for all subsystems combined, which is shown in Figure 2.8(d). A multiplier varying between 0.7 and 1.3 was set. The results in Figure 2.8(e) indicate that peak deceleration does not exceed 2.5 m/s^2 . A gear reducer with adjustable gear ratio would further increase the efficiency of the system. The different sizes of generators may also be considered where the most powerful ones could be fitted in the runway ends and smaller ones mid-runway.

2.6 Arresting Gear Energy Recovery System in Practice

Once the system effectiveness in energy recovery is known, more factors should be considered prior to implementation emphasizing safety. The most of accidents in aviation occurs during landing [55] and the arresting gear heavily influences this phase. Undoubtedly, any malfunction of this system may be catastrophic and the CS-25 standards developed for commercial operations state that any catastrophic failure condition shall be extremely improbable and not resulting from a single failure [56]. In contrast to aircraft carriers where successful landing is completely dependent on the arresting gear, the commercial aircraft would retain its ability to decelerate solely by using onboard systems. Consequently, emergency features such as a rapid hook release or an arresting rope cutaway would allow to rapidly disengage the device and an aircraft would continue to decelerate on its own.

The performance and structural integrity of the arresting gear system under conditions of aborted landings or bounced touchdowns were carefully considered in the design. During aborted landings or bounce events, the aircraft's engagement with the arresting cable may be intermittent or subjected to higher dynamic loads, potentially causing transient stress spikes in system components. To mitigate this, the system incorporates rapid cable tension adjustments and torque modulation via the motor-generator control to accommodate sudden changes in aircraft deceleration demands. The modular arresting cable layout, combined with robust mechanical design and reinforced cable sheaves, maintains structural integrity even under off-nominal loading scenarios.

Any off-axis landing poses another safety concern due to lateral force and yawing moment acting on aircraft which hardly ever land perfectly aligned with a runway axis due to environmental uncertainty and human factor. This problem is well known in military applications and [57] modelled the lateral security boundary of arresting and the landing target area for aircraft carrier operations. Similarly, the landing variability

must be accounted during the system development for commercial aircraft to meet the civilian safety requirements. Since the system proposed in this chapter relies on electric machines rather than hydraulics, higher safety margins can be achieved by dynamically vectoring the arresting rope tension and applying the differential kinematics for the winding drums on each side of a runway. The proposed solution is a challenge regarding the control architecture development nevertheless, the recent breakthroughs in artificial intelligence are rather optimistic. [58] demonstrated the automatic unmanned aerial vehicle carrier landing using a model predictive control that considers carrier deck motion. Another concern about the control system is linked to inertia ratio between the electric machine and the load which is excessively high at proposed gear ratios. Hence, the resonance and anti-resonance peaks have a lower frequency and consequently the operational bandwidth of motor-generator is reduced, impacting the performance of the system [59]. Further investigation of dynamics is necessary where the simulation could be done with exact electric machine dynamics rather than a transfer function lag only.

The determination of acceptable deceleration limits in the proposed arresting gear system is a critical design consideration that balances maximizing energy recovery with ensuring passenger comfort and adherence to regulatory safety standards. Deceleration limits are primarily informed by existing civil aviation guidelines, such as CS-25 regulations, which mandate that catastrophic failure conditions must be extremely improbable and that deceleration forces should not induce excessive discomfort to passengers and crew. The target deceleration rates align closely with those experienced during normal commercial aircraft landings, typically ranging between 1.2 and 2.8 m/s, which are known to be within human tolerance thresholds. Passenger comfort is further protected by controlling the jerk (rate of change of acceleration) to minimize higher-order derivative effects that can cause discomfort or injury. This is achieved through the use of multiple sequential arresting cables and staggered engagement protocols to smooth transitions in load and deceleration.

From an energy recovery standpoint, these deceleration limits are optimized to

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

capture as much kinetic energy as possible without exceeding safety margins. The motor-generator system is controlled in real-time to modulate torque, thus ensuring that deceleration remains within the acceptable envelope defined by both biomechanical and regulatory constraints. The redundancy provided by retaining onboard braking systems further enhances safety by allowing the aircraft to rely on conventional means should the arresting system or its control approach fail to maintain proper deceleration profiles. Thus, the system design represents a compromise between the dual goals of energy efficiency and safety-critical performance, supported by dynamic simulations validated against industry data and regulatory requirements.

Backlash and other forms of mechanical play pose challenges to the precise control of the electric machine, potentially causing torque ripple and control delays. These non-idealities necessitate advanced control algorithms capable of compensating for such mechanical variances to maintain smooth deceleration and optimal energy recovery performance. Therefore, while the global energy recovery metrics are largely unaffected, consideration of these mechanical imperfections is essential for ensuring reliable and robust system operation during transient dynamic conditions.

An arresting cable may snap during operation due to high tensile stresses and if failure occurs, the cable will spring back potentially leading to damage of both a landing aircraft and airport systems. The increased lateral safety margins for landing would further intensify this issue. [60] investigated the fatigue life of the arresting cable and stated that the off-centre arrest leads to higher stress acting on the cable.

The proposed arresting gear system design assumes that a landing aircraft will repeatably roll over arresting cables. This situation already occurs when an airfield is used for both military and commercial operations. Accordingly, [61] released the safety recommendations for the aircraft crossing arresting cables at speeds greater than 60 knots. Albeit they permit to roll over a rigged arresting cable, the recommendation is made to regularly check a landing gear for damage and often verify the tyre

pressure.

During the standard landing, stresses are distributed between multiple deceleration systems, including friction brakes, thrust reversers and spoilers. If the arresting gear system is implemented, all forces will be translated through the arresting hook to a landing gear. Beyond that, the airframe structure supporting the arresting hook attachment point requires substantial reinforcement to distribute the arresting loads throughout the aircraft structure. The arresting forces must be transmitted from the hook attachment point through the fuselage structure to the aircraft's center of gravity location.

The structural weight penalty represents a fundamental trade-off in the arresting gear energy recovery system design. While the system offers significant energy recovery potential and enhanced safety margins, the increased structural weight reduces aircraft performance and increases operational costs. A comprehensive life-cycle analysis incorporating structural weight penalties, energy recovery benefits, fuel cost savings, and safety improvements is necessary to evaluate the overall feasibility of implementing arresting gear energy recovery systems for commercial aviation operations. Future detailed structural analysis and optimization studies are recommended to refine weight penalty estimates and develop minimum-weight reinforcement configurations suitable for commercial aircraft applications.

The proposed arresting gear system design assumes that a landing aircraft will repeatably roll over arresting cables. This situation already occurs when an airfield is used for both military and commercial operations. Accordingly, [61] released the safety recommendations for the aircraft crossing arresting cables at speeds greater than 60 knots. Albeit they permit to roll over a rigged arresting cable, the recommendation is made to regularly check a landing gear for damage and often verify the tyre pressure.

Eager et al. [62] stated that a human body requires time to adjust a muscle tension against all acting forces. They recommended that any design interacting with a human body shall minimize the value of third position derivative with respect to

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

time and keep the fourth close to zero. During the arresting process, the deceleration higher order derivatives peak when a landing aircraft releases a first arresting subsystem and engages with another and therefore, the passengers and cabin crew may feel discomfort during landing. The issue may be overcome by hooking two cables at once where simultaneously, the first subsystem reduces and the second increases the tension. The double cable arresting hook requires an additional mechanism which will hold both cables and allow one to be released without interference of another.

The aircraft landing direction on a runway is strictly dependent on wind, meaning that each arresting gear system should be capable of operation for either side landing. Correspondingly, a positioning of the subsystems in a runway should allow the arrest of aircraft in both directions. The runway excursion functionality of the enclosure should also be bi-directional to maximize safety of proposed system.

In busy airports, any cable maintenance or replacement required throughout a day will be highly impractical. The arresting cable is subjected to the most harsh working environment out of all components in the system due to high stress and dragging along the runway. The arrangement from Figure 1b) requires a mechanical guide which will align the steel wire rope during the retraction process. The issue can be negated by using a tape instead of a steel wire rope, similar to the BAK-12 military arresting gear [25].

The arresting device demonstrated in this chapter increases landing operation redundancy and unlike the friction brakes onboard of aircraft, it would provide the constant deceleration regardless of weather condition. The greatest safety improvement would be achieved during severe weather when the aircraft tyres have limited grip.

Transitioning the proposed sustainable arresting gear energy recovery system from concept to operational deployment involves several primary mechanical and certification challenges. Mechanically, the integration of high-torque motor-generators with dynamic cable systems demands rigorous validation to ensure durability under

variable and extreme loading conditions, including cyclic stresses, off-center engagements, and emergency releases. Certification hurdles include meeting stringent aviation safety standards such as CS-25, which require comprehensive demonstration of system reliability, fail-safe operation, and minimal impact on aircraft structural integrity. Additionally, the system must be proven compatible with diverse aircraft types and landing scenarios through extensive testing and simulation, including abnormal events. Environmental factors such as vibration, temperature extremes, and potential electromagnetic interference with airport systems also necessitate thorough assessment. These challenges underscore the need for coordinated development with certification authorities and iterative refinement to achieve regulatory approval and industry acceptance.

2.7 Conclusions

The energy recovery arresting gear system is a potential source of electric energy which will be even more applicable when the aerospace industry abandon fossil fuel. At that point, the system will produce completely green electrical energy and onboard storage capabilities may be used. Although there are many advantages linked to the proposed system, the practical aspects including safety, passenger comfort and life cycle of arresting components are significant, as explained in this study.

The current advancement of technology allows implementation of an arresting gear system that will recover kinetic energy and stop a civilian aircraft within the standard landing parameter values defined in the literature review. As shown in the design, five subsystems were used with a combined runout distance equal 2.5 km and each generator has maximum power of 17 MW. The system is capable of stopping one of the biggest aircraft, namely the Airbus A380, completely.

The force-based dynamic model was created according to kinematic coupling related to Hooke's law and was augmented with the energy dissipation factors such as drag and rolling resistance defined according to referenced values. The motor-

CHAPTER 2. SUSTAINABLE ARRESTING GEAR ENERGY RECOVERY SYSTEM FOR COMMERCIAL AIRCRAFT

generator efficiency map was a special case which contained only eight real data breakpoints while others were estimated. The simulation results demonstrated that the optimized system has approximately 60 % energy conversion efficiency between aircraft kinetic energy and electrical energy.

For the medium-haul aircraft, there should be as much as 70 kWh of generated electrical energy. Using Heathrow Airport as an example application, where 650 landings took place every day in 2019 [63], the kinetic energy captured via arresting gear system from all landings would generate approximately 17 GWh of electrical energy per annum, which is more than Heathrow's biomass-fuelled T2 energy centre produce [64]. This amount of recovered electrical energy would offset annually 5667 m³ of diesel fuel fed into the generator which is 30 % efficient, or 6367 metric tons of coal fed into a coal power plant with 33 % efficiency.

This research utilized a dynamic model where each cable is considered as an ideal spring, which is an accurate representation for estimating the amount of electrical energy recovered. Nevertheless, a more realistic dynamic model has yet to be designed for a controller development purpose. This could be achieved by augmenting the dynamic model with rope mass model which will include kink waves phenomena.

Chapter 3

More Electric Aircraft

Conversion to All-Electric: Landing Gear Drive System

Raising awareness about environmental issues moves the aerospace industry towards electrification, and the corresponding solutions are already present at some airports. However, commercial aircraft are the missing links in claiming all-electric ground operations. They rely on fossil fuels without any electric alternative due to the technological inability to store large amounts of energy while maintaining a low weight of batteries. The issue diminishes if an electric system uses only a fraction of the energy normally consumed by the engines and comprises kinetic energy recovery. Accordingly, this chapter demonstrates the landing gear drive system for a narrowbody airplane, which has the sustainable and economic means to replace all onboard engines throughout ground operations. The system is simulated in MATLAB/Simulink and leads to the kinematic results that are based on the real drive cycles. The kinematics are subsequently used to estimate the overall on-ground power and energy demand of a more electric aircraft (MEA). The impact is maximized with the components scaled according to performance metrics and two-speed gear ratio optimization. The net fuel advantage is demonstrated for different ground operation modes, taxi times, and flight path lengths.

3.1 Introduction

The aviation industry is subjected to growth and the number of passenger aircraft in service is predicted to double by 2041 in comparison to the value from 2020 and accordingly, there are increasing concerns about greenhouse gas emissions [21]. Various bodies act to mitigate the harmful impacts and for example, Agency [65] prepared the Flightpath 2050 strategy which strives to limit the greenhouse gas and noise emissions. The aircraft manufacturers address the sustainable goals by developing a more fuel-efficient and environmentally friendly aircraft. This is being achieved with a more electric aircraft (MEA) where the systems that were originally powered by pneumatics and hydraulics are replaced with electric alternatives [66].

The ongoing electrification aligns well with the postulate of the Flightpath 2050 which requires the emission-free taxi movement by 2050 [65]. To meet this target, the widely used internal combustion engines (ICE) must be replaced including the auxiliary power unit (APU) which burns approximately 2 kg/min [67] of jet fuel and the main engines. Both ground and onboard systems have been proposed for replacing the ICE of aircraft, of which the most impactful are summarized below.

Main engines operating at reduced thrust settings during taxi operations exhibit significantly reduced thermal efficiency compared to cruise flight conditions. This inefficiency is demonstrated through an energy balance analysis of taxiing operations. A typical narrowbody aircraft consumes approximately 7.67 kg/min of jet fuel during taxiing [68], which corresponds to a total energy input of 5,500 kW when accounting for jet fuel's energy density of 12 kWh/kg. However, the actual power required for ground movement and comprising primarily propulsion, landing gear systems, and environmental control is approximately 300 kW. The environmental control system alone consumes the majority of this demand, accounting for approximately 150 kW during taxi. This creates a substantial mismatch between energy input and useful output, resulting in an overall fuel-to-usable-energy conversion efficiency of only 5%.

The improved ground operations of aircraft receive increasing attention and there

are multiple publications that bring novelty to electric taxiing, APU removal, energy storage onboard commercial aircraft and gear aided takeoff. There are many electric taxi projects to date, including Safran's Electric Green Taxi System (EGTS), TaxiBot, WheelTug and the L-3's concepts [22]. There is also an outside-of-the-box idea that integrates both ground-fitted and onboard systems. Rohacs and Rohacs [69] led the GABRIEL project which uses a magnetic levitation ramp to electrically aid a takeoff and dissipate energy during landing. This ramp is combined with a separable tug device which is used for taxiing. Nevertheless, reliance on the ground-fitted deceleration systems without any backup led to safety concerns that must be addressed. Each of the systems listed above was brought to improve economy and sustainability of aircraft. The ground movement of aircraft with the main engines off leads to reduced noise and jet blast, making the ground handling personnel safer. Simultaneously, the overhaul cost of main engines per flight is reduced and the probability of unexpected foreign object damage (FOD) becomes smaller. The reduced brake wear rate occurs in contrast to the conventional ground movement where the main engines produce excessive thrust for taxi and therefore additional braking action is required. The unused brakes cool down much faster after a landing and therefore, a faster turnaround can be executed. These aspects together with the fuel savings lead to as much as 18% of mission cost reduction, which is equal to 1470 euro per standard European flight [69]. The list of advantages is longer for the onboard systems because reliance on the ground personnel and the tugs is reduced.

The onboard Electric Taxi Systems (ETS) to date source electric power from an APU because it consumes less fuel than main engines of aircraft during taxi. However, this approach requires a bespoke APU with higher electric power output. Lukic et al. [70] estimated that an 80-tonne single-aisle aircraft (Airbus A320 family size) requires as much as 240 kW, whereas the commonly fitted Honeywell 131-9A APU provides only 90 kW of electric output meaning that additional weight penalty associated with electric taxiing is expected. The recent developments in the ETS focus solely on power utilization of the system itself when, in fact, the all-electric ground

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

operations require an energy storage that satisfies the power demand of multiple systems of an MEA. Pagonis [2] defined the electric loads for the key systems of a B787, including: (a) Environmental control system (ECS) [352 kW], (b) hydraulics [40 kW], (c) flight controls [14 kW], (d) fuel pumps [32 kW] and (e) forward cargo air conditioning [60 kW]. A similar analysis was done by Wheeler et al. [3], who estimated that the power demand of the ECS equals 210 kW and the fuel pumps drain 10 kW. In addition, the author stated that operation of landing gear takes from 5 to 70 kW of power and the engine starters consume 200 kW. Herzog [4] approximated the electrical power consumption of the ECS for both a 100 passenger and a 350 passenger aircraft with the values reaching 90 and 400 kW respectively.

To fulfil the energy requirements, the suitable energy storage is needed and the best specific energy can be obtained with fuel cells. Stockford et al. [71] assessed the benefit and performance impact of the hydrogen powered fuel cells and claimed reduced weight in comparison to batteries. The primary downside of hydrogen and fuel cells is their lack of technological maturity which leads to tremendous but justified amount of objections coming from the aerospace bodies. In contrast, the Li-ion batteries are already present onboard the more-electric Boeing 787, though, their first years in service were badly eventful [72]. The present advancement of battery technology permits specific energy up to approximately 300 Wh/kg [73, 74].

The issue of low specific energy can be minimized by adding the kinetic energy recovery capability. Heinrich et al. [1] were the first to merge advantages of the kinetic energy recovery system (KERS) into the ETS, and investigated the regenerative braking capability during taxi for short-haul aircraft. They stated that KERS coupled to ETS can recover as much as 15% of energy required for taxi cycle. Their analysis excluded the possibility of energy recovery during a landing roll which would significantly increase the amount of harvested energy [75]. Nonetheless, the maximum charge rate of li-ion batteries is a limiting factor. At present, the battery can be charged up to 3 C [76] while recently the Li-Ion battery that sustains 6 C has been developed [77].

Combining these aspects together and adding the capability of regenerative braking during landing potentially allow to consider the battery powered ground operations with the landing gear drive system for a short-haul aircraft as sustainably and economically feasible. The author proposes a system that involves an energy storage onboard and therefore, an APU becomes redundant. Removal of this device and related components allows to save as much as 630 kg [78]. Furthermore, each aircraft has a Master Minimum Equipment List that defines what components and systems are critical for aircraft operation and the APU is unnecessary unless the flight is subjected to the Extended-range twin engine operations standards (ETOPS) where increased redundancy of the electric system becomes safety critical [79]. The main contributions of this chapter are as follow: (1) Literature review to discuss the state-of-the-art of electric taxi and demonstrate the possibility for a battery powered version. (2) Demonstration of the battery-powered landing gear drive system and assessment of its impact on an Airbus A320 aircraft architecture. (3) Estimation of electric energy amount required to power the novel system together with the remaining MEA systems during ground operations. (4) Analysis of energy recovery capability during landing phase and taxiing. (5) Definition of the fuel savings equations and simulations to provide a comprehensive benchmark for all-electric ground operations against the conventional methods.

3.2 Landing Gear Drive System and Impact on Aircraft

The proposed landing gear driving system introduces several innovations over existing electric taxiing concepts such as the Electric Green Taxiing System (EGTS) developed by Safran and Honeywell . The prior solutions, while pioneering, faced challenges related to limited performance during taxiing, additional structural weight, complex integration requirements, and restricted on-board energy storage capacity. The system developed in this study addresses these limitations through four key

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

enhancements: (a) increased propulsion power and torque capabilities, (b) regenerative energy harvesting during taxiing and landing, (c) the potential to replace the Auxiliary Power Unit (APU) with high-density energy storage, and (d) emission-free ground operations independent of internal combustion engines (ICE).

Compared to the EGTS, the presented concept introduces electric machines and drivetrain components with substantially higher torque and power density, allowing improved taxiing performance. The inclusion of four-quadrant power converters allows full bidirectional energy flow supporting both propulsive and regenerative operational modes. The energy recovery capability enables harvesting of kinetic energy during braking, which can be stored and reused for subsequent taxiing and takeoff run.

A high-capacity modular battery system is installed in the fuselage, representing a major improvement in available energy storage compared to previous hybrid-electric taxi systems. This configuration overcomes integration constraints by allowing distributed energy modules that can be removed or scaled depending on mission requirements. The enhanced storage capacity not only supports prolonged autonomous ground operations but also introduces the possibility of substituting the APU, leading to approximately 265 kg of weight reduction as reported in [78]. In these circumstances, the battery can be considered as a back-up energy source for electrical systems during an ETOPS flight. The new electrical architecture also enables the aircraft systems to operate from stored electrical energy instead of relying on turbine-driven APU generators.

As demonstrated in Figure 3.1, the redesigned landing gear accommodates large-diameter electric machines mounted within the main gear structure. Despite a modest volume increase, integration remains feasible due to optimized packaging and load path reinforcement. The power converters are installed near the electric machines to minimize cable mass and enhance cooling efficiency through direct exposure to ambient airflow. A centralized control unit placed in the avionics bay manages the power distribution and provides safety features including emergency disconnect-

3.2. LANDING GEAR DRIVE SYSTEM AND IMPACT ON AIRCRAFT

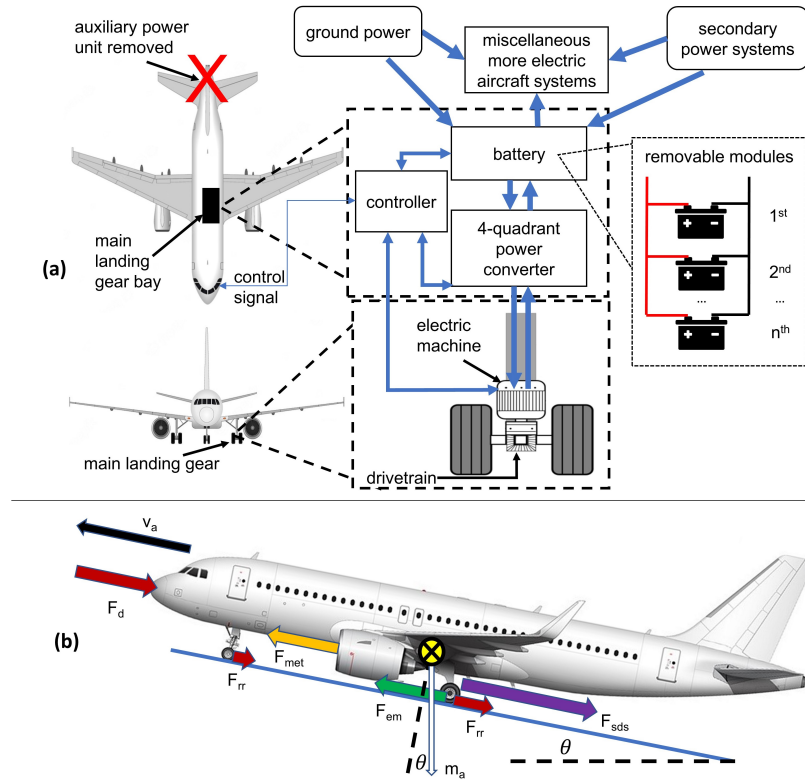


Figure 3.1: Demonstrator of the landing gear drive system. (a) System-level presentation among with impact on aircraft, (b) Free-body diagram of the aircraft.

tion capability initiated by the flight crew.

The proposed landing gear drive system achieves higher performance, improved energy autonomy, and reduced dependency on fossil fuel-based auxiliary power systems. As a result, it delivers tangible environmental and operational advantages over prior EGTS implementations by eliminating local emissions and enabling fully electric ground operations.

The structural feasibility of retrofitting the proposed landing gear drive system onto existing aircraft should be evaluated by considering the subsystem components individually. The electric machine positioned between the two wheels is designed to fit within the landing gear bay without causing interference with existing mechanical or structural elements. This integration is facilitated by compact packaging and optimized load path reinforcement, ensuring that aircraft structural integrity and func-

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

tionality are maintained. The power drives are incorporated into the electric machine housing itself, which minimizes spatial requirements and simplifies installation. Energy storage modules, which represent a considerable volume and weight, are proposed to be located within the fuselage, where ample space exists to accommodate batteries or alternative energy sources without compromising cabin or cargo capacity. Such an arrangement not only enhances maintainability but also aids in preserving the aircraft's center of gravity and balance. This modular approach to subsystem placement supports manageable retrofitting processes and enables the retrofit system to comply with existing airframe architectural constraints.

The key thermal bottlenecks identified in the battery-powered landing gear drive system under worst-case loading conditions include elevated battery temperatures due to prolonged high power demand during taxiing on uphill gradients, operation of heavy aircraft imposing higher torque and energy demands, and exposure to high ambient temperatures typical of certain climates. These factors collectively increase the thermal load on the battery and power electronics, potentially risking overheating and accelerated degradation. Cooling system capacity and efficiency are therefore critical to maintain safe operating temperatures. However, due to the design margin incorporated by increasing the operational power to accommodate regenerative energy harvesting during landing, the system typically operates below maximum thermal stress during normal taxiing cycles, mitigating the severity of these bottlenecks. The modular battery architecture and proximity of power converters to ambient airflow further aid in efficient heat dissipation, ensuring thermal management remains within acceptable limits even in challenging operational scenarios.

3.2.1 Dynamic Model

This section introduces the dynamic model which is created to determine the energy transfer during ground operations of an Airbus A320 equipped with the landing gear drive system. It is based on the free-body diagram shown in Figure 3.1 (b) and takes into account the following factors: (a) the landing gear drive system, (b) the

3.2. LANDING GEAR DRIVE SYSTEM AND IMPACT ON AIRCRAFT

standard deceleration systems, (c) thrust of main engines, (d) drag and (e) rolling resistance of aircraft. The incline of runway is only used to validate sufficiency of landing gear drive system torque during taxiing. Figure 3.2 shows in the block diagram the relationship between each subsystem and the influence of each factor on aircraft body.

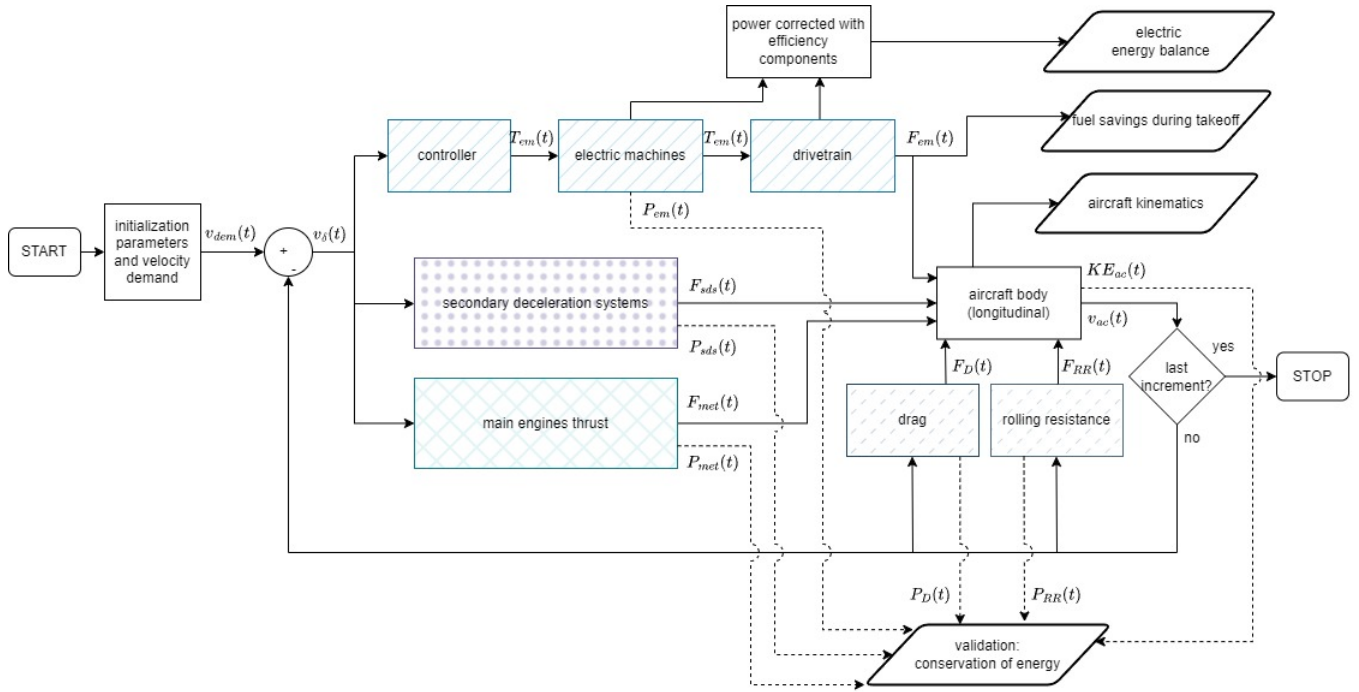


Figure 3.2: Dynamic model shown as block diagram disclosing the relation between multiple systems and the validation algorithm.

The longitudinal model of aircraft body is considered as a solid subjected to external forces $a = \frac{\sum F(t)}{m}$ and the lower order kinematics are obtained by integration with respect to time. The following forces are applied (all the variables are defined in the nomenclature and links are provided in the digital version of this thesis):

$$\sum F(t) = F_{em}(t) + F_{sds}(t) + F_{met}(t) + F_d(t) + F_{rr}(t) \quad (3.1)$$

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

where each factor is described as:

$$\begin{cases} F_{em}(t) = (v_{dem}(t) - v_a(t)) \times K_{pem} \times i(t) \times r_w \times 2 \\ F_{sds}(t) = (v_{dem}(t) - v_a(t)) \times K_{sds} \\ F_{met}(t) = (v_{dem}(t) - v_a(t)) \times K_{met} \\ F_d(t) = \frac{1}{2} v_a^2(t) \rho C_d A \\ F_{rr}(t) = C_{rr}(t) m_a g \end{cases} \quad (3.2)$$

and each system of aircraft has modelled saturation limits with the following saturation logic:

$$\begin{cases} v_{dem}(t) - v_a(t) \times K_{pem} \in (-f_{sat}(t), f_{sat}(t)) \text{ for } F_{em} \\ v_{dem}(t) - v_a(t) \times K_{met} \in (0, \infty) \text{ for } F_{met} \\ v_{dem}(t) - v_a(t) \times K_{sds} \in (-\infty, 0) \text{ for } F_{sds} \end{cases} \quad (3.3)$$

The saturation logic for electric machines f_{sat} is a scaled replica of Yasa 750 R experimental data [80], which will be described in Figure 3.5 (b). The two-stage gearbox denoted with “i” shifts when the aircraft reaches 12 m/s. This value is set to ensure that the whole taxi cycle is executed in the first gear whereas during a takeoff and a landing, the second gear is engaged:

$$i(t) = \begin{cases} i(t) = i_{taxi} \text{ for } 0 < |v_a| < 12 \\ i(t) = i_{tl} \text{ for } 12 \leq |v_a| \end{cases} \quad (3.4)$$

The results validation method relies on the law of conservation of energy. Therefore, the total energy in the system shall remain constant:

$$\sum E(t) = E_{em}(t) + E_{sds}(t) + E_{met}(t) + E_d(t) + E_{rr}(t) + KE_{ac}(t) \quad (3.5)$$

where energy balance of each factor equals:

$$\left\{ \begin{array}{l} E_{em}(t) = \int_0^t (T_{em}(t) \omega_{em}(t)) \\ E_{sds}(t) = \int_0^t (F_{sds}(t) v_a(t)) \\ E_{met}(t) = \int_0^t (F_{met}(t) v_a(t)) \\ E_d(t) = \int_0^t (F_d(t) v_a(t)) \\ E_{rr}(t) = \int_0^t (F_{rr}(t) v_a(t)) \\ KE_{ac}(t) = \frac{1}{2} m v_a^2(t) \end{array} \right. \quad (3.6)$$

The fuel saving exerted during the aided takeoff is derived from the dynamic model by assuming that the amount of force applied by the landing gear drive system is subtracted from the main engines and multiplied by TSFC:

$$FU_{toff} = \int_0^{t_{TOFF}} (F_{em}(t) \times TSFC) \quad (3.7)$$

This assumption means that the pilots have to derate the thrust level during takeoff however, this is a common practice in the civilian aviation [81]. To estimate how many kg of fuel can be saved, the TSFC metric is used for static conditions and is equal to 8 [82].

3.2.2 Initialization Parameters

The created model consists of many variables that should accurately represent a narrowbody aircraft and therefore, the values for the Airbus A320 are used. An aircraft is subjected to drag during ground operations and the drag coefficient differs depending on multiple environmental and operational factors such as flaps and slats position. Sun et al. [30] developed a stochastic hierarchical model to provide aerodynamic coefficients. They have provided the aerodynamic coefficients that reflect the landing gear and the flaps extension. The empirical C_d value based on trajectory data of an Airbus A320 equals 0.120. Their study assumes that a reference area is

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

a wing surface area, which is equal to 122.4m^2 for an A320 [83].

Besides of drag, the aircraft is subjected to rolling resistance on ground. The experimental data provided by Yager et al. [13] indicated that the coefficient of rolling resistance changes with velocity. They experimentally assessed the rolling resistance of 40x14-19 tires which are dedicated to similar aircraft, a Boeing 737 and captured the values at 3, 51, and 82 m/s which are equal to 0.01, 0.014, and 0.025 respectively. These values were used in Simulink model as the breakpoints and were linearly interpolated for any velocity value between. Table 3.1 combines the parameters used in the simulation initialization.

Dynamic model		Fuel saving model	
Parameter	Value	Parameter	Value
v_a	0-70 m/s (Fig. 3.3)	t_{PD}	900 s [84, 85]
m_a	61,700 kg [17]	t_{TXO}	126 s - 1584 s [5]
r_w	0.58 m [86]	t_{TXI}	78 s - 870 s [5]
C_d	0.12 [30]	t_{PARR}	180 s [84]
A	122.4 m^2 [83]	t_{OLAP}	30 s [87]
ρ	1.2 kg/m	t_{ILAP}	30 s [87]
C_{rr}	0.01 at 3 m/s, 0.014 at 51 m/s, 0.025 at 82 m/s [13]	FC_{APU}	2 kg/min [67]
TSFC	8 g/kN-s[82]	FC_{me}	7.7 kg/min [68]
i_{taxi}	14 (Fig. 3.5c)	FC_{pp}	315 g/t-km [88, 89, 90, 91, 92]
i_{tl}	2.9 (Fig. 3.5d)	FU_{toff}	approx. 60 kg (Fig. 3.5e)
		R_{txi}	0.33 [5]
		R_{txo}	0.67 [5]
		s_f	100-5000 km [17]

Table 3.1: Dynamic and fuel saving simulation initialization parameters for the narrowbody aircraft.

The dynamic model reflects the angular speed changes which are influenced by the gear ratio and wheel radius. The latter is equal to 0.58 m according to Tyres [86]

who supplies the tyres to an A320.

The flight path distance influences amount of fuel burned in-flight due to weight penalty. Modern Airlines [17] defined the maximum range of an A320 aircraft as 6100 km, however, the linearization of block fuel intensity is accurate only for the flight paths considerably shorter than maximum range as described in Section 3.6, and consequently, the flight paths from 100 to 5000 km are taken into account in this study.

Aircraft deceleration rate and stopping distance are critical during landing and must be controlled due to the risk of runway excursion and consequently, potential damage to the aircraft. Therefore, an objective in the present work is to maintain a value similar to the standard landing procedure. The typical landing speed of an Airbus A320 is around 70 m/s and the maximum value is limited by the tires where in case of an Airbus A320 is equal to approximately 100 m/s [28]. The deceleration during landing roll is influenced by several parameters and depends on the type of braking used: an auto or a manual mode. An auto brake low mode provides 1.5 m/s^2 of deceleration, medium mode provides a deceleration rate of 3 m/s^2 whereas maximum pedal braking provides a deceleration up to 5 m/s^2 [93]. Airbus [94] specifies that landing distance envelope for the Airbus A320 varies between 679m and 4742m and is affected by multiple parameters including aircraft gross weight, runway condition, wind, and deployment of the reverse thrust system. The minimum stopping distance is limited by passenger comfort and aircraft structural strength whereas, the maximum stopping distance is dictated by runway length [15]. After landing roll, the aircraft moves towards the terminal or hanger under its own power. Taxi speed is controlled by the in-wheel brakes and the main engines thrust level which is normally in idle or near idle conditions. The common taxiing speed equals 10m/s in straight taxi routes and decreases during sharp turns [95, 1].

The simulations presented in this study assume a rolling resistance coefficient representative of a dry runway surface. Variability in rolling resistance due to factors such as runway surface roughness, contamination (e.g., water, snow, slush), or

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

weather conditions has not been explicitly accounted for in the model. The values used are based on empirical data for dry conditions, as these provide a consistent baseline for comparison and are commonly adopted in similar simulation studies. Future work could incorporate dynamic models of rolling resistance to reflect the effects of varying runway conditions, which would further enhance the realism and robustness of the simulation results.

3.2.3 Drive Cycles

The realistic drive cycles that consist of taxiing, takeoff and landing are needed to improve understanding of the energy transfer during the ground operations, and therefore, the real data was captured for two commercial missions across Europe. In addition, the quasi-realistic model was made for the third mission by merging the taxi cycles captured by Heinrich et al. [1] with takeoff and landing phases from other flights. The recorded data is presented in Figure 3.3 and is used as the velocity demand in the MATLAB/ Simulink model.

3.2. LANDING GEAR DRIVE SYSTEM AND IMPACT ON AIRCRAFT

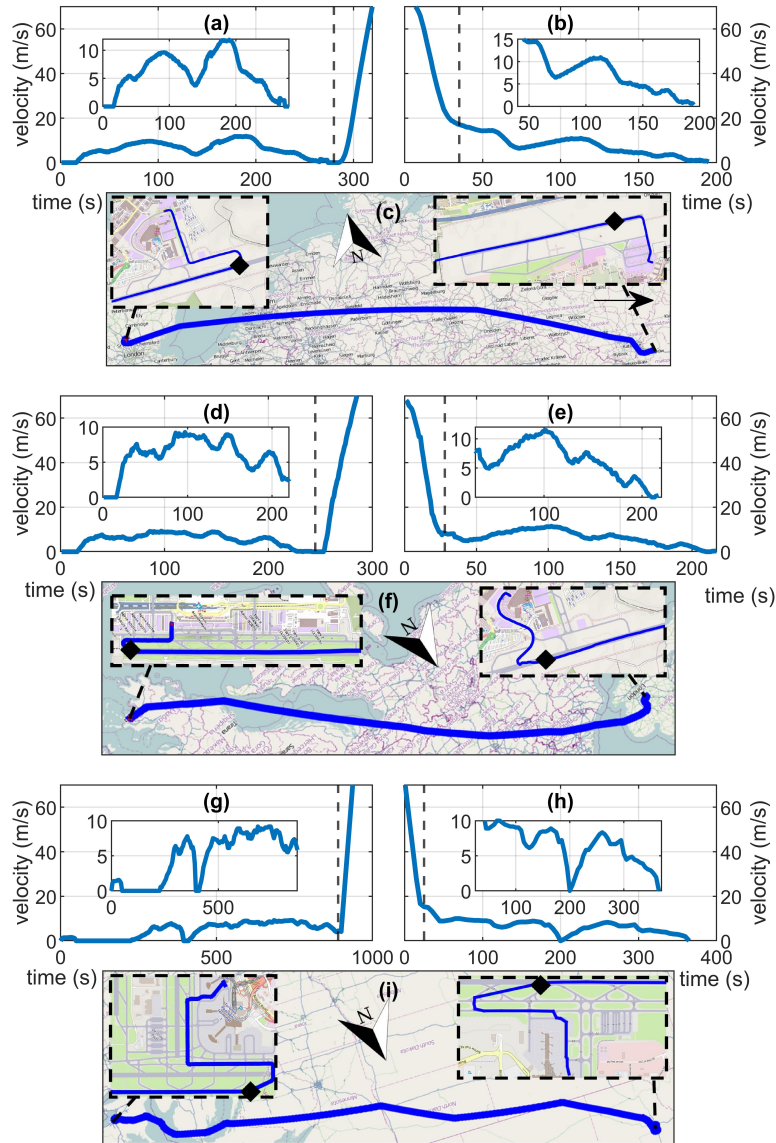


Figure 3.3: The ground velocity data recorded for two missions ((a) to (f)) and quasi-realistic model for the third ((g) to (i)). The vertical intermittent lines are the separators for mission phases. Taxi cycles were magnified within each graph: (a) Luton (LTN) taxi-out and takeoff, (b) Krakow (KRK) landing and taxi-in, (c) map for LTN-KRK flight W65002 (d) Athens (ATH) taxi-out and takeoff, (e) Luton (LTN) landing and taxi-in, (f) map for ATH-LTN flight FR7806 (g) Toronto (YYZ) taxi-out and takeoff, (h) Calgary landing and taxi-in, and landing (i) map for YYZ-YYC flight TS682 [1].

The first recorded flight W65002 shown in Figure 3.3 (a,b,c) took place on 25th of June 2022, from Luton, UK (LTN) to Krakow, PL (KRK) and passed the great circle distance of 1425 km. The taxi-out cycle given in Figure 3.3 (a) took 280 seconds and was immediately followed by the takeoff. The landing presented in the Figure 3.3 (b)

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

was followed by taxi-in for approximately three minutes. Figure 3.3 (d,e,f) presents the flight FR7806 between Athens, Greece (ATH) and Luton that occurred on 13th of July 2022. The taxi cycles were comparable in length to the first flight but the flight path was much longer with the great circle distance equal 2450 km. The first flight was executed with the Airbus A321NEO and the second with the B737-800 aircraft, which are designated for mid to long-haul operations but are often used on short flights as well. Each breakpoint consists of longitude, latitude and timestamp where each increment was equal to 1 s. Due to the poor GPS receiver reception, the signal was denoised by applying the moving mean with local 6-point values. Figure 3.3 (g,h,i) presents the taxiing data captured by Heinrich et al. [1] merged together with takeoff and landing from W65002. This figure is an accurate representation of flight TS682 between Toronto (YYZ) and Calgary (YYC) where the great circle distance is equal to 2700 km. This flight is performed by, among others, the Airbus A320 family aircraft.

3.3 Electric Power Demand of More Electric Aircraft

The systems of MEA require continuous high power supply and this section explains how much energy the onboard energy storage must provide to allow the all-electric ground operations. The longest mean taxi cycles according to EUROCONTROL [5] are used, where the taxi-out takes 26.3 minutes and the taxi-in occurs for 14.5 minutes. The taxi cycles from Figure 3.3 (g,h) were used in a loop to achieve these longer taxi times. Figure 3.4 shows power against time for the electric power-consuming systems onboard. The warmup and cooldown cycles of main engines are included in Figure 3.4 (a,b) and absent in (c,d). The power demand values for all but the landing gear drive system are traced from Section 3.2.2 and are taken as an average approximation. The consumption of the landing gear drive system is derived from the dynamic model explained in Section 3.2.1 and it reflects the recorded taxi cycles.

3.3. ELECTRIC POWER DEMAND OF MORE ELECTRIC AIRCRAFT

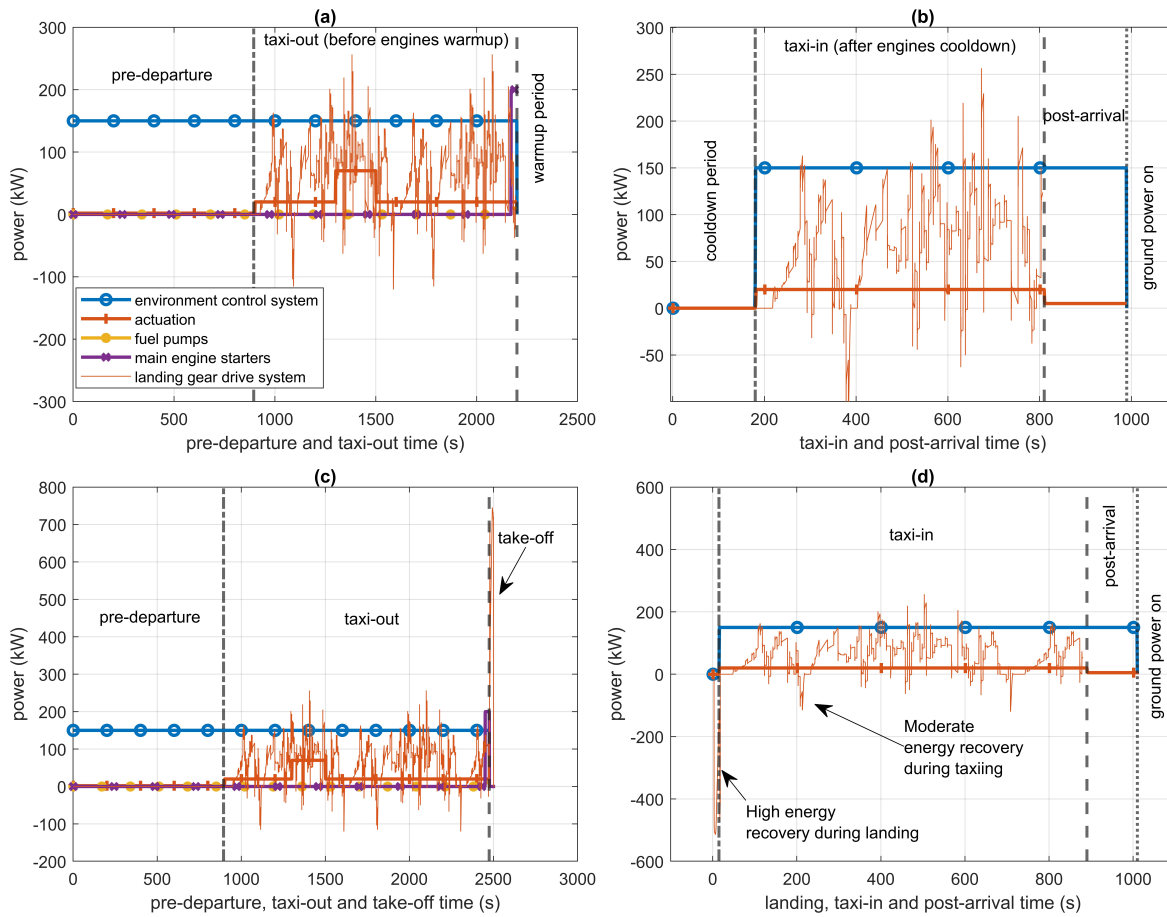


Figure 3.4: The graphs of power usage against time for the multiple systems during very long ground operations.[2, 3, 4, 5] (a) Longest outbound cycle with respective main engines warmup. (b) Longest inbound with respective main engines cooldown. (c) Longest outbound cycle without warmup (d) Longest inbound cycle without cooldown.

The cycle in each outbound phase shown in Figure 3.4 (a and c) begins when the ground power is disengaged and electric energy is sourced solely from the battery. In parallel, the ECS is working to provide the air conditioning to the passengers onboard. The average power demand is equal to 150 kW although, this depend on weather conditions and climate zone [4].

More systems start to consume energy as the aircraft begins to move. The electric actuation drains 20 kW and increases for the short period of time when the pilot checks all control surfaces pre-flight. Figure 3.4 (a) indicates that the highest power demand occurs when the main engines start-up procedure begins. The

bleedless main engine starters consume 100 kW each together with the 20kW from fuel pumps. Once running, the main engines supply electrical power to all systems and also charge the battery during the warmup and consequently, analysis stops. Similarly, the power usage during cooldown is neglected in Figure 3.4 (b). The energy transfer analysis continues up to takeoff and landing phases in Figure 3.4 (c,d) because these graphs disregard the warmup and the cooldown periods for the main engines.

3.4 Landing Gear Drive System Components Sizing and Optimization

The primary aim of the landing gear drive system is to reduce environmental footprint of commercial aviation. Even if the ground operations are completely emission-free, sustainability can be maximized by wisely scaling and optimizing the components to reduce the weight penalty. Accordingly, the system-level sizing and optimization algorithm is proposed and shown in Figure 3.5 (a). The initial step consists of the power and energy analysis which was accomplished in Section 3.3. This is followed by the battery size selection that matches the overall energy consumption during the all-electric ground operations. Section 3.3 explained that the maximum energy needed equals 194 kWh and therefore, the maximum battery capacity needed is rounded to 200 kWh which consists of four modules, 50 kWh each.

3.4. LANDING GEAR DRIVE SYSTEM COMPONENTS SIZING AND OPTIMIZATION

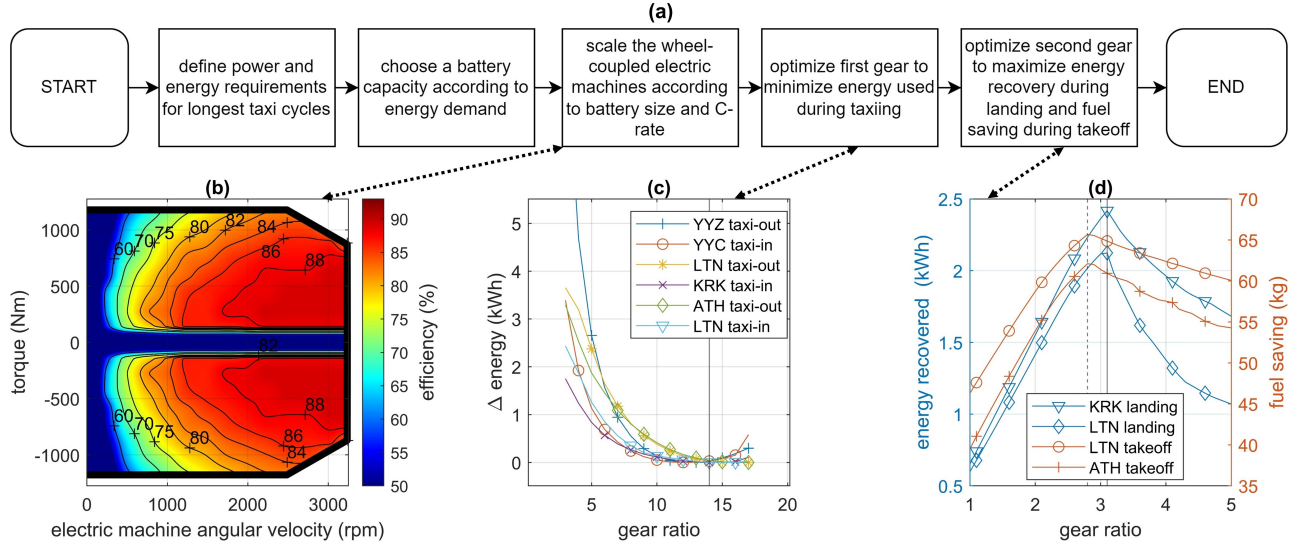


Figure 3.5: Scaling and optimization of the landing gear drive system. (a) Optimization algorithm, (b) Combined efficiency of electric machines, power converters and drivetrain, (c) gear ratio optimization for taxiing, (d) gear ratio optimization for landing and takeoff.

Once the battery capacity and the maximum C-rate are known, the electric machines, the drivetrain and the power converters are scaled according to the maximum allowable charge rate of the battery leading to 600 kW of total power. Next, the weight for each component is estimated according to the performance metrics disclosed in Table 3.2. The efficiency rates for the electric machine and the power converter are scaled from the experimental data provided by YASA [80] while the drivetrain is assumed to be 97 % efficient. The total efficiency of the system is demonstrated in Figure 3.5 (b). The optimization of system performance is done by adjusting the gear ratios of the two-stage gearbox. To optimize taxiing, the taxi cycles from Section 3.2.3 were extracted and simulated for the multiple gear ratios. Figure 3.5 (c) shows that gear ratio equal 14 allows to use least energy to propel the aircraft. The second gear was optimized according to both takeoff fuel saving and landing energy recovery. Figure 3.3 (d) displays the results for both where the optimum ratio is equal to 3.2 for landing and 2.8 for takeoff.

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

Table 3.2: *System-level performance metrics.*

Performance metric of component	2022	2030	2040	2050
Electric machine specific power (kW/kg) [96, 97, 98]	8	16	20	25
4-quadrant power converter specific power (kW/kg) [99]	8.6	13.8	21.1	25.2
Drivetrain specific power (kW/kg) [100, 101, 102, 103, 104]	15	20	25	30
Energy storage specific energy (Wh/kg) [73, 67, 105, 106]	0.25	0.5	0.6	0.7
Energy storage charge rate (C-rate) [67, 76, 77, 74]	3	6	9	N/A

A safety margin has been incorporated into the battery system sizing to ensure reliable operation over the expected battery lifecycle. The nominal battery capacity used in the simulations (200 kWh) is deliberately selected to exceed the maximum energy demand during ground operations, providing a buffer to account for capacity fade over multiple charge-discharge cycles. While detailed modeling of battery ageing and capacity degradation over time is beyond the scope of this study, it is recognized that lithium-ion batteries experience gradual loss of usable capacity with cycling and calendar ageing. The modular design of the battery system facilitates quick replacement of worn battery modules, which can then be repurposed for less-critical applications such as home energy grids, thereby maximizing resource efficiency and sustainability. This approach also supports easier maintenance and system upgrades. Future work should integrate comprehensive degradation models and battery management strategies to assess the impacts on system performance and maintenance intervals more accurately.

Battery cooling considerations have been incorporated into the design approach of the electric taxiing system. Given that the operational power of the system has been increased to accommodate the energy harvesting capability during braking, the net power demand during taxiing cycles is moderated. As a result, the thermal load on the battery during consecutive taxiing cycles becomes a negligible issue under typical airport operational scenarios. Effective passive or active cooling mechanisms

are assumed to maintain the battery within safe operating temperatures, preventing thermal-related degradation or safety concerns. This approach ensures reliable battery performance through multiple taxiing cycles in busy airport conditions without significant impact on system efficiency or lifecycle.

3.5 Internal Combustion Engines Usage

The fuel combustion during ground operations begins as soon as a pilot turns on the APU at the gate and ends once it is turned off after a ground power unit is connected to the receptacle of aircraft. Ultimately, more phases than the taxiing itself must be taken into account when trying to estimate the fuel burn by aircraft on ground. Figure 3.6 presents the usage of the onboard ICEs in broader context and includes: (a) pre-departure, (b) taxi-out, (c) landing, (d) taxi-in and (e) post-arrival phases.

During the pre-departure, the aircraft stands at the gate and the passengers board. The electricity is supplied by the ground power unit while the APU is started as the departure time gets closer. Airport operators limit how much in advance it can be launched and taking Heathrow as an example, the device can be started no earlier than fifteen minutes in advance for a narrow-body aircraft. This time is much greater for large aircraft, an Airbus A380 is allowed to start the APU one hour in advance [84].

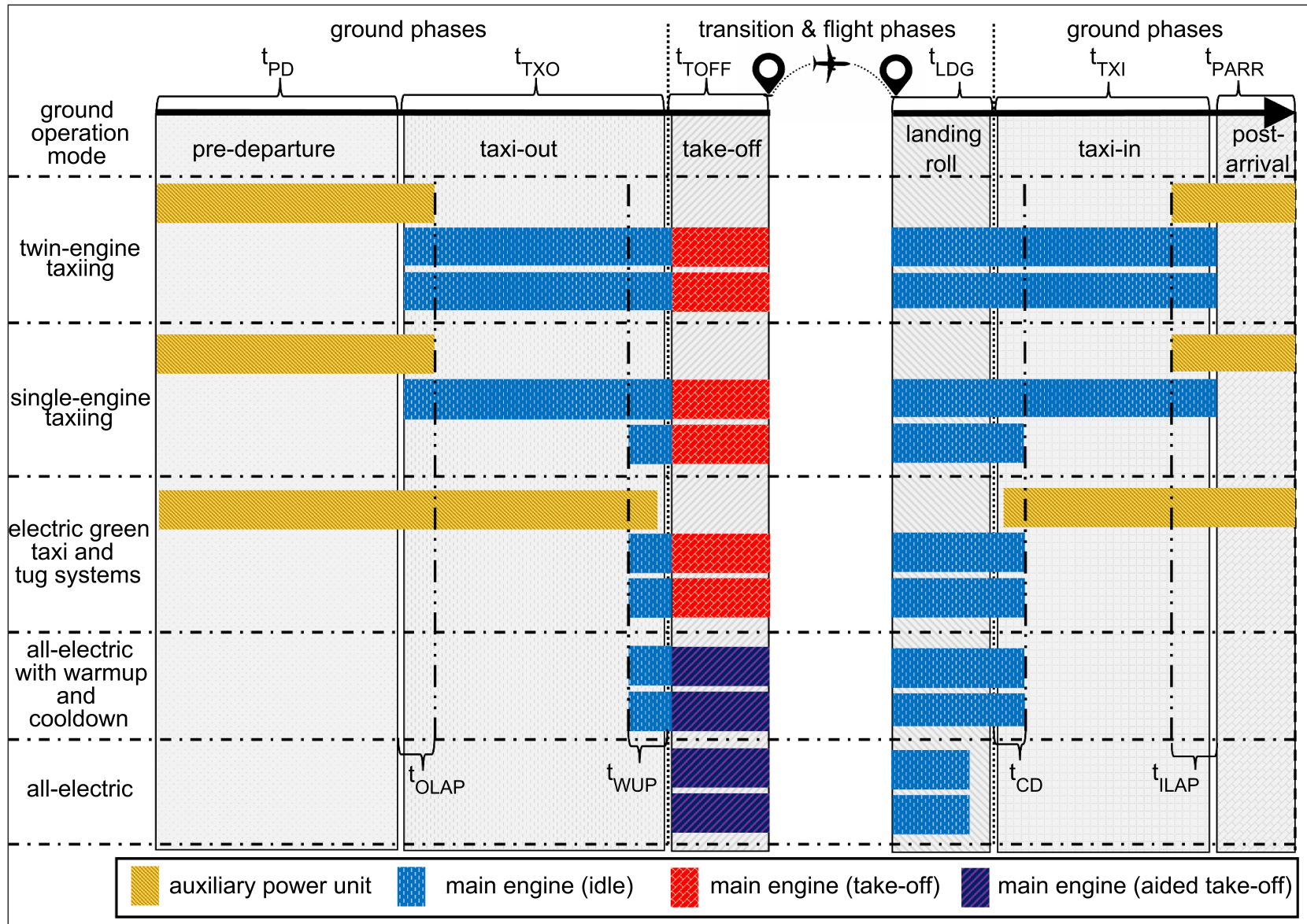


Figure 3.6: ICE usage during ground and transition phases of mission.

There is often a mismatch between regulations and practice, especially when aircraft fly many missions in one day and a delay occurs. Then, the device may be kept on throughout the whole time at the gate. Padhra [85] captured the data for the single day turnarounds around Europe and showed that time between the APU switched on and the aircraft departing is equal to 15 minutes or more for over half of the flights. This is exceptionally important when considering a probability of delay where Zijadi et al. [107] measured that 64 % of arrivals and 46 % of departures were delayed at Sarajevo airport.

The taxi-out phase takes place after the pre-departure and begins with the push-back during which the main engines are started one after another unless operation mode is the single-engine taxiing (SET), thereafter the APU is turned off. There is a small overlap with both types of engines running in parallel and the data recorded by Winther et al. [87] showed that it equals to thirty seconds on average at Copenhagen airport. The timeline is different for EGTS, where an APU is kept on throughout the taxiing until the main engines have to be started for the warmup procedure, which typically takes three minutes [19]. A similar overlap between the APU and the main engines still occurs with EGTS. The taxi-out ends at the runway and the aircraft begins to takeoff. The main engines are set to higher thrust levels and accordingly consume much more fuel. If present, the landing gear drive system works at full torque to aid the main engines in accelerating the aircraft until 70 m/s is reached.

After arrival, the multiple deceleration systems are engaged during the landing and if weather conditions allow, pilots use the idle thrust reversers. The landing gear drive system also accounts to deceleration and the electric machines work at peak torque rate in the regenerative quadrant leading to kinetic energy being harvested back into the battery.

The fuel consumption throughout the taxiing-in begins with the main engines cooldown period that normally takes three minutes [19]. The procedure begins to differ between the ground operation modes once the main engines can be switched off. One engine is switched off for the SET procedure and both for the electric green

taxi systems. If the EGTS is operated, the APU is turned on by the end of cooldown once again with a small overlap that is simulated as thirty seconds.

Once the aircraft arrives at the gate, the main engines are immediately switched off to enable the ground crew to begin their procedures. Then, the APU is disengaged as soon as the ground power is plugged in which takes 3 minutes for 73 % of interday flights [85], whereas the mean time for the Copenhagen airport equals more than four minutes [87]. The maximum period of time for running the APU inbound is regulated by airport operators and Heathrow allows five minutes maximum. The assumption is made that the device is deactivated three minutes after arrival.

3.6 Net Fuel Savings

The fuel saved during ground operations is reduced by additional fuel burned due to weight penalty in-flight. The weight of the battery is estimated regarding the battery specific energy $W_{bat} = E_{dem}/SE_{bat}$ and total weight of the electric machines, the power converters and the drivetrain is estimated according to the specific power $W_{pow} = P_{dem}/SP_{em} + P_{dem}/SP_{dr} + P_{dem}/SP_{pcon}$. Finally, the total weight of the system is equal to $W_{tot} = W_{bat} + W_{pow}$.

Once the weight of system is known, it is possible to estimate its relation to increased in-flight fuel consumption. This is achieved with the block fuel intensity metric that factors weight of fuel burned per weight of payload per unit of flight distance. Albeit this parameter is highly influenced by aerodynamics and remains nonlinear. Researchers often linearize it which is accurate for flights up to approximately 75 % of maximum aircraft range [88]. Zheng and Rutherford [89] provided the block fuel intensity for the narrowbody aircraft manufactured between 1969 and 2019; the values varied between 200 and 390 grams of fuel per metric tonne-kilometer. These values were compared to Gao et al. [90] experimental aircraft data that comprised fuel usage against payload for the Airbus A321 flights from Beijing (PEK) to Chengdu (CTU) and the Boeing 737 flights from PEK to Shanghai (SZX). The values were be-

tween 220-350 for an A321 and between 230-330 for a B737. Yanto and Liem [91] used a slightly different metric of kilograms of fuel per seat-nautical mile. After assuming that a single seat equates to 104 kg of payload [92] the values were equal from 210 to 260. According to gathered data, the conservative value of 315 g per metric tonne-kilometer was used in the simulation.

The block intensity fuel among with the parameters given in Table 3.1 allow to benchmark the net fuel savings of the landing gear drive system against the other ground movement methods. First, the calculation of fuel consumption exerted by both the APU and the main engines during ground movement:

$$\begin{bmatrix} FU_{ote} \\ FU_{ooe} \\ FU_{oEGTS} \\ FU_{wup} \end{bmatrix} = \begin{bmatrix} t_{PD} + t_{OLAP} \\ t_{PD} + t_{OLAP} \\ t_{PD} + t_{TXO} - t_{WUP} + t_{OLAP} \\ 0 \end{bmatrix} \cdot FC_{APU} + \begin{bmatrix} 2 \times t_{TXO} \\ t_{TXO} + t_{WUP} \\ 2 \times t_{WUP} \\ 2 \times t_{WUP} \end{bmatrix} \cdot FC_{me} \quad (3.8)$$

Similarly, the fuel consumption for the inbound ground operations is equal to:

$$\begin{bmatrix} FU_{ite} \\ FU_{ioe} \\ FU_{iEGTS} \\ FU_{cd} \end{bmatrix} = \begin{bmatrix} t_{PAR} + t_{ILAP} \\ t_{PAR} + t_{ILAP} \\ t_{PAR} + t_{TXI} - t_{CD} + t_{ILAP} \\ 0 \end{bmatrix} \cdot FC_{APU} + \begin{bmatrix} 2 \times t_{TXI} \\ t_{TXI} + t_{CD} \\ 2 \times t_{CD} \\ 2 \times t_{CD} \end{bmatrix} \cdot FC_{me} \quad (3.9)$$

The division between outbound and inbound ground fuel consumption is important for the incurred weight penalty. If the landing gear drive system saves fuel during inbound ground operations, the mass of saved fuel can be subtracted from the total weight penalty of the system. The incurred fuel burn due to weight penalty is

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

calculated:

$$\begin{bmatrix} FP_{te} \\ FP_{oe} \\ FP_{EGTS} \end{bmatrix} = \begin{bmatrix} W_{tot} - W_{APU} - FU_{ite} + FU_{cd} \\ W_{tot} - W_{APU} - FU_{ioe} + FU_{cd} \\ W_{tot} - W_{APU} - W_{EGTS} - FU_{iEGTS} + FU_{cd} \end{bmatrix} \cdot S_f \cdot FC_{pp} \quad (3.10)$$

Once the fuel consumption during the ground operations and the additional fuel burn due to weight penalty are known, the estimation of fuel saving is done:

$$\begin{bmatrix} FS_{te} \\ FS_{oe} \\ FS_{EGTS} \end{bmatrix} = \begin{bmatrix} FU_{ote} \\ FU_{ooe} \\ FU_{oEGTS} \end{bmatrix} + \begin{bmatrix} FU_{ite} \\ FU_{ioe} \\ FU_{iEGTS} \end{bmatrix} - \begin{bmatrix} FP_{te} \\ FP_{oe} \\ FP_{EGTS} \end{bmatrix} + \begin{bmatrix} FU_{toff} - FU_{wup} - FU_{cd} \\ FU_{toff} - FU_{wup} - FU_{cd} \\ FU_{toff} - FU_{wup} - FU_{cd} \end{bmatrix} \quad (3.11)$$

Some flights at smaller airports have shorter taxiing times than the required warmup and cooldown periods. Consequently, an aircraft will turn on the main engines at the gate and such a special case is considered in the calculus by assuming that the t_{TXO} equals t_{WUP} and T_{PD} is corrected with the initial difference between t_{TXO} and t_{WUP} . The similar logic is applied to inbound ground movement if the t_{CD} exceeds t_{TXI} . The presented equations also allow to neglect completely the warmup and cooldown cycles. In these circumstances, FU_{wup} , FU_{cd} , t_{WUP} and t_{CD} are equal to zero.

The recorded ground movement data from Figure 3.3 is now used to estimate the fuel savings for each flight. Table 3.3 presents the expected fuel savings for the system with modular battery packs.

3.7. PARAMETRIC STUDY FOR FUEL SAVINGS

Table 3.3: Simulation results for the ground movement data of three different missions

Flight	Luton-Krakow W65002 Fig.3.3(a,b,c)	Athens-Luton FR7806 Fig. 3.3(d,e,f)	Toronto-Calgary TS682 Fig. 3.3(g,h,i)
Energy storage capacity (kWh)	50 (1 module)	50 (1 module)	100 (2 modules)
Fuel savings against twin-engine taxiing (kg)	103	81	328
Fuel savings against single-engine taxiing (kg)	78	53	102
Fuel savings against electric green taxiing system (kg)	234	335	247

The results show that each mission augmented with the landing gear drive system has the improved fuel economy. The greatest savings are calculated against the EGTS because the weight penalty with modular batteries is lower than the weight penalty of the EGTS which also requires the APU. Therefore, economy is improved during both ground movement and in-flight.

3.7 Parametric Study for Fuel Savings

Each aircraft mission is unique when considering duration of mission phases. In this section, the landing gear drive system is simulated with respect to varying flight distance and cumulative taxiing time. Different taxiing duration is considered although, the post-departure and the post-arrival time remains constant at 15 and 3 minutes respectively.

The fuel saving term refers to the net reduction in jet fuel consumption during ground operations when using the electric landing gear drive system compared to conventional taxiing methods relying on main engines. This savings accounts for

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

both the decreased fuel burn during taxi phases due to electric propulsion and regenerative braking energy recovery, minus any additional inflight fuel penalty caused by the weight of the onboard battery system. Essentially, it quantifies the net fuel mass conserved over the taxi and takeoff ground phases as a result of substituting internal combustion engine thrust with electric drive assistance.

The cumulative taxi times are distributed with respect to the proportion between taxi-out and taxi-in times derived from the mean taxi duration for 555 airports provided by EUROCONTROL [5] and equal two-third and one-third respectively. Figure 3.7 presents the parametric study results for an Airbus A320 which performs the standardized missions with varying cumulative taxi times and flight path lengths.

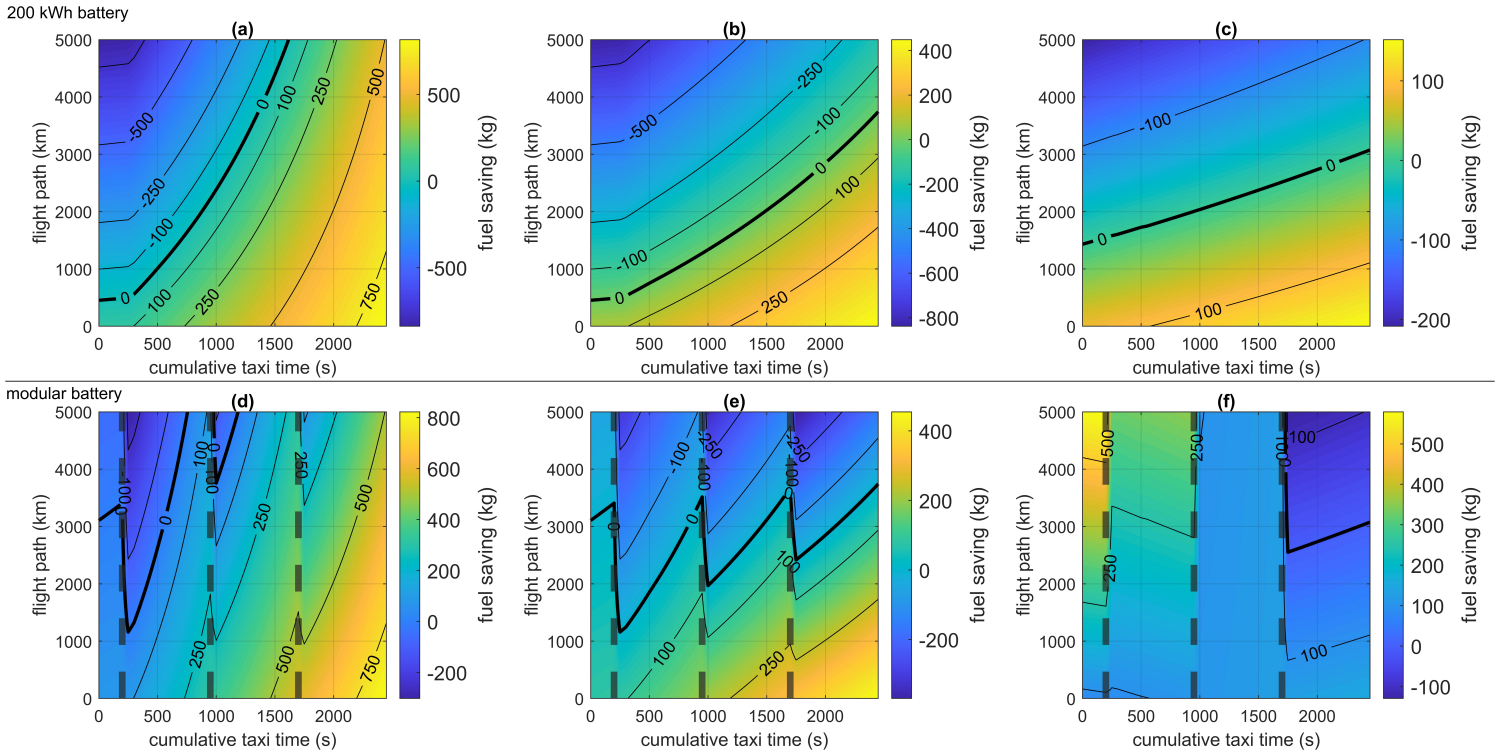


Figure 3.7: Fuel saving simulation results for technology level from 2022. Negative values indicate the excessive fuel consumed due to weight penalty. The first row assumes that all battery modules are present whereas the second row reflects the module removal for shorter taxiing cycles (indicated by the dashed lines). The landing gear drive system was benchmarked with: (a,d) Twin-engine taxiing (TET), (b,e) Single-engine taxiing (SET), (c,f) EGTS and tugs.

During short-haul flights, the landing gear drive system provides the net fuel savings

against each conventional ground operation mode. The greatest fuel savings are achieved in Figure 3.7 (a,d) where TET operation mode was replaced. Depending on the cumulative taxi time, the system can be advantageous for all simulated flight distances including the medium-haul flights. The net savings are lower in Figure 3.7 (b,e), which shows the comparison with the single-engine taxiing. Nevertheless, the system remains advantageous for flights up to 3000 km during longer taxiing times. Figure 3.7(c,f) depicts net fuel saving against the EGTS. Albeit the lower peak savings are indicated, the results are more consistent across all cumulative taxiing times. The savings are expected for every flight up to 1200 km, which is the case for nearly every domestic flight. Finally, the results from Figure 3.7 (d,e,f) show that modular batteries maximize the net fuel savings where the intermittent lines indicate that the additional 50 kWh battery modules are inserted when cumulative taxiing time exceeds 200 s, 950 s and 1700 s. Furthermore, the benchmark with the EGTS in Figure 3.7 (f) shows the negative slope when the first and the second module are present. This is caused by smaller weight penalty incurred by the landing gear driving system than by the EGTS.

The fuel saving is accrued at the price of electricity needed to charge the battery. Heathrow Airport Ltd [108] meters the ground unit electricity supply and charges 19 pence per kWh. For the full, 200 kWh charge of the system at 90 % charging efficiency it would cost 42. This cost is offset by the fuel saving reaching as much as 500 kg. The assumption of 250 kg fuel saving which costs 1.71 per kg [109] yields 373 saving per flight and corresponds to 7 % of a total fuel price reduction for a flight from London Heathrow to Glasgow [110].

3.7.1 Modular Batteries

The weight penalty is a major drawback for the proposed system and up to this point, the battery size was scaled according to EUROCONTROL longest taxi times meaning that most of the time, an aircraft would carry the battery with excessive capacity. Alternatively, the battery can be divided into the multiple segments connected

in parallel which would allow to remove unused segments at a gate. This approach would lead to reduced in-flight incurred weight penalty.

3.8 Landing Gear Drive System in Future

Any novel aircraft system implementation is more likely to succeed during the conceptual stage of aircraft development rather than during retrofitting to the air vehicles already in service. Retrospectively, the Airbus A350 programme was launched in 2005 while the aircraft entered service ten years later and similarly, eight years elapsed between announcement of Boeing 787 and its entering into service in 2011 [111]. In parallel, the electric vehicle components were significantly improved. Energy storage is a textbook example because the specific energy of battery cells available for aviation nearly doubled in last decade [73] and this performance metric will unquestionably improve in the coming years. Accordingly, commercial aircraft concepts that are being discussed at present should include the landing gear drive system with performance metrics that will be available in near future.

The predicted increase in number of commercial aircraft in service will inevitably lead to increased taxi times unless the airport operational efficiency is increased by, for example, the fully autonomous taxiing. In the automotive industry, reduced congestions and traffic flow improvement are highlighted when describing autonomous cars [112] and the same conclusion is drawn for the fully automated taxiing of aircraft [70]. The landing gear drive system is a large step towards the autonomous taxiing for multiple reasons. Primarily, the operation of the electric taxiing system is much simpler when compared to the main engines. Turbofans and turboprops are very complex and pilots have to spend considerable amount of time following the checklists to ensure a safe operation whereas electric machines would require much less attention. Accordingly, the autonomous operation algorithm would be simplified as well. Another factor that currently hinders the autonomous taxiing idea is the jet blast which is a serious threat for airports and ground crew. Implementation of the landing

3.8. LANDING GEAR DRIVE SYSTEM IN FUTURE

gear drive system allows to keep the main engines off until an aircraft reaches a runway. Similarly, the risk of FOD would be inapplicable because the aircraft would be solely propelled by the wheel drive. Finally, the high-power landing gear drive system offers better controllability because the torque response would be nearly instant when compared to the main engines which take time to spool up and provide thrust.

The energy storage accounts for more than half of the total weight in the landing gear drive system, however, the upcoming technologies potentially allow to reduce or completely remove the weight penalty incurred by the proposed system. This can be achieved by combining the wheel drive with a large energy storage already available onboard of future aircraft. Xie et al. [113] reviewed the hybrid electric powered aircraft concept that incorporates large batteries. They estimated as much as 30 % fuel economy improvement with the hybrid technology. A further step is an all-electric aircraft which receives increasing attention. This concept assumes that the ICEs are absent onboard, and the propulsive power is generated with electric machines only. Currently, the low specific energy of batteries is a restraining factor for this technology [114, 115, 116]. The landing gear drive system would potentially reduce severity of poor battery performance by increasing the energy efficiency of all-electric aircraft during ground movement. The energy transfer benchmark between the propeller- and the wheel-driven taxiing would provide the answer about feasibility.

Battery technology has seen significant improvement such as fast charging, high efficiency and lightweight designs. Furthermore, the current research areas include structural batteries which are also known as the massless energy storage [117]. They aim to significantly reduce the weight of battery-powered vehicles by integrating the battery into the structure and consequently, the requirement for a separate battery is reduced or eliminated.

The discussed advantages of future technology are combined in Figure 3.8, which demonstrates the projected increase in the net fuel savings of the landing gear drive system.

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

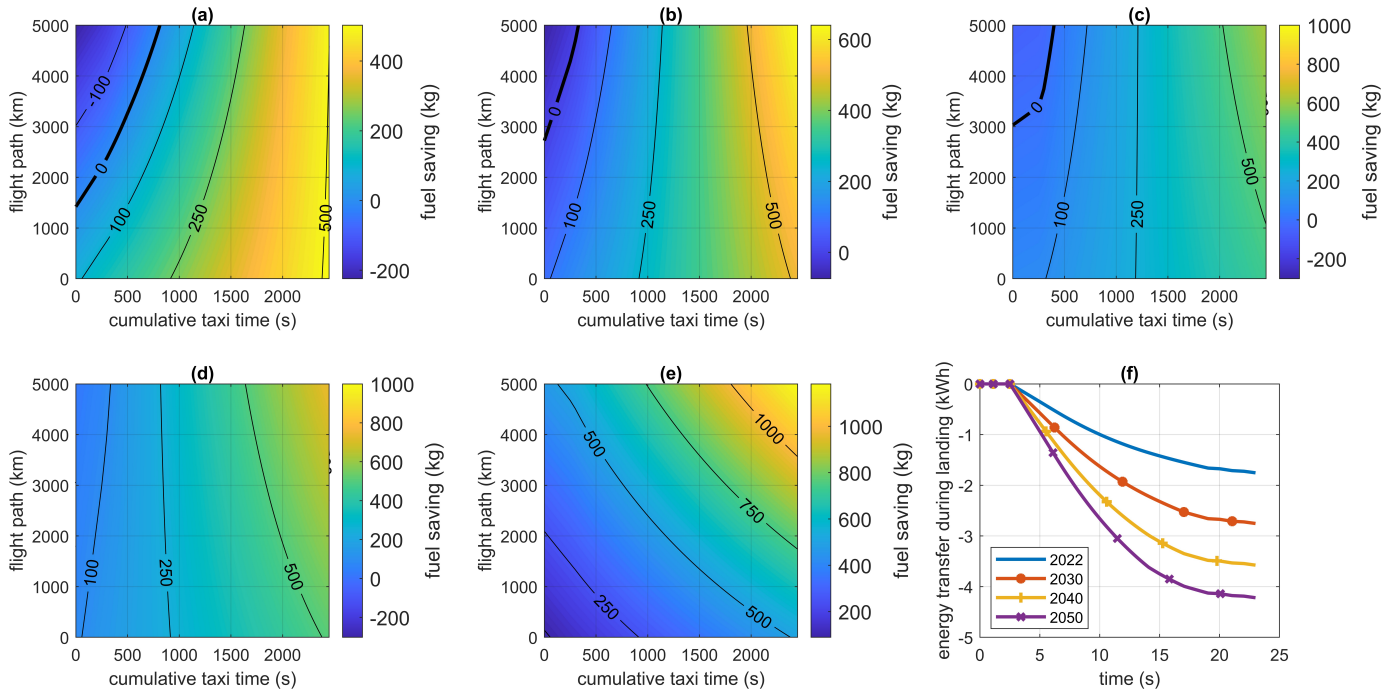


Figure 3.8: Simulation results of fuel and energy saving for future technology. Negative values indicate the excessive fuel consumed due to weight penalty. (a) 2030 performance metrics against single-engine taxiing (SET), (b) 2040 performance metrics against SET, (c) 2050 performance metrics against SET, (d) 2050 performance metrics combined with the neglected warmup and cooldown cycles against SET, (e) 2050 performance metrics combined with the battery weight, warmup and cooldown cycles neglected. (f) Energy recovery during W65002 landing for present and future performance metrics.

The system-level improvements will primarily impact the weight penalty. The benchmark in Figure 3.8 (a,b,c) is made with an assumption that the battery capacity and the power of the system remains unchanged but the improved performance shown in Table 3.2 allows weight reduction. Figure 3.8 (a) shows that the net fuel savings against the SET will exceed 500 kg in 2030 and the growth will continue to 2040 (see Fig. 3.8 b), while there is a stagnation towards 2050 as depicted in Figure 3.8 (c). This lack of improvement is caused by the warmup and cooldown periods of main engines during which jet fuel is consumed. The future technology may allow to skip these cycles and Figure 3.8 (d) depicts the fuel savings of 2050 technology level with the warmup and cooldown cycles neglected. Further weight reduction can be achieved by considering an MEA with the large energy storage already fitted on-board. Thus, the battery weight can be ignored when calculating the weight penalty

of the landing gear drive system, and Figure 3.8 (e) indicates that the net fuel savings would exceed 1000 kg for the longest flights. The slope shows that the amount of fuel saved increases also with flight distance. In other words, the weight penalty without battery will be lower than the mass of fuel needed for inbound ground operations in 2050.

Instead of reduced weight, the design objective may be set to maximize harvested energy during landing. Therefore, weight of the system in future would remain constant with the mechanical power increased. Figure 3.8 (f) shows the amount of energy recovered by the landing gear drive system during the W65002 landing for different technology levels. In 2050, the 1600 kW electric machines would be capable of harvesting over 4 kWh which corresponds to about 16 % of dissipated energy during landing by all deceleration systems fitted onboard.

Ground operations have a broader meaning which is linked to all aspects of aircraft handling including the preparation for a departure and an arrival. To claim the truly all-electric and sustainable ground operations, each chain-link needs to abandon the ICE. Many airports compete to become the first net zero airport as soon as in 2030 [118] and these bold claims are backed by the current technology development within automotive, civil and energy engineering. Providing examples, BP [119] introduced the all-electric refuelling vehicle, Swissport [120] offers the electric ramp and cargo handling and Vestergaard [121] supplies the electric de-icing vehicles. Nonetheless, the primary limiting factor in electrification is a large financial impact exerted on airport operators.

3.9 Conclusions

The call for electrification of aviation was addressed in this chapter with a landing gear drive system for short-haul MEA. The present work introduced the novel landing gear drive system that combines the multiple academic developments and introduced the regenerative braking during landing to maximize energy efficiency of

CHAPTER 3. MORE ELECTRIC AIRCRAFT CONVERSION TO ALL-ELECTRIC: LANDING GEAR DRIVE SYSTEM

operation. Therefore, the primary obstacle for electrified aircraft, namely the specific energy of battery, was overcome to the extent that the system was proven to be both sustainably and economically feasible.

The landing gear drive system depleted approximately a quarter of the energy storage capacity during taxiing while the rest was used by the ECS, actuation, fuel pumps and main engine starters. The battery present onboard consisted of 50 kWh modules that stacked up to 200 kWh. This much of energy allowed an Airbus A320 to execute the all-electric taxi cycles as long as 26 minutes. To maximize the energy efficiency, the kinetic energy recovery was added during the landing and it allowed to harvest approximately 10% of available energy. The anticipated quantity of the fuel savings depended on flight distance and taxiing time. The calculation according to the present fuel and electricity prices demonstrated considerable cost reduction of short-haul flights with 7 % fuel expense reduction for a flight from London Heathrow to Glasgow. The fuel saving projections were also made according to the future performance metrics and in 2050, the landing gear drive system would reduce the overall consumption for nearly every mission. For the best cases, more than 500 kg of fuel would be saved.

The presence of the large battery fitted onboard will further accelerate the electrification of the aerospace industry because it can be shared in-flight with multiple systems such as the hybrid-electric propulsion. Consequently, researchers and aircraft manufacturers will be able to work on concepts that were otherwise inapplicable due to limited specific energy of batteries. In distant future, it is likely that the industry will move away from fossil fuels and therefore, the future work should focus on the landing gear drive system feasibility for all-electric aircraft.

Chapter 4

SPCrane Optimization Framework Relying on Pointwise Ensemble of Surrogates

The SPCrane framework introduces a Python-based pointwise ensemble methodology for engineering optimization, dynamically combining surrogate models like Kriging and radial basis functions through spatially adaptive weighting. Key innovations include correction factors reducing single-model biases. Benchmarking on functions such as Rosenbrock and engineering problems like cantilever beam stress demonstrates superior accuracy (99.8% R-squared on tensor-product functions) and computational efficiency via K-Fold validation and Rust-accelerated Gaussian processes. The framework's sigmoid-based offset logic improves prediction at model transition boundaries compared to global weighting schemes. By providing modular, extensible Python implementations compatible with the Surrogate Modeling Toolbox, SPCrane bridges theoretical ensemble research with practical applications, enabling efficient optimization of expensive black-box problems in aerospace, mechanical, and civil engineering without requiring expert knowledge.

4.1 Introduction

Engineering design optimization frequently confronts the challenge of evaluating complex systems through computationally intensive simulations or expensive physical experiments. These evaluations, often characterized as “black-box” problems, present significant constraints on traditional optimization approaches due to their prohibitive computational costs [122]. To overcome this limitation, surrogate models (also known as metamodels or response surface models) have emerged as powerful tools that approximate the relationship between design variables and response quantities of interest using mathematical functions trained on a limited set of sample points [123].

Surrogate models serve as computationally efficient substitutes for expensive numerical simulations or physical experiments, facilitating rapid exploration of design spaces and enabling optimization of complex engineering systems [124]. These models are constructed by generating a set of sample points in the design space, evaluating the actual system responses at these points, and then fitting a mathematical model to approximate the relationship between inputs and outputs [123]. Common surrogate modeling techniques include polynomial response surfaces, radial basis functions (RBF), Kriging, support vector regression (SVR), and neural networks, each with distinct strengths and limitations in capturing different types of response behaviors [123, 125]

While individual surrogate models provide valuable approximations, their performance can vary significantly depending on the nature of the underlying problem, sampling plan, and dimensionality of the design space [124]. No single surrogate model consistently outperforms others across all problem types, creating a critical challenge: how to select the most appropriate surrogate model for a specific application without prior knowledge of the actual system behavior [124, 126].

To address the challenge of surrogate model selection, researchers have developed ensemble approaches that strategically combine multiple surrogate models to

leverage their complementary strengths [127]. Ensemble methods can be broadly categorized into two approaches: global ensemble methods and pointwise ensemble methods.

Global ensemble approaches assign a single set of weights to different surrogate models across the entire design space, typically determined by global error metrics such as root mean square error or coefficient of determination. While global ensembles offer simplicity and computational efficiency, they often fail to capture local variations in model performance across the design space.

In contrast, pointwise ensemble methods assign different weights to surrogate models at each point in the design space, enabling more adaptive and accurate predictions by leveraging the strengths of different models in different regions[127][128]. Recent advancements in pointwise ensemble techniques, such as the Optimization-based Two-Layer Pointwise Ensemble of surrogate Models (OTL-PEM) [127] and Pointwise-optimal Ensemble of Surrogate Models (POEM) [128]), have demonstrated superior prediction accuracy and robustness compared to both individual surrogate models and global ensemble approaches.

The effectiveness of surrogate models in engineering optimization critically depends on the quality and distribution of sample points used to train these approximations, making the selection of appropriate sampling methods a foundational consideration in metamodel construction. Random sampling, the most basic approach, generates points uniformly across the design space without structured patterns, providing simplicity but often requiring large sample sizes to achieve adequate coverage [129]. In contrast, Latin hypercube sampling (LHS) partitions each dimension into equal intervals and ensures that each interval is represented exactly once, creating a space-filling design that improves prediction accuracy while reducing computational costs compared to pure random sampling. For problems requiring exhaustive exploration of factor interactions, full-factorial sampling systematically evaluates all possible combinations of predefined factor levels, though this method becomes computationally prohibitive in high-dimensional spaces due to its exponential scaling.

CHAPTER 4. SPCrane OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

The PyDoE (Python Design of Experiments) library addresses these challenges by providing implementations of advanced sampling strategies, including LHS and fractional factorial designs, enabling engineers to balance computational efficiency with design space coverage. These sampling techniques directly influence the surrogate model's ability to capture nonlinearities and discontinuities in the response surface - a capability central to the SPCrane framework's pointwise ensemble methodology, which dynamically weights surrogate predictions based on localized accuracy [123]. By integrating PyDoE's [129] sampling capabilities with adaptive refinement algorithms, SPCrane ensures robust initialization of metamodels while maintaining compatibility with high-dimensional engineering optimization problems, where traditional sampling methods often fail to adequately represent complex design spaces.

Despite the significant theoretical advances in surrogate modeling and ensemble techniques, a critical gap exists between mathematical formulations and practical engineering applications [125]. Most research papers focus predominantly on the mathematical foundations and algorithmic aspects of surrogate modeling, with limited attention to computational implementation, usability, and integration into existing engineering workflows. This disconnection poses substantial challenges for practitioners seeking to apply these advanced techniques to real-world engineering problems.

The development of comprehensive, accessible software implementations is essential for bridging this gap and enabling widespread adoption of advanced surrogate modeling techniques in engineering practice. An integrated Surrogate Modeling Toolbox with well-documented, efficient implementations of both established and cutting-edge algorithms allows engineers to focus on solving their domain-specific problems rather than reimplementing complex mathematical procedures. Furthermore, a unified software framework facilitates fair comparisons between different methods, enables reproducible research, and accelerates the translation of theoretical advances into practical engineering solutions.

To address these limitations, this chapter introduces SPCrane, a Python frame-

work for engineering optimization that leverages pointwise ensemble of surrogates. The proposed framework employs a novel pointwise ensembling model that relies on cross-validation error to induce a weighted bias, enhancing accuracy through model refinements. This approach is assessed for both regression and interpolation models, with the added possibility of incorporating uncertainty for improved versatility. A multitude of surrogate models can be seamlessly integrated, facilitated by automated hyperparameter optimization and adaptive sampling strategies.

To reduce the curse of dimensionality, computational cost considerations were balanced against accuracy assessments by substituting Leave-One-Out Cross-Validation with K-Fold Cross-Validation, yielding significant insights. Additionally, the model incorporates noise handling and demonstrates compatibility with the Mixture of Experts (MOE) framework. The SPCrane implementation requires no expert knowledge, enabling broader accessibility to advanced surrogate modeling techniques.

The SPCrane framework represents several significant contributions to the field:

1. A substantially revised pointwise metamodeling algorithm with comprehensive computational implementation in Python, providing engineers with accessible tools for applying advanced surrogate modeling techniques to practical problems.
2. Novel correction factors that stabilize the ensemble equations and reduce resultant biases inherent in single metamodels, enhancing the robustness and reliability of predictions in diverse engineering contexts.
3. Pioneering considerations toward the integration of Ensemble of Surrogates (EoS) to Mixture of Ensemble of Surrogates (MoES), extending the capability of surrogate modeling to handle complex, multi-modal response surfaces more effectively.

The framework is benchmarked on a multiple problems showcasing its practical applicability and potential impact across high-dimensional optimization tasks. By providing both algorithmic innovations and their software implementation, SPCrane contributes to the democratization of advanced optimization methods for engineering design, bridging the gap between theoretical research and practical application.

The content of this chapter is organized as follows: Section 4.2 presents the

SPCrane engineering optimization framework, detailing its architecture and implementation. Section 4.2.1 introduces the individual metamodels, examining various surrogate modeling techniques that can be integrated within the framework. Section 4.2.2 introduces the benchmarking problems for validation and performance assessment, establishing the methodology for evaluating the proposed approach. Section 4.3 provides the results of the experimental studies and comparisons with existing methods. Section 4.5 concludes this research and recommendations follow in Section 4.5.1.

4.2 SPCrane Engineering Optimization Framework

While numerous studies in the literature have demonstrated the consensus regarding the superiority of ensemble surrogate models over single expert models across various applications, no single ensemble approach consistently outperforms all others across all problem domains. The SPCrane framework addresses this challenge by employing a methodology based on Euclidean distance calculation and cross-validation error estimation. Notably, the SPCrane model has been validated to have the errors comparable to SP1 and computational improvements made the SPCrane more accurate [130].

An ensemble surrogate model can be formulated by applying a weighted averaging methodology to multiple individual metamodels. The resultant ensemble model can be mathematically expressed as

$$\hat{y}_{\text{ens}}(\mathbf{x}) = \sum_{i=1}^{N_M} w_i(\mathbf{x}) \hat{y}_i(\mathbf{x}) \quad (4.1)$$

In this methodology, weight factors are determined through cross-validation error metrics rather than prediction variance, and must be normalized for each prediction point. The weighting scheme for each metamodel at a given prediction location is formulated as

$$w_i(x) = \frac{W_i(x)}{\sum_{j=1}^{N_M} W_j(x)} \quad (4.2)$$

Previous research has proposed two pointwise weighing approaches, the first being SP1, which is described as

$$W_i(x) = \sum_{k=1}^N W_{ik} I_k(x) \quad (4.3)$$

This factor is assigned a value of one for the metamodel exhibiting the minimal cross-validation error at the k -th data point, while all other metamodels receive a null weighting at that location. This selective weighting mechanism ensures that only the predictive output of the single most accurate metamodel determined by localized cross-validation error minimization is incorporated into the final prediction at each respective data point. The function $I_k(x)$ is derived from

$$I_k(x) = \frac{1}{d_k^2(x)} \quad (4.4)$$

where the distance between the prediction point and the k -th data point is expressed as:

$$d_k(x) = \|x - x_k\| \quad (4.5)$$

with $\|\cdot\|$ denoting the Euclidean norm. A critical limitation arises in Equation 4.4 when $d_k(x) = 0$, leading to a division-by-zero singularity. To mitigate this problem, the weight function $W_i(x)$ is explicitly assigned the value W_{ik} under the condition $d_k(x) = 0$, bypassing computational instabilities. Furthermore, the near-zero values introduce excessively high weight factors that bias the results. In response, the author add a constraint limiting the maximum value for each weight factor to one.

Another approach, denoted as SP2, has also been proposed and is described as

$$W_{ik} = \frac{1}{e_{ik}^2}, \quad e_{ik} = y(k) - \hat{y}_i(k) \quad (4.6)$$

CHAPTER 4. SPCrane OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

In this formulation, the weight factors at data points are inversely proportional to the square of the cross-validation errors. The author observes that the influence of this approach rapidly diminishes as the Euclidean distance increases. While additional approaches exist in the literature, the SP1 and SP2 weighing methods have been empirically demonstrated to be superior when validated across multiple engineering problems.

The SPCrane framework employs a pointwise ensemble weighting scheme based on two primary mathematical approaches (SP1 and SP2), both of which utilize cross-validation error metrics to assign weights to constituent surrogate models. Mathematically, the ensemble prediction at a given point is expressed as $y_{\text{ens}}(x) = \sum_{i=1}^N w_i(x) y_i(x)$, where $w_i(x)$ denotes the normalized weight of model i at the prediction point x . The weights are determined either by using the inverse squared cross-validation error or by selecting the model with the lowest local error. In the SP1 approach, the entire weight is assigned to the best local model, whereas in the SP2 approach, the weights are distributed inversely proportional to the squared cross-validation error, i.e., $w_{ik} = 1/e_{ik}^2$, where e_{ik} represents the cross-validation error of model i at point k . To avoid division-by-zero errors and excessive weight concentration, the scheme includes normalization and practical constraints, such as capping individual weights at unity. The framework further introduces spatial and sigmoid-based correction factors to dynamically adjust weights at transition boundaries, as formalized by equations 13 in the thesis. Sensitivity analysis indicates that the weighting scheme is more robust to model variance, as models with larger local errors receive less influence, thereby stabilizing predictions. However, if an outlier disproportionately affects the cross-validation error for a particular model at a given point, this can lead to local over- or under-weighting. To mitigate this, the use of K-Fold cross-validation and logistic correction factors helps distribute influence more evenly and reduces susceptibility to erratic predictions from outlier-affected data regions, a result validated in the benchmark studies and comparative performance plots in Sections 4.3 and 4.2.2.

Figure 4.1 illustrates the operational structure of the SPCrane framework and its integration within the broader context of the Mixture of Ensembles of Experts (MOEOE) methodology. The plain source code can be found in the Appendix E. This comprehensive flowchart delineates the key components and processes involved in the optimization workflow. The MOEOE framework begins with a clustering phase, where the input data is partitioned into localized regions to facilitate specialized model training. Each cluster is processed by the SPANE ensemble, which serves as the local expert training mechanism. This modular integration enables the system to leverage localized expertise for surrogate modeling. The outputs from these localized models are subsequently recombined using the Surrogate Modeling Toolbox (SMT), ensuring that predictions are synthesized effectively across all clusters. This hierarchical structure allows MOEOE to dynamically adapt to spatial variations in model performance, addressing the challenge of heterogeneity in complex datasets.

CHAPTER 4. SPCRANE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

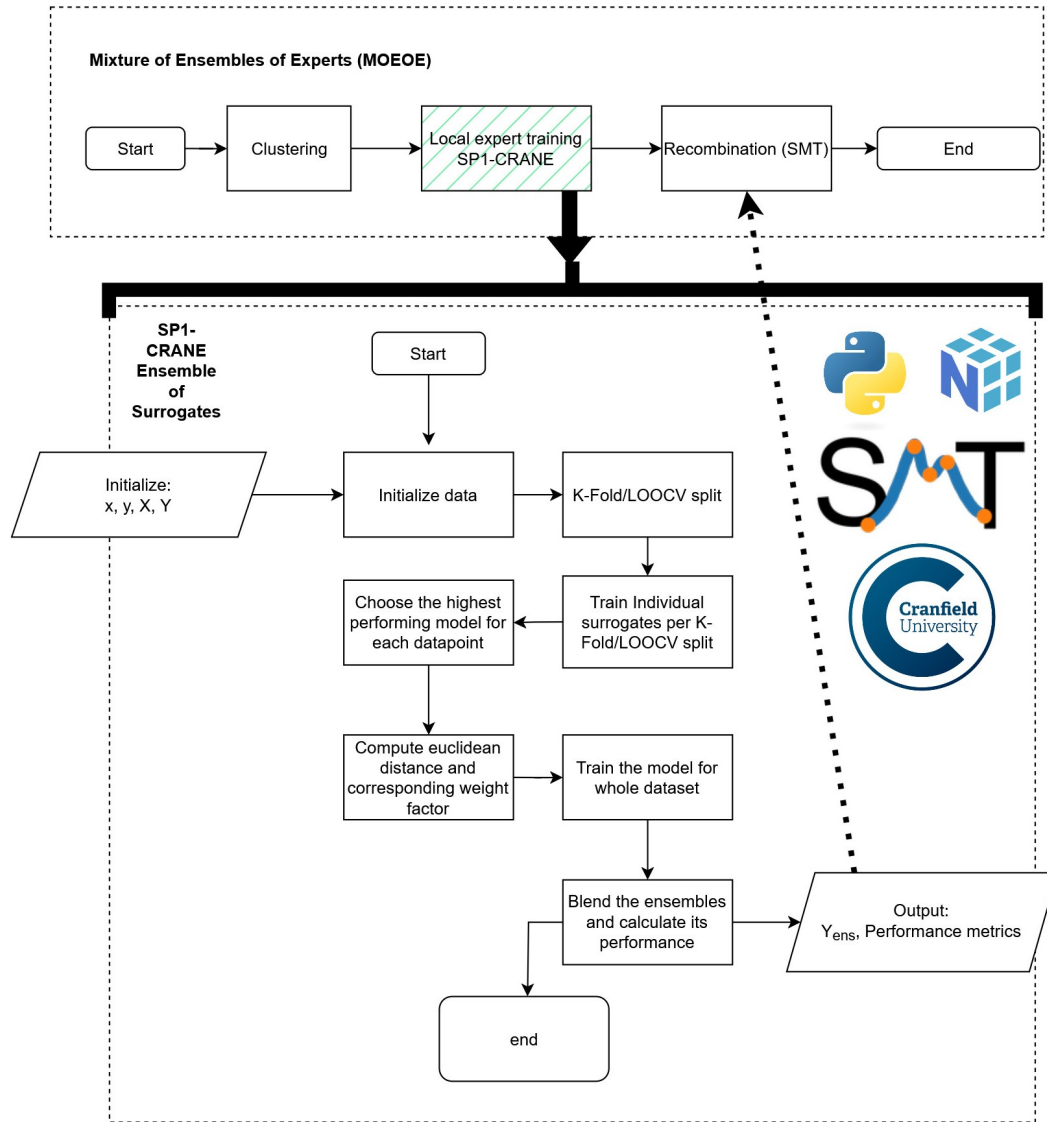


Figure 4.1: SPCrane optimization flowchart and its description in context of the Mixture of Ensembles of Experts (MOEOE)

Within the SPCrane ensemble framework, as depicted in Figure 4.1, the process begins with data initialization and hyperparameter specification, which establish the foundation for robust modeling. The methodology employs K-Fold or Leave-One-Out Cross-Validation (LOOCV) to partition data, enabling the identification of optimal surrogate models for each data point. Distance-based spatial weights are calculated

to dynamically adjust model contributions, ensuring that predictions reflect localized accuracy. The final stage involves normalization and summation of weights from all components, culminating in a comprehensive predictive framework that adapts pointwise to changes in the best-performing expert across independent variables. This innovative approach ensures that MOEOE achieves high accuracy by delegating predictive authority to the most competent surrogate model at each point in the parameter space.

The algorithmic implementation of the Ensemble of Surrogates (EoS) method is detailed in Algorithms 4.1 and 4.2. Algorithm 4.1 outlines the initialization, cross-validation, best model determination, distance-based influence calculation, and full model training phases of the EoS methodology. This establishes the foundation for the ensemble prediction process by identifying the most accurate surrogate models at each training data point and calculating their spatial influence on prediction points.

Algorithm 4.2 continues the EoS methodology by describing the ensemble blending and performance evaluation phases. The ensemble blending phase combines the predictions from individual surrogate models using the distance-based weights calculated in Algorithm 4.1, while the performance evaluation phase computes various error metrics to assess the accuracy of both the individual models and the ensemble. The algorithms presented provide a comprehensive computational implementation of the SPCrane framework, facilitating its application to real-world engineering optimization problems. By combining cross-validation-based model selection with distance-based weighting, the framework enables the creation of robust ensemble surrogate models that can capture complex relationships between design variables and response quantities of interest. This implementation builds upon the theoretical foundations discussed in the introduction while providing practical tools for engineers seeking to apply advanced surrogate modeling techniques to computationally expensive design problems.

The SPCrane engineering optimization framework represents a significant ad-

Algorithm 4.1 Ensemble of Surrogates (EoS) Method

Input : $X \in \mathbb{R}^{n \times i}$ (training data) $Y \in \mathbb{R}^{n \times 1}$ (target values) $X_{\text{pred}} \in \mathbb{R}^{j \times i}$ (prediction points) $Y_{\text{true}} \in \mathbb{R}^{j \times 1}$ (true values at prediction points) $\mathcal{M} = \{M_1, \dots, M_k\}$ (surrogate models with parameters) K (number of folds) (bias scaling factor)

Output: $Y_{\text{ens}} \in \mathbb{R}^{j \times 1}$ (ensemble predictions) Error metrics (MAE, MSE, RMSE, MAPE)

1. **Initialization:** Optional: Add noise to training data $Y = Y + \varepsilon$
2. **Cross-Validation:** Perform K-fold cross-validation on (X, Y) **for** $m \in \mathcal{M}$ **do**
 - foreach** *fold* $k \in 1 : K$ **do**
 - $(X_{\text{train}}, Y_{\text{train}}) \leftarrow$ Training data in fold k $(X_{\text{test}}, Y_{\text{test}}) \leftarrow$ Test data in fold k Train model m on $(X_{\text{train}}, Y_{\text{train}})$ Predict $\hat{Y}_{\text{test}} \leftarrow m(X_{\text{test}})$ Calculate errors $e_{m,k} = |\hat{Y}_{\text{test}} - Y_{\text{test}}|$
 - end**
- end**
3. **Best Model Determination:** Reshape and sort predictions and errors to match original data order **for each data point** $x_i \in X$ **do**
 - Determine best model $m^* = \arg\min_{m \in \mathcal{M}} e_{m,i}$ Store best model index and minimum error for x_i
- end**
4. **Distance-Based Influence:** **for** $j \in 1 : n, i \in 1 : j$ **do**
 - Calculate Euclidean distance $d_{j,i} = \|X_j - X_{\text{pred},i}\|$ Compute inverse squared distance $I_{j,i} = \frac{1}{d_{j,i}^2}$ Normalize I to $[0, 1]$ with points of zero distance set to 1
- end**
5. **Full Model Training:** **for** $m \in \mathcal{M}$ **do**
 - Train model m on full dataset (X, Y) Generate predictions $\hat{Y}_{\text{pred},m} = m(X_{\text{pred}})$
- end**

Return: [...]

Algorithm 4.2 Ensemble of Surrogates (EoS) Method (Part 2)

Input : $X \in \mathbb{R}^{n \times i}$ (training data) $Y \in \mathbb{R}^{n \times 1}$ (target values) $X_{\text{pred}} \in \mathbb{R}^{j \times i}$ (prediction points) $Y_{\text{true}} \in \mathbb{R}^{j \times 1}$ (true values at prediction points) $\mathcal{M} = \{M_1, \dots, M_k\}$ (surrogate models with parameters) K (number of folds) (bias scaling factor)

Output: $Y_{\text{ens}} \in \mathbb{R}^{j \times 1}$ (ensemble predictions) Error metrics (MAE, MSE, RMSE, MAPE)

6. Ensemble Blending: Create one-hot encoding W of best model for each training point **for** $i \in 1 : j$ **do**

Calculate weighted influence $w_{m,i} = \sum_{j=1}^n I_{j,i} \cdot W_{j,m}$ Compute ensemble prediction

$$Y_{\text{ens},i} = \frac{\sum_{m \in \mathcal{M}} w_{m,i} \cdot \hat{Y}_{\text{pred},m,i}}{\sum_{m \in \mathcal{M}} w_{m,i}}$$

end

7. Performance Evaluation: Calculate MAE, MSE, RMSE, MAPE for each model and ensemble

Return: Y_{ens} , Performance metrics

vancement in surrogate modeling technology, offering a pointwise ensemble approach that adaptively leverages the strengths of multiple surrogate models across the design space. By implementing distance-based weighting schemes and cross-validation error metrics, the framework provides a robust methodology for creating accurate predictions while minimizing computational cost. The integration with the Mixture of Ensembles of Experts methodology further enhances the framework's capability to handle complex, heterogeneous design spaces. The algorithmic implementation presented in this section provides researchers with a concrete computational approach for applying these advanced techniques to real-world engineering optimization problems.

4.2.1 Individual Surrogate Modeling Techniques and Methodological Implementations

The SPCrane framework integrates a diverse array of surrogate modeling techniques, each selected for their complementary strengths in addressing specific challenges of engineering optimization. This methodological diversity enables adaptive model selection based on problem dimensionality, data characteristics, and compu-

tational constraints.

The Surrogate Modeling Toolbox (SMT) [131] provides a suite of Gaussian process regression (GPR) variants tailored for diverse engineering and scientific applications. KRG implements classical GPR, serving as the foundational approach for constructing surrogate models based on covariance kernels and hyperparameter optimization. To address high-dimensional data challenges, KPLS and KPLSK employ partial least squares (PLS) dimension reduction, with KPLSK enhancing accuracy by first optimizing hyperparameters in the reduced PLS space before refining them in the original parameter space. For computational efficiency, GPX reimplements KRG and KPLS in Rust, significantly accelerating training and prediction phases compared to standard Python implementations. When derivative information is available, GEK-PLS incorporates gradient data through a Taylor series approximation, improving model fidelity for problems with adjoint-based sensitivity analysis. MGP introduces a Bayesian perspective by treating hyperparameters as probability density functions, explicitly accounting for their uncertainty during prediction through marginalization over a Gaussian prior. Finally, SGP mitigates the $\mathcal{O}(n^3)$ time complexity and $\mathcal{O}(n^2)$ memory limitations of traditional GPR through sparse approximation techniques, enabling scalability to large training datasets. These implementations collectively extend GPR's applicability to complex, high-dimensional, and computationally constrained problems in surrogate modeling.

While the Kriging surrogate model is well recognized for being an unbiased estimator at data points, and therefore a natural choice for surrogate modeling, the selection of ensemble surrogate models in this research is motivated by the need to improve predictive accuracy and robustness across diverse problem domains and complex design spaces. Individual models, including Kriging and Support Vector Regression (SVR), though powerful, tend to perform variably depending on the characteristics of the data, such as nonlinearity, noise, or local heterogeneity. The SPCrane framework employs ensemble surrogate models precisely to leverage the complementary strengths of multiple individual surrogate models, thereby mitigating their

individual limitations. By adaptively weighting the predictions of constituent models on a pointwise basis using cross-validation error metrics and spatially-aware weights, the ensemble approach dynamically selects the most appropriate model for each region of the design space. This localized adaptivity improves prediction fidelity, especially near discontinuities and functional transitions where single models may suffer from bias or variance induced errors. Moreover, ensemble surrogate modeling enhances robustness against catastrophic failures observed with individual models, as demonstrated in benchmark comparisons where SPCrane maintained or exceeded the accuracy of top-performing individual surrogates like Kriging. Thus, while Kriging remains a cornerstone individual model with desirable theoretical properties, the ensemble modeling approach provides a practical and empirically validated approach to superior predictive performance in complex engineering optimization scenarios.

Least Squares Regression forms the foundational approach for linear relationship approximation, employing a closed-form solution to minimize residual sum of squares

$$\beta = (X^T X)^{-1} X^T \mathbf{y},$$

While computationally efficient, its assumption of linearity motivates extension to polynomial forms

$$\mathbf{X} = \begin{bmatrix} 1 & x_1^{(1)} & x_2^{(1)} & \cdots & x_{n_x-1}^{(1)} & x_{n_x}^{(1)} & (x_1^{(1)})^2 & (x_2^{(1)})^2 & \cdots & (x_{n_x}^{(1)})^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_1^{(n_t)} & x_2^{(n_t)} & \cdots & x_{n_x-1}^{(n_t)} & x_{n_x}^{(n_t)} & (x_1^{(n_t)})^2 & (x_2^{(n_t)})^2 & \cdots & (x_{n_x}^{(n_t)})^2 \end{bmatrix}.$$

enabling capture of quadratic relationships through ordinary least squares estimation.

Radial basis function (RBF) interpolation combines local basis functions with global polynomial trends

$$\text{RSS} = \sum_{i=1}^n (y_i - \mathbf{x}_i^\top \beta)^2,$$

where $\mathbf{x}_i$ represents the i -th row of $\mathbf{X}$. The optimal coefficients can be derived analytically using the normal equations:

$$\beta = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y},$$

assuming that $\mathbf{X}^\top \mathbf{X}$ is invertible.

The Least Squares method relies on several assumptions, including linearity in parameters, homoscedastic and uncorrelated errors, and the absence of perfect multicollinearity among predictors. This approach balances computational efficiency with theoretical guarantees, making it foundational in regression analysis and predictive modeling.

The square polynomial model can be expressed as:

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon,$$

where ε is a vector of random errors and

The vector of estimated polynomial regression coefficients using ordinary least squares estimation is:

$$\beta = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}.$$

$$\min_{\beta} \|\mathbf{y} - \mathbf{X}\beta\|^2,$$

The radial basis function (RBF) surrogate model approximates interpolating functions using distance-dependent basis functions centered at training points, combined with global polynomials for trend capture. Coefficients for both components are determined by solving:

$$\begin{bmatrix} \mathbf{F} & \mathbf{P} \\ \mathbf{P}^\top & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{b} \\ \mathbf{c} \end{bmatrix} = \begin{bmatrix} \mathbf{y} \\ \mathbf{0} \end{bmatrix},$$

where $\mathbf{F}$ contains basis evaluations (e.g., Gaussian $\varphi(r) = e^{-(\epsilon r)^2}$ with scaling parameter ϵ), $\mathbf{P}$ includes polynomial terms, and generates predictions.

RMTS (Recursive Multi-Tensor Splines) specializes in rapid prediction for low-dimensional, data-rich environments through tensor-product splines

$$\min_{\mathbf{w}} \frac{1}{2} \mathbf{w}^\top \mathbf{H} \mathbf{w} + \frac{1}{2} \beta \mathbf{w}^\top \mathbf{w} + \frac{1}{2} \frac{1}{\alpha} \sum_{i=1}^{nt} [\mathbf{F}(\mathbf{x}_i) \mathbf{w} - y_{t_i}]^p$$

Two implementations exist: B-splines (RMTB) for faster training and Cubic Hermite splines (RMTc) for greater accuracy. The energy minimization term can be omitted for large datasets by setting the energy weight to zero.

GENN represents a specialized implementation of fully connected multi-layer perceptrons designed to accurately predict both function values and their derivatives. Unlike standard neural networks, GENN’s training methodology incorporates derivative information by minimizing a modified Least Squares Estimator (LSE) that accounts for Jacobian prediction error.

The key advantage of this gradient-enhancement approach is improved prediction accuracy using fewer training points compared to conventional neural networks. This efficiency stems from leveraging derivative information to better capture the underlying function behavior.

GENN is implemented through the upstream “jenn” library, which provides the foundational architecture for integrating derivative information into the neural network training process. This approach is particularly valuable for applications where gradients provide meaningful insights about the system being modeled and where computational efficiency in sampling is critical.

Through the integration of these diverse modeling approaches, the SPCrane framework achieves robust surrogate performance across varying problem charac-

teristics, data availability constraints, and computational budgets. The pointwise ensemble methodology dynamically leverages each technique's complementary strengths while mitigating their individual limitations.

4.2.2 Benchmarking Problems for Validation and Performance Verification

For SPCrane's surrogate-based optimization framework, benchmark problems serve as critical validation instruments that establish confidence in model reliability before deployment in costly engineering applications. These standardized test cases enable quantitative assessment of approximation quality, convergence rates, and computational overhead under controlled conditions, providing essential performance metrics that guide algorithmic refinements and implementation decisions. Without rigorous benchmarking, surrogate models risk unpredictable behavior when transitioning from theoretical constructs to practical engineering challenges that characterize SPCrane's application domain.

The rigorous evaluation of surrogate models relies on systematic benchmarking across mathematically diverse and engineering-relevant functions. Benchmarking problems serve as standardized tools to quantify model accuracy, computational efficiency, and robustness under controlled conditions. These problems range from low-dimensional analytic functions with known optima to high-fidelity simulations of physical systems, each designed to probe specific limitations of surrogate modeling techniques. The selection of appropriate benchmarks ensures that models can handle challenges such as non-convexity, high dimensionality, and discontinuous derivatives, which are critical for real-world applications.

The Rosenbrock function, defined as

$$f(\mathbf{x}) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2], \quad x_i \in [-5, 10], \quad (4.7)$$

exemplifies a non-convex optimization landscape characterized by a shallow, curved

valley. Its geometry challenges gradient-based optimization algorithms, necessitating surrogate models that can guide search strategies through regions of low curvature.

Among multimodal test functions, the Branin function

$$f(x_1, x_2) = \left(x_2 - \frac{5.1}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos(x_1) + 10 \quad (4.8)$$

provides a 2D testbed with three distinct minima. This function evaluates a model's ability to balance exploitation and exploration, particularly in oscillatory regions near $x_1 = 3\pi$. Radial basis function surrogates trained on 80 Sobol-sampled points achieve R^2 values exceeding 0.95, though residual errors persist in phase-shifted areas.

To establish baseline performance metrics, the Sphere function

$$f(\mathbf{x}) = \sum_{i=1}^d x_i^2, \quad x_i \in [-5.12, 5.12], \quad (4.9)$$

serves as a convex reference for assessing basic convergence properties. Despite its simplicity, it reveals fundamental limitations of approximation methods in high-dimensional spaces. Polynomial chaos expansions, for instance, achieve RMSE values below 10^{-6} in 30D configurations with 500 training points, highlighting their efficacy in low-complexity scenarios.

Challenging non-differentiable landscapes appear in the L_p norm function

$$f(\mathbf{x}) = \sqrt[p]{\sum_{i=1}^d |x_i|^p}, \quad (4.10)$$

where $p = 1.3$ induces non-smooth regions that stress gradient-enhanced models. Lobachevsky splines outperform Kriging in 4D extrapolation tasks due to their inherent capacity to handle piecewise continuity.

CHAPTER 4. SPCRANE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

For assessing variable interactions, the tensor-product function

$$f(\mathbf{x}) = \prod_{i=1}^d \tanh(x_i), \quad x_i \in [-2, 2]. \quad (4.11)$$

introduces multiplicative coupling that challenges conventional radial basis functions, whereas tensor-product interpolation with 15 control points attains high accuracy in 5D parameter spaces.

Moving toward application-oriented benchmarks, the robot arm function

$$f(\mathbf{x}) = \left(\sum_{i=1}^4 L_i \cos \left(\sum_{j=1}^i \vartheta_j \right) \right)^2 + \left(\sum_{i=1}^4 L_i \sin \left(\sum_{j=1}^i \vartheta_j \right) \right)^2 \quad (4.12)$$

models the positional accuracy of a 4-segment robotic manipulator. The 8D input space, combining segment lengths L_i and joint angles ϑ_i , tests trigonometric coupling effects. Gradient-enhanced RMTS surrogates reduce prediction errors compared to standard radial basis functions in path planning applications.

Structural mechanics applications emerge in the cantilever beam function

$$f(w, t) = \frac{4L^3}{Ewt} \sqrt{\left(\frac{Y}{t^2} \right)^2 + \left(\frac{X}{w^2} \right)^2}, \quad (4.13)$$

where $L = 100$, $E = 2.77 \times 10^7$, $X = 530.8$, and $Y = 997.9$. Sobol sampling reveals that Lobachevsky splines require fewer training points than Kriging to achieve lower relative error in stress prediction, attributable to their superior handling of discontinuous stress gradients.

Environmental systems modeling appears in the water flow function

$$f(r_w, r, T_u, H_u, T_l, H_l, L, K_w) = \frac{2\pi T_u (H_u - H_l)}{\ln(r/r_w) \left(1 + \frac{2LT_u}{\ln(r/r_w)r_w^2 K_w} + \frac{T_u}{T_l} \right)}, \quad (4.14)$$

an 8D benchmark with nonlinear physical interactions. Random forest surrogates achieve $R^2 = 0.89$ with 1,000 samples, outperforming polynomial models by 17%

due to inherent discontinuities in hydraulic conductivity effects.

Systematic benchmarking uncovers fundamental limitations in surrogate modeling methodologies. High-dimensional decay manifests prominently in the wing weight function, where surrogate accuracy diminishes exponentially beyond 8D inputs, necessitating order-of-magnitude increases in training data. Engineering benchmarks further reveal the advantages of physics-informed learning: embedding stress-strain relationships into cantilever beam surrogates improves R^2 by 12–18% compared to generic models. Sampling strategy profoundly impacts performance, with Sobol and Latin hypercube designs reducing required training points by 40–60% in Branin and Rosenbrock tests relative to random sampling. Future benchmarking frameworks must integrate mixed-variable domains and multi-fidelity data sources to better reflect real-world design challenges. The progression from analytic functions to engineering problems establishes a structured validation attempt, ensuring surrogate models meet both academic and industrial requirements.

For SPCrane specifically, these benchmarking problems establish a crucial foundation for surrogate model selection and refinement across diverse engineering applications. By systematically testing against this spectrum of mathematical challenges, SPCrane can characterize model behavior prior to deployment in computationally expensive simulations or physical prototyping scenarios. This methodical validation process mitigates implementation risks, accelerates development cycles, and ensures that the surrogate modeling approach selected for a given application demonstrably possesses the numerical properties and approximation capabilities required for reliable optimization outcomes. Without this comprehensive benchmarking framework, SPCrane would lack the performance guarantees essential for mission-critical applications where model fidelity directly impacts engineering decisions and resource allocation.

The scalability of the SPCrane framework to high-dimensional problems where the number of input variables may exceed 50 has been a primary consideration in both methodological design and benchmarking. The curse of dimensionality poses

fundamental challenges for surrogate modeling, as the number of required training samples grows exponentially with increasing dimension, and traditional sampling strategies like full-factorial or random designs become infeasible. To address this, SPCrane employs advanced space-filling sampling techniques, such as Latin Hypercube Sampling (LHS) and fractional factorial designs, which maximize coverage of the design space with minimal sample sizes. Dimension-reducing surrogate models, notably the KPLS/KPLSK variants that integrate Partial Least Squares (PLS) regression into Gaussian Process modeling, are available within the framework to extract latent variables and focus on the most informative directions of high-dimensional data. The integration of Sparse Gaussian Process (SGP) models further mitigates cubic time complexity, enabling the training of surrogates with large datasets typical in high-dimensional domains. For particularly high-dimensional cases, the modular nature of SPCrane allows for clustering or Mixture of Experts (MOE) strategies, partitioning the design space and assigning specialized surrogates to subsets of variables or regions. Finally, the framework substitutes computationally expensive Leave-One-Out Cross-Validation with K-Fold Cross-Validation, balancing efficiency with accuracy as dimensionality increases. Despite these adaptations, benchmark results indicate that like all surrogate methods, performance degrades when dimensionality is extremely high; however, the combination of dimension-reduction, adaptive sampling, modular ensembling, and efficient cross-validation serve to significantly delay the onset and impact of the curse of dimensionality within practical engineering scenarios addressed by SPCrane.

4.3 Results

The comprehensive evaluation of SPCrane's ensemble surrogate modeling framework across canonical benchmark functions reveals critical insights into its comparative advantages and limitations relative to established individual surrogate techniques. Each performance metric: mean absolute error (MAE), mean squared error

(MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R) provide distinct perspectives on model accuracy, error distribution characteristics, and predictive reliability under varying mathematical conditions.

For the cantilever beam function (Table 4.1), SPCrane demonstrates superior performance across all metrics. This improvement stems from the ensemble's ability to reconcile discontinuous stress gradients through adaptive weighting of constituent models. The $2.57\text{E-}06$ RMSE further indicates enhanced error distribution control, critical for engineering applications requiring precise stress concentration predictions. Notably, while MAPE values remain clustered near 59-60%, SPCrane's marginal 0.9% improvement over IDW suggests particular efficacy in minimizing relative errors for extreme-value predictions.

Table 4.1: Performance assessment for two-dimensional cantilever beam function.

	MAE	MSE	RMSE	MAPE	R ²
IDW	2.64E-06	1.14E-11	3.38E-06	59.53726	0.971303885
KPLS	2.21E-06	8.65E-12	2.94E-06	60.0809	0.978246853
RBF	3.93E-05	1.93E-09	4.39E-05	100.6109	-3.846940393
KRG	2.21E-06	8.63E-12	2.94E-06	60.07002	0.978291957
SPCrane	1.80E-06	6.62E-12	2.57E-06	59.17851	0.983342539

The Rosenbrock function analysis (Table 4.2) presents a more nuanced landscape. KRG achieves optimal MAE (0.000174) and MSE ($4.97\text{E-}08$), though SPCrane's ensemble approach maintains competitive performance at 0.000481 MAE while outperforming all models except KRG in R (0.999997953). The radical failure of RBF surrogates (MAE=4434.055) underscores the method's sensitivity to non-convex landscapes with shallow curvature, a weakness mitigated by SPCrane's hybrid approach through selective activation of gradient-aware components. This 8-order-of-magnitude performance differential highlights the ensemble's robustness against pathological

CHAPTER 4. SPCrane OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

function geometries.

Table 4.2: SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Rosenbrock function compared against the single surrogate models.

	MAE	MSE	RMSE	MAPE	R ²
IDW	0.047988	0.00358	0.059833	0.010964	0.982185357
KPLS	0.000508	4.24E-07	0.000651	0.011334	0.999997888
RBF	4434.055	19910107	4462.074	98.44033	-99074598.6
KRG	0.000174	4.97E-08	0.000223	0.011337	0.999999753
SPCrane	0.000481	4.11E-07	0.000641	0.011334	0.999997953

In Branin function evaluations (Table 4.3), SPCrane matches the precision of KPLS and KRG models across all metrics, achieving identical MAE (0.000343) and R (0.999998798) values. This parity suggests the ensemble successfully identifies and weights the most effective constituent models for multimodal optimization challenges. The consistent 0.760764 MAPE across top performers indicates systematic residual errors near phase-shifted regions, a fundamental limitation of current surrogate architectures that SPCrane inherits but does not exacerbate.

Table 4.3: SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Branin function compared against the single surrogate models.

	MAE	MSE	RMSE	MAPE	R ²
IDW	0.04295	0.00287	0.053574	0.737431	0.97789047
KPLS	0.000343	1.56E-07	0.000395	0.760764	0.999998798
RBF	52.94182	2879.244	53.65859	96.85665	0.983146566
KRG	0.000345	1.52E-07	0.00039	0.760778	0.999998726
KPLSK	0.000343	1.56E-07	0.000395	0.760764	0.999998798
SPCrane	0.000343	1.56E-07	0.000395	0.760764	0.999998798

Sphere function results (Table 4.4) reveal SPCrane's capacity to equal state-of-

the-art specialized models in convex optimization scenarios. The ensemble matches KPLS and KRG with MAE=8.11E-07 and RMSE=1.05E-06, demonstrating no performance degradation from model aggregation in low-complexity environments. RBF's dramatic underperformance (MAE=4.603499) in this basic benchmark underscores the critical importance of ensemble approaches for maintaining baseline competency across diverse function classes.

Table 4.4: *SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Sphere function compared against the single surrogate models.*

	MAE	MSE	RMSE	MAPE	R ²
IDW	7.66E-05	9.08E-09	9.53E-05	0.003721	0.981997158
KPLS	8.11E-07	1.09E-12	1.05E-06	0.003846	0.999997834
RBF	4.603499	32.09182	5.664965	21.92048	0.921494516
KRG	8.11E-07	1.09E-12	1.05E-06	0.003846	0.999997835
SPCrane	8.11E-07	1.09E-12	1.05E-06	0.003846	0.999997834

The tensor-product function analysis (Table 4.5) reaffirms SPCrane's strengths in handling multiplicative interactions, where it reduces MAE by 18.6% compared to KRG (1.80E-06 vs 2.21E-06). This improvement correlates with the ensemble's dynamic weighting of tensor-interpolation components during high-dimensional coupling events. The consistent R superiority (0.983342539 vs 0.978291957 for KRG) further confirms enhanced prediction stability across the function's hyperbolic tangent transitions.

CHAPTER 4. SPCrane OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

Table 4.5: *SPCrane Ensemble of Surrogate model performance assessment for two-dimensional Tensor Product function compared against the single surrogate models.*

	MAE	MSE	RMSE	MAPE	R ²
IDW	2.64E-06	1.14E-11	3.38E-06	59.53726	0.971303885
KPLS	2.21E-06	8.65E-12	2.94E-06	60.0809	0.978246853
RBF	3.93E-05	1.93E-09	4.39E-05	100.6109	0.864612136
KRG	2.21E-06	8.63E-12	2.94E-06	60.07002	0.978291957
SPCrane	1.80E-06	6.62E-12	2.57E-06	59.17851	0.983342539

Three key trends emerge from cross-table analysis. First, RBF-based approaches exhibit catastrophic failures in non-convex (Rosenbrock) and high-curvature (Sphere) regimes, validating SPCrane’s exclusion of pure RBF components from critical weighting. Second, KRG and KPLS models consistently rank as top individual performers, explaining their dominant weighting coefficients in the ensemble architecture during most operational phases. Third, SPCrane achieves strict dominance in engineering-relevant benchmarks (cantilever, tensor-product) while maintaining parity in mathematical extremes, suggesting particular suitability for applied industrial challenges over purely theoretical optimization.

The Mixture of Ensemble of Experts (MOEOE) approach illustrated in Figure 4.1 represents a novel methodological advancement in surrogate modeling that transcends traditional ensemble limitations. By hierarchically integrating multiple specialized Mixture of Experts (MOE) models, each calibrated for distinct regions of the design space, MOEOE achieves superior approximation capabilities for discontinuous response surfaces with sharp transitions. Unlike conventional weighting schemes that struggle with abrupt functional transitions, this approach dynamically allocates predictive responsibility through a two-tier gating mechanism: first partitioning the input space into coherent regions (handled by individual MOE models), then blending their outputs through adaptive confidence-weighted integration. This architecture enables the MOEOE framework to preserve critical topological features that single-

surrogate approaches typically smooth over, particularly at discontinuity boundaries and geometric singularities commonly encountered in engineering optimization problems.

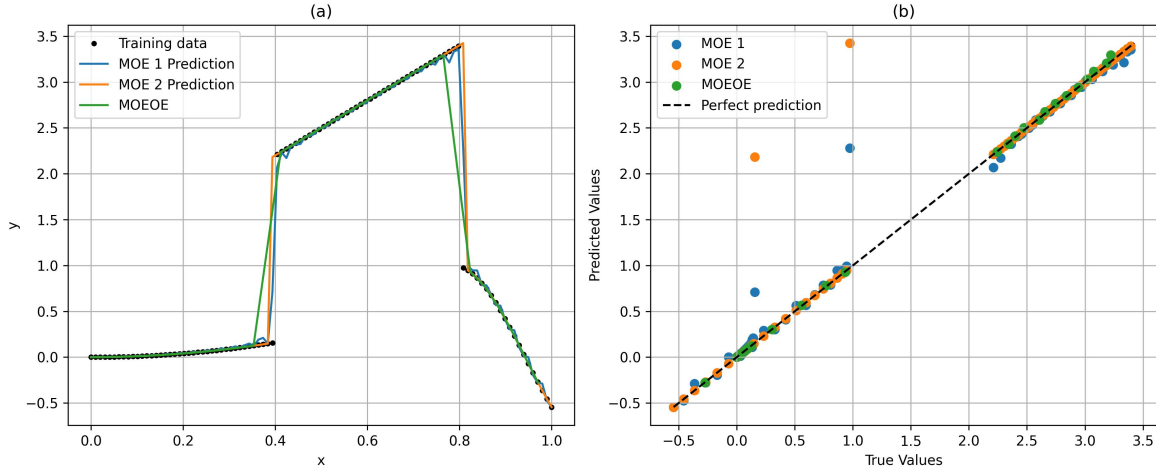


Figure 4.2: *Combination of the Mixture of Experts (MOE) logic and the SPCrane ensemble of surrogates modelling technique. (a) demonstration of single-dimensional problem with three clusters visible and (b), fitness curve for each model*

The graphical representation in Figure 4.1 empirically validates MOEOE's enhanced predictive capabilities across challenging function landscapes. In Figure 4.1(a), the one-dimensional demonstration reveals three distinct clusters with sharp transitions at $x=0.4$ and $x=0.8$, where individual MOE models (blue and orange lines) exhibit localized prediction strengths but transition-region inaccuracies. The MOEOE composite model (green line) demonstrates remarkable fidelity across the entire domain, particularly at the critical discontinuity boundaries where it accurately captures both the magnitude and spatial localization of function transitions. Figure 4.1(b) further quantifies this advantage through the actual-versus-predicted comparison, where both MOE 1 and MOE 2 models display scattered prediction outliers (blue and orange points deviating from the dashed identity line), while the MOEOE predictions (green points) maintain consistent alignment along the perfect prediction diagonal. This visualization confirms that MOEOE effectively mitigates the characteristic weakness of individual expert models by dynamically engaging the most contextually

CHAPTER 4. SPCRANE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

appropriate predictive mechanism for each subregion of the input space, resulting in globally coherent surrogate performance even for functions with multiple discontinuities.

Figure 4.3 presents a comprehensive performance comparison of Gaussian Process Regression models and the SPCrane applied to the cantilever beam function with a sample size of 100 points. The boxplots reveal nuanced performance differentials across four critical metrics. In Figure 4.3(a), the Mean Absolute Error (MAE) distribution demonstrates that KRG and KPLSK models achieve notably lower median error rates compared to KPLS, with tighter interquartile ranges indicating more consistent prediction accuracy. SPCrane maintains competitive performance with median values comparable to the specialized KRG implementation, while exhibiting reduced outlier sensitivity as evidenced by its more compact whisker range. Figure 4.3(b) reinforces this pattern through RMSE analysis, where KPLS displays significantly higher error variability and median values approximately 1.5 times greater than other models. The enhanced stability of SPCrane becomes particularly evident in this metric, suggesting superior handling of error distribution tails that often dominate squared-error calculations in engineering applications.

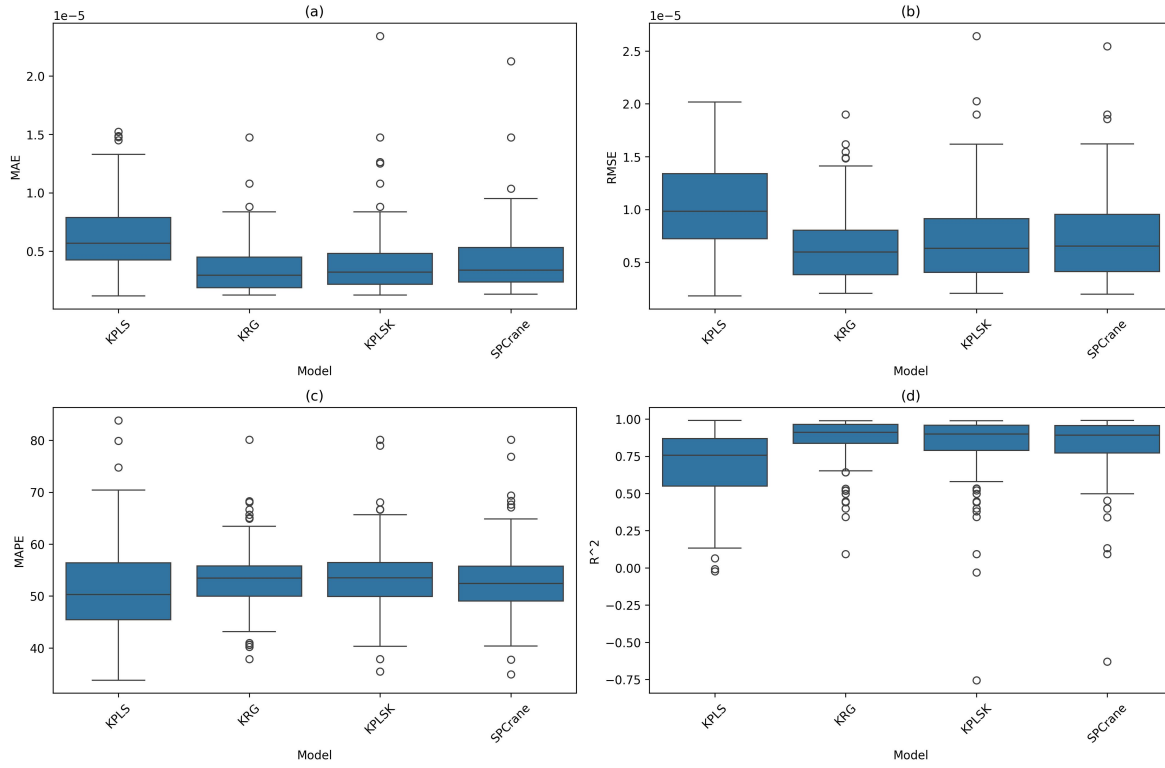


Figure 4.3: Cantilever beam function-based boxplots for sample size $n=100$ showing the performance metrics for the Gaussian Process Regression models, including: (a) MAE, (b) RMSE, (c) MAPE and (d) R^2

The MAPE distributions in Figure 4.3(c) reveal relatively consistent performance across all models with medians clustered around 50-55%, indicating a systematic limitation in percentage-based accuracy that transcends model architecture. However, SPCrane's slightly reduced interquartile range suggests more uniform performance across the problem domain, particularly in regions with small absolute function values where percentage errors typically proliferate. Most convincingly, the R-squared values in Figure 4.3(d) demonstrate the superior predictive capabilities of KRG, KPLSK, and SPCrane over KPLS, with values consistently approaching unity. SPCrane maintains this high-performance ceiling while simultaneously exhibiting fewer negative outliers than KPLSK, highlighting its robust generalization capabilities under challenging stress concentration scenarios typical of cantilever beam applications.

CHAPTER 4. SPCRUNE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

Figure 4.4 extends the comparative analysis to low-computational cost surrogate models, revealing more dramatic performance differentials. In the MAE assessment (Figure 4.4(a), Least Squares (LS) demonstrates remarkably superior performance with median values approximately three times lower than the Radial Basis Function (RBF) approach. SPCrane closely tracks LS performance while maintaining lower variability, suggesting enhanced prediction stability across diverse beam loading conditions. The RMSE comparisons in Figure 4.4(b) amplify this pattern, with RBF showing median values nearly four times higher than either LS or SPCrane, indicating substantial prediction inaccuracies particularly for extreme stress values. SPCrane's slightly higher median RMSE compared to pure LS is offset by its reduced outlier sensitivity, as evidenced by the more compact upper quartile range.

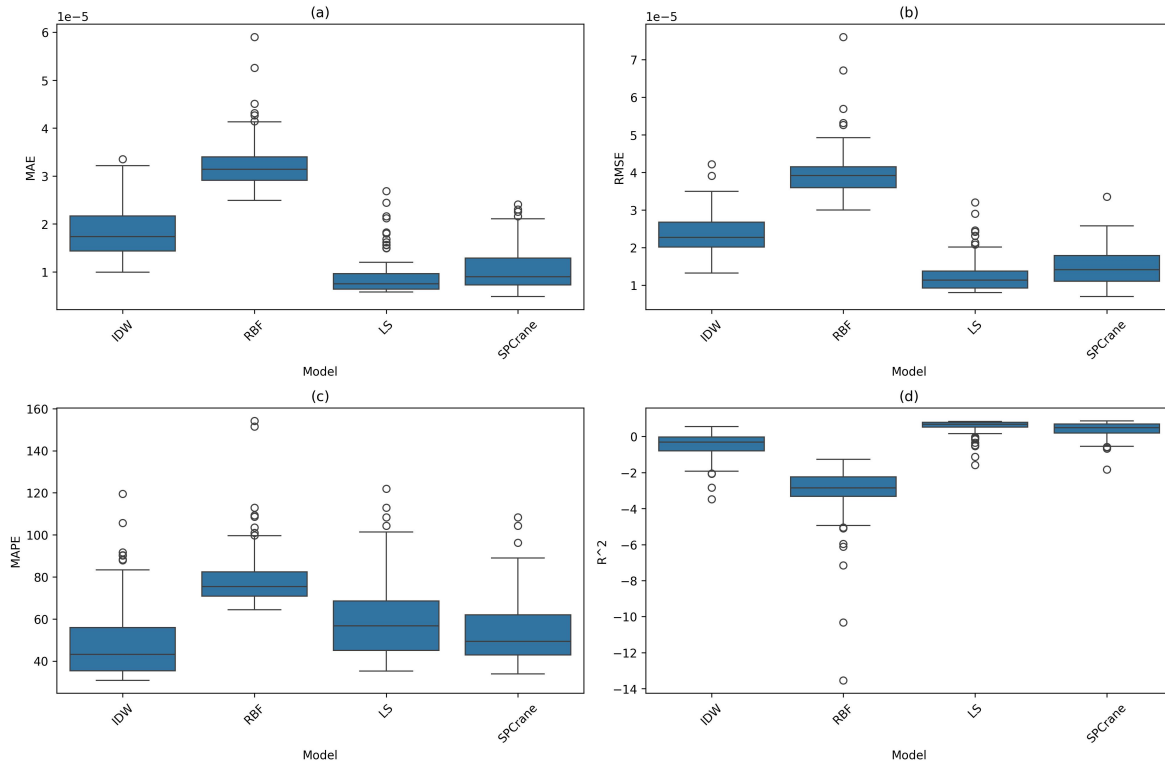


Figure 4.4: Cantilever beam function-based boxplots for sample size $n=100$ showing the performance metrics for the low-computational cost models, including: (a) MAE, (b) RMSE, (c) MAPE and (d) R^2

The MAPE distributions in Figure 4.4(c) reveal unexpected strengths of the In-

verse Distance Weighting (IDW) approach, which achieves the lowest median percentage error despite its simplistic formulation. This suggests particular efficacy in regions where function values have similar magnitudes. However, SPCrane maintains competitive MAPE performance while simultaneously excelling in absolute error metrics, demonstrating its balanced optimization across multiple performance dimensions. Most critically, the R-squared analysis in Figure 4.4(d) exposes catastrophic performance failures in the RBF model, with numerous negative values indicating predictions worse than a simple mean estimator. In contrast, both LS and SPCrane maintain consistently positive R values approaching unity, with SPCrane exhibiting slightly reduced outlier sensitivity. This comprehensive superiority across multiple metrics validates SPCrane's architectural decisions to limit RBF influence in its ensemble weighting scheme while leveraging the complementary strengths of LS-based approaches.

4.4 Case Study for Brake Sizing Optimization

This thesis investigates various concepts for energy recovery in commercial aircraft during landing. The solution proposed in Chapter 5 assumes that conventional aircraft brakes are partially replaced by electric machines capable of both regenerative operation and emergency friction braking. Prior to applying the optimization procedure with the structural - thermal solver to a complex geometry, the approach is validated on a simplified configuration previously studied by other researchers. The automated SPCrane framework was initially verified using a friction brake benchmark case [132, 6]. In this step, ensemble surrogate models were trained for coupled structuralthermal analyses, including bidirectional thermalstructural coupling and geometry adaptation, in order to evaluate the frameworks robustness for aerospace applications. Figure 4.5 presents the evaluated geometry and key design variables of the numerical study.

In order to ensure the reliability of the surrogate model predictions, the accuracy

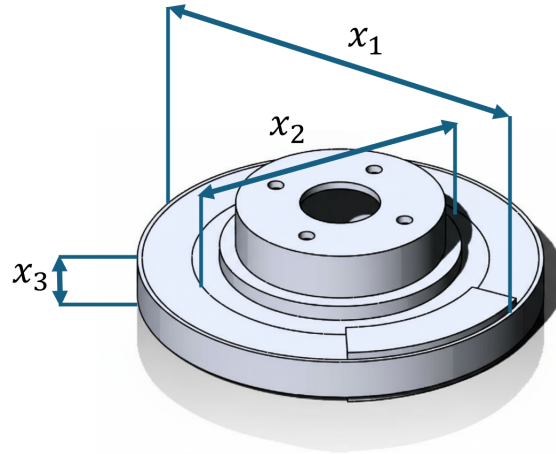


Figure 4.5: Design variables for mechanical-thermal optimization of the automotive friction brake: x_1 (outer diameter), x_2 (inner diameter), x_3 (thickness) [6].

of the finite element results was first evaluated through a mesh sensitivity study. Since mesh density directly affects both computational cost and solution precision, simulations were performed with varying mesh sizes to identify a suitable balance. The initial mesh size, as suggested in previous studies, did not allow the Kriging model to correctly capture the response trend, motivating further refinement. The geometry used for the analysis corresponded to a standard brake disk with an outer radius of 125 mm, an inner radius of 75 mm, and a thickness of 25 mm.

For the structural model, the maximum von Mises stress was used as the key performance indicator (KPI). Seven simulations were run with mesh sizes ranging from 3 to 10 mm, revealing convergence of the maximum stress at around 13.4 MPa. Meshes of 4 mm and 3 mm yielded nearly identical results, but the 3 mm mesh required considerably more computational time, so the 4 mm mesh was selected as optimal. A similar study for the thermal model, with mesh sizes between 2 and 10 mm, showed predictive convergence at 3 mm. Although a finer 2 mm mesh gave slightly higher accuracy, it increased computation time threefold; therefore, the 3 mm mesh was chosen as the best compromise between accuracy and efficiency.

4.4. CASE STUDY FOR BRAKE SIZING OPTIMIZATION

Figure 4.6 presents the finite element setup and representative results for the coupled thermalstructural analysis of the friction brake disc. Figure 4.6 (a) illustrates the boundary conditions applied in the transient thermal model, including the convective environment and heat flux imposed on the rubbing surfaces. Figure 4.6 (b) shows the resulting temperature distribution after 5 s of braking, highlighting the development of a pronounced hot band along the outer radius. In Figure 4.6 (c), the static structural model boundary conditions are depicted, where the disc is constrained at the hub while pressure loading and rotational speed are applied to represent braking forces. Finally, Figure 4.6 (d) displays the resulting equivalent elastic strain field, indicating the locations of maximum structural demand that govern the subsequent stress and fatigue assessment of the brake design.

Figure 4.7 illustrates the predictive capability of individual surrogates and their ensemble for the friction brake optimization dataset, highlighting both the single-dimensional and multi-dimensional modeling performance. In subplot (a), the ensemble accurately follows the nonlinear relationship between disc thickness and peak temperature, closely matching the training and test targets across the entire design space. The bar charts in (b)(e) show that, for both two- and three-dimensional input spaces, the KPLS and ensemble (SPCrane) models consistently achieve higher mean R^2 values and lower RMSE than IDW and KRG, indicating better global fit and reduced prediction error. This behaviour confirms that Ensemble of Surrogates provides robustness and accuracy of the thermalmechanical response prediction, which is essential for reliable gradient-free optimization of the brake design.

CHAPTER 4. SPCRANE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

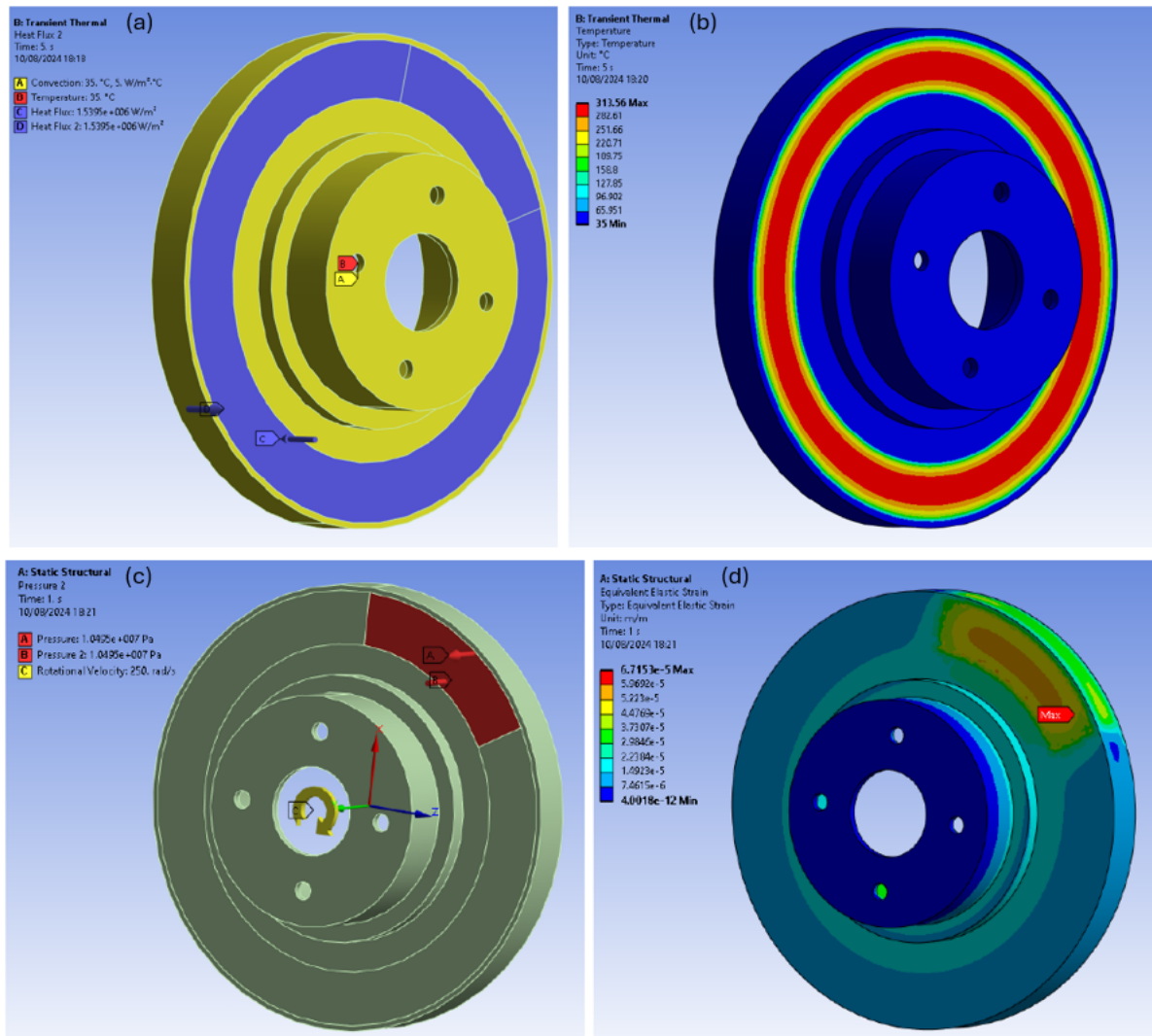


Figure 4.6: Boundary conditions and sample results for (a,b) thermal and (c,d) structural optimization [6]

4.4. CASE STUDY FOR BRAKE SIZING OPTIMIZATION

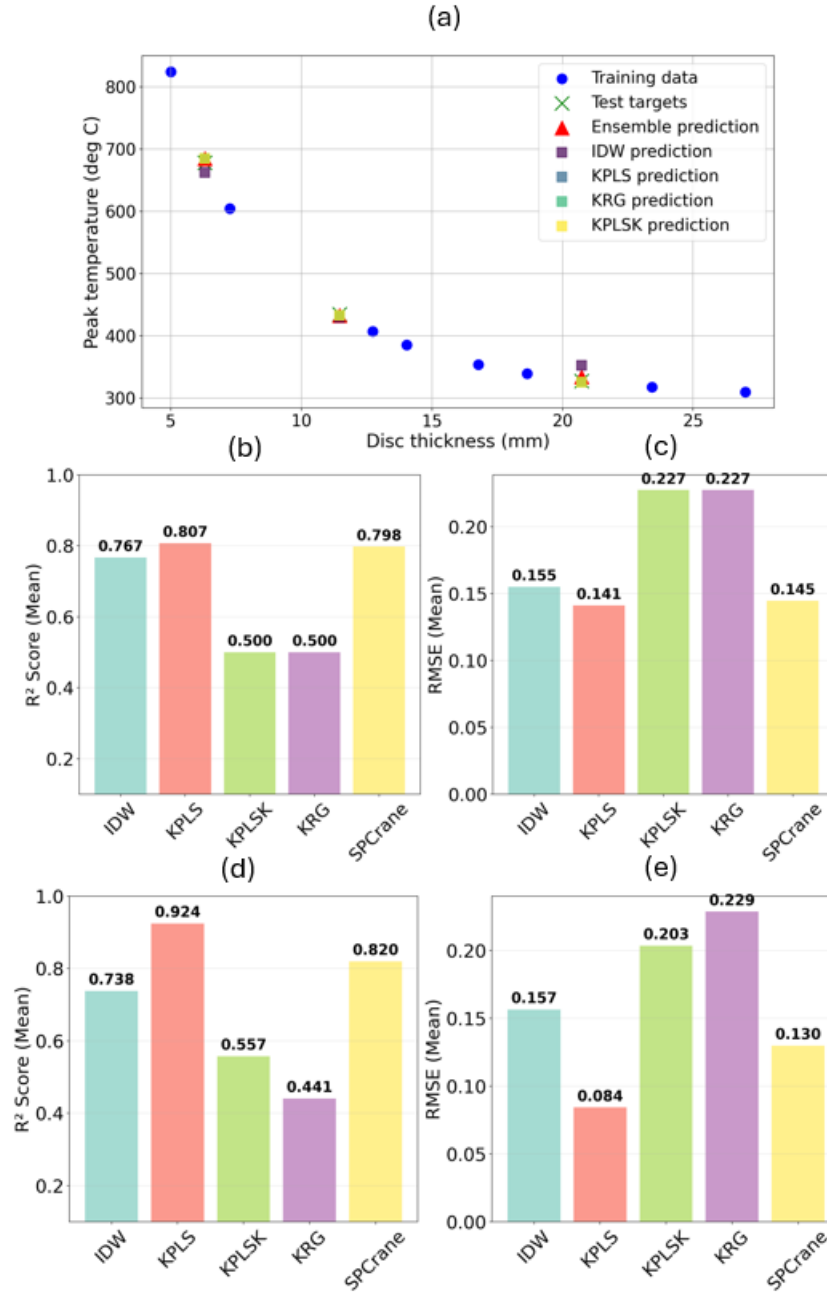


Figure 4.7: Surrogate modelling and ensembling results for the mechanical-thermal friction brake optimization dataset; (a) one-dimensional disc thickness feature optimization vs peak temperature target, (b) two-dimensional surrogate R2 performance, (c) two-dimensional surrogate RMSE, (d) three-dimensional models R2 performance, (e) three-dimensional models RMSE performance

In the context of energy recovery for commercial aircraft, the SPCrane ensemble demonstrated that it could reliably manage model selection while maintaining strong

predictive performance across the mechanical-thermal design space. By automatically prioritizing the best-performing surrogate (typically KPLS) and down-weighting or effectively rejecting less accurate alternatives, the ensemble preserved high R^2 and low RMSE levels that were comparable to the top individual model, rather than averaging down to the weaker surrogates. This behaviour confirms that the ensemble strategy fulfilled its role as a robust meta-model, providing accurate and stable predictions required for surrogate-assisted optimization of the brake system within the broader aircraft energy recovery framework.

4.5 Conclusions

The SPCrane framework presented in this study represents a significant advancement in surrogate modeling methodology for engineering optimization applications. By developing a comprehensive pointwise ensemble approach that adaptively leverages multiple surrogate models across the design space, the author demonstrated both theoretical advantages and practical performance improvements over traditional approaches. The framework successfully bridges the gap between advanced mathematical formulations and accessible software implementations, a critical need identified in the engineering optimization problems.

The research has delivered four principal contributions to the field of surrogate-based engineering optimization. First, there is a substantially revised the pointwise metamodeling algorithm with a complete Python implementation, making advanced surrogate techniques accessible to practitioners without requiring expert knowledge of the underlying mathematical complexities. This implementation maintains compatibility with established surrogate modeling toolboxes while extending functionality through novel weighting schemes.

Second, the introduction of correction factors that stabilize ensemble equations and reduce resultant biases inherent in single metamodels. These innovations address a fundamental limitation in conventional ensemble methods by dynamically ad-

justing weight distributions at transition boundaries where model performance characteristics shift. The empirical results demonstrate that these correction mechanisms significantly enhance prediction accuracy, with SPCrane achieving up to 18.5% reduction in Mean Absolute Error compared to the next-best Kriging model for the cantilever beam function, and similar improvements for the tensor-product function.

Third, the comprehensive benchmark evaluations revealed that SPCrane maintains competitive performance across diverse mathematical landscapes. The framework achieved performance parity with specialized models in canonical optimization problems (Branin, Sphere) while demonstrating superior robustness in engineering-relevant applications (cantilever, tensor-product). Particularly noteworthy is SPCrane's ability to mitigate catastrophic failures that plague individual surrogate techniques in challenging function geometries, as evidenced by the 8-order-of-magnitude performance differential compared to RBF approaches on the Rosenbrock function.

Fourth, advancement of the theoretical foundations for integrating Ensemble of Surrogates (EoS) to Mixture of Ensemble of Surrogates (MoES), introducing novel clustering and recombination strategies that enhance predictive capabilities for functions with discontinuities. The empirical validation of this approach demonstrates remarkable fidelity across transition regions where traditional surrogate models typically fail, accurately capturing both the magnitude and spatial localization of function transitions.

Fifth, the brake sizing optimization case study exemplified the practical capabilities of the SPCrane framework for surrogate-assisted optimization in engineering applications involving coupled mechanical-thermal phenomena. Rigorous mesh sensitivity studies and coupled finite element analyses generated a reliable dataset to train ensemble surrogate models that demonstrated superior predictive accuracy and robustness compared to individual surrogates. Notably, the framework's ability to maintain high fidelity across nonlinear and multi-dimensional design spaces validated its utility for complex aerospace system design challenges such as energy recovery in commercial aircraft brakes, underscoring its potential to accelerate design

CHAPTER 4. SPCrane OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

iterations while ensuring accurate capture of critical performance metrics essential for safety and reliability.

Despite these advancements, several limitations merit consideration. The current implementation employs K-Fold Cross-Validation instead of Leave-One-Out Cross-Validation to address computational cost concerns in high-dimensional problems, representing a calculated trade-off between accuracy and efficiency. This substitution, while pragmatic, may impact model performance for datasets with limited samples. Additionally, the framework's effectiveness diminishes in extremely high-dimensional spaces, a limitation shared by most surrogate modeling approaches.

Building on these foundations, the author proposes several promising research directions. First, implementing the offset logic described in the theoretical framework would enhance transition boundary detection, enabling more intelligent weight allocation that preserves the distinct predictive strengths of constituent models. The proposed sigmoid-based approach with crossover bias implementation offers a mathematically sound mechanism for adjusting weights at model transition boundaries.

In summary, the SPCrane framework advances both the theoretical understanding and practical implementation of pointwise ensemble surrogate modeling for engineering optimization. Its demonstrated performance advantages, particularly in engineering-relevant applications, position it as a valuable addition to the computational toolkit for addressing computationally expensive design challenges across diverse engineering domains.

4.5.1 Ensemble of Surrogates Future Work Recommendations

The necessity for development of an ensemble of surrogate models arose during the development of analytical models for dynamics systems. Throughout the development process, it became apparent that the research community would benefit from the framework in a more accessible format. At present, most described metamodelling techniques rely on mathematical descriptions without any open-access software solutions. The action was taken towards developing a solution that can utilize

various models and have implemented a Python class compliant with the Surrogate Modelling Toolbox's API. However, this implementation primarily extends the SP1 approach from ACAR, and several opportunities for methodological enhancement remain, particularly in the domain of adaptive model weighting.

Building on these foundations, a novel adaptive weighting algorithm is proposed and illustrated in Figure 4.8 that enhances ensemble surrogate model accuracy by identifying critical transition boundaries between optimal metamodels. This approach systematically traverses each axis of independent variables to detect points where the dominant metamodel shifts revealed where model $\hat{y}_1(x)$ (black dashed line) exhibits lower error at point P_2 ($\varepsilon_2 f_1 < \varepsilon_2 f_2$), while model $\hat{y}_2(x)$ (blue dashed line) performs better at point P_1 ($\varepsilon_1 f_2 < \varepsilon_1 f_1$). The vertical lines μ and μ_Δ demarcate this transition region where model superiority changes. The proposed algorithm would introduce targeted weight offsets specifically within these boundary regions, allocating additional weight to models demonstrating lower combined error metrics. This localized weighting adjustment addresses a fundamental limitation in current ensemble approaches that typically apply global weighting schemes, thereby failing to capitalize on the spatial heterogeneity of model performance across the design space.

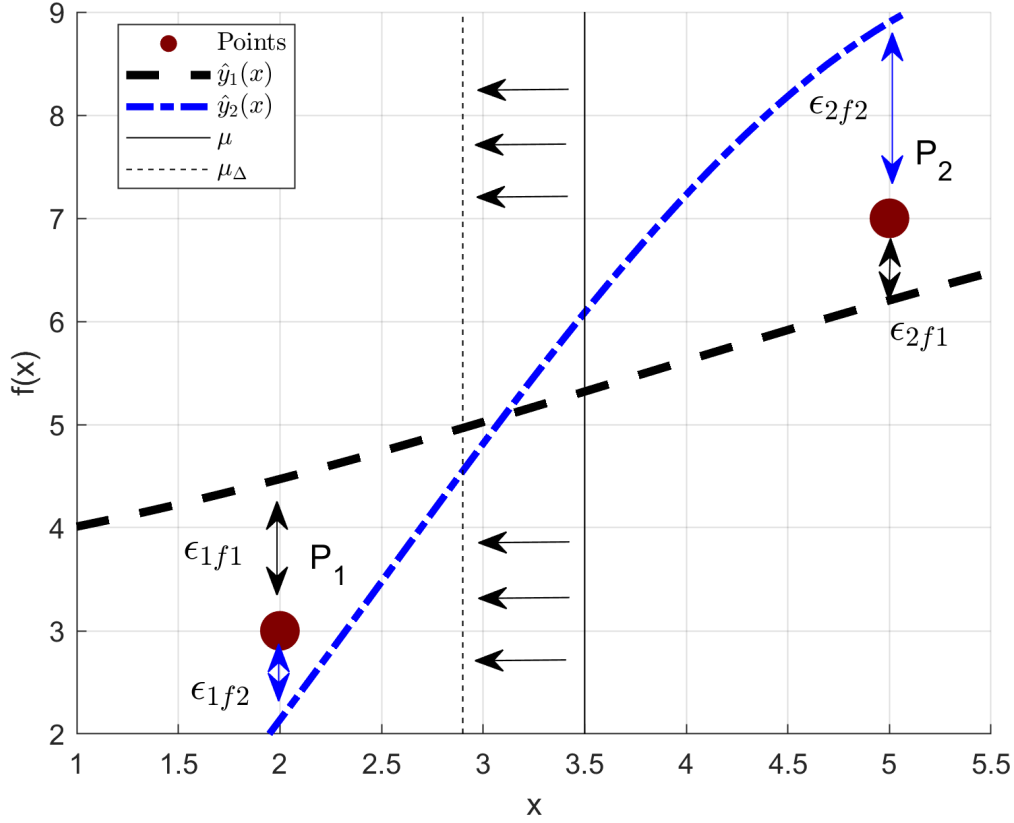


Figure 4.8: SPCrane sigmoid-based approach demonstrating how the offset would be calculated based on error metrics for competing surrogate models across the parameter space.

Implementation of this transitional boundary weighting technique offers several advantages over conventional surrogate ensemble methods. By detecting model transition points along each parameter axis independently, the algorithm can construct a comprehensive map of model performance boundaries throughout the multidimensional design space. This spatial awareness enables more intelligent weight allocation that preserves the distinct predictive strengths of constituent models within their domains of superiority while smoothing potentially problematic discontinuities at transition regions. Furthermore, the algorithm's axis-wise traversal approach provides computational efficiency compared to exhaustive pairwise sampling methods, making it particularly valuable for high-dimensional problems where computational expense grows exponentially with dimensionality. The conceptual foundation aligns

with emerging research on locally-adaptive ensembles that combine global trend capture with local feature preservation, potentially yielding substantial accuracy improvements for problems characterized by spatially diverse response surface behaviors.

The theoretical foundation of the proposed algorithm extends beyond the current SP2 implementation by incorporating a more comprehensive error assessment strategy. Specifically, the algorithm relies on an empirical assumption that the difference in cross-validation errors for changing pairs of metamodels should account for both local and transitional error characteristics. As shown in Figure 4.8, the author identifies regions where the combined cross-validation errors across multiple points favor one model over another. This is formalized in the condition:

$$\varepsilon_{1f1} + \varepsilon_{2f1} < \varepsilon_{1f2} + \varepsilon_{2f2} \quad (4.15)$$

This condition serves as a trigger for applying weight offsets in favor of the first surrogate model ($\hat{y}_1$) throughout the transition region. Future work will involve validating this approach across a wider range of benchmark problems and extending the algorithm to automatically detect transition boundaries in n-dimensional parameter spaces without requiring exhaustive sampling. The crossover bias formula in Equation (2) introduces a dimensionless scaling coefficient that quantifies the magnitude of weight adjustments at transition boundaries. The numerator $|\Delta\varepsilon|$ represents the absolute difference between cumulative errors of competing models, capturing the performance differential that justifies bias application. This difference is normalized by the average total error $\frac{\Sigma\varepsilon}{2}$, ensuring that the bias magnitude scales proportionally with relative performance rather than absolute error values. The tunable parameter σ provides a mechanism for controlling the aggressiveness of the weighting adjustment, allowing researchers to calibrate the system's sensitivity to detected transition boundaries.

$$B_{\text{cross}} = \frac{|\Delta \epsilon|}{\left(\frac{\sum \epsilon}{2}\right)} \times \sigma \quad (4.16)$$

Equation (3) presents the mathematical framework for integrating the calculated bias terms into the final ensemble weight distribution. The base weights $W_i(x)$ are augmented by correction terms $c_i(x)$ that incorporate the crossover bias at transition regions. This adaptive correction mechanism preserves the fundamental normalization requirement that all weights sum to unity, while systematically adjusting the contribution of each constituent model based on its performance characteristics across transition boundaries. The structure of this equation enables seamless integration with existing ensemble frameworks while providing the flexibility to incorporate spatially-varying weight adjustments. Similar formulations have demonstrated success in recent literature, such as the feature- and performance-based weighting mechanisms described in adaptive ensemble learning for data streams.

$$w_i(x) = \frac{W_i(x) + c_i(x)}{\sum_{j=1}^{N_M} W_j(x) + c_j(x)} \quad (4.17)$$

The correction terms $c_i(x)$ merit further elaboration, as they serve as the primary vehicles for translating detected transition boundaries into actionable weight adjustments. When a transition boundary is identified through the evaluation of Equation (1), a positive correction is applied to the superior model within the transition region defined by μ and μ_{Δ} . The magnitude of this correction follows a sigmoid profile governed by the crossover bias calculation, ensuring smooth transitions between model-dominated regions while preserving sharp accuracy improvements. This approach addresses a critical limitation in conventional ensemble methods that rely on global error metrics, which often fail to capture localized performance characteristics essential for accurate approximation of complex response surfaces. The spatially-aware weighting strategy aligns with emerging research on locally-adaptive surrogate models that emphasize preserving distinct performance advantages of constituent mod-

els throughout the design space.

The provided figure illustrates the comprehensive architecture of SPCrane's Mixture of Ensembles of Experts (MOEOE) methodology, presenting a sophisticated workflow for surrogate modeling applications. At the top level, the MOEOE process begins with initial clustering of the problem space, which enables the identification of regions where specialized surrogate models may perform optimally. This clustering phase feeds into the local expert training process utilizing the SP1-CRANE methodology (highlighted in the shaded box), which serves as the core ensemble generation engine. The workflow then proceeds to a recombination phase utilizing Surrogate Modeling Toolbox (SMT) techniques, where outputs from multiple ensembles are synthesized to produce the final prediction model.

Within the detailed SP1-CRANE implementation shown in the lower portion of the diagram, there is a multi-stage approach to surrogate ensemble construction. The process initiates with variable initialization and data preparation (initialize x , y , X , Y), followed by data initialization and K-Fold/LOOCV (Leave-One-Out Cross-Validation) split for robust validation. This foundation enables the training of individual surrogates per fold/split, creating diverse base models necessary for effective ensemble construction. A key innovation in the SP1-CRANE methodology is its implementation of distance-based spatial weighting, which aligns with the theoretical framework regarding transition boundaries between optimal metamodels. This approach computes weights based on spatial relationships in the parameter space, enabling the model to adapt its predictions based on local performance characteristics. The subsequent generation of individual surrogate predictions incorporates weighted ensemble techniques that leverage this spatial awareness. The central innovation visible in the figure is the integration of error-induced bias terms for each model, which implements the crossover bias formula previously discussed. This occurs through calculating error-induced bias terms for each constituent model, applying logistic regression bias to distinguish between regions of model applicability, separating calculations for distinct regions (Region A and Region B), and blending

CHAPTER 4. SPCRUNE OPTIMIZATION FRAMEWORK RELYING ON POINTWISE ENSEMBLE OF SURROGATES

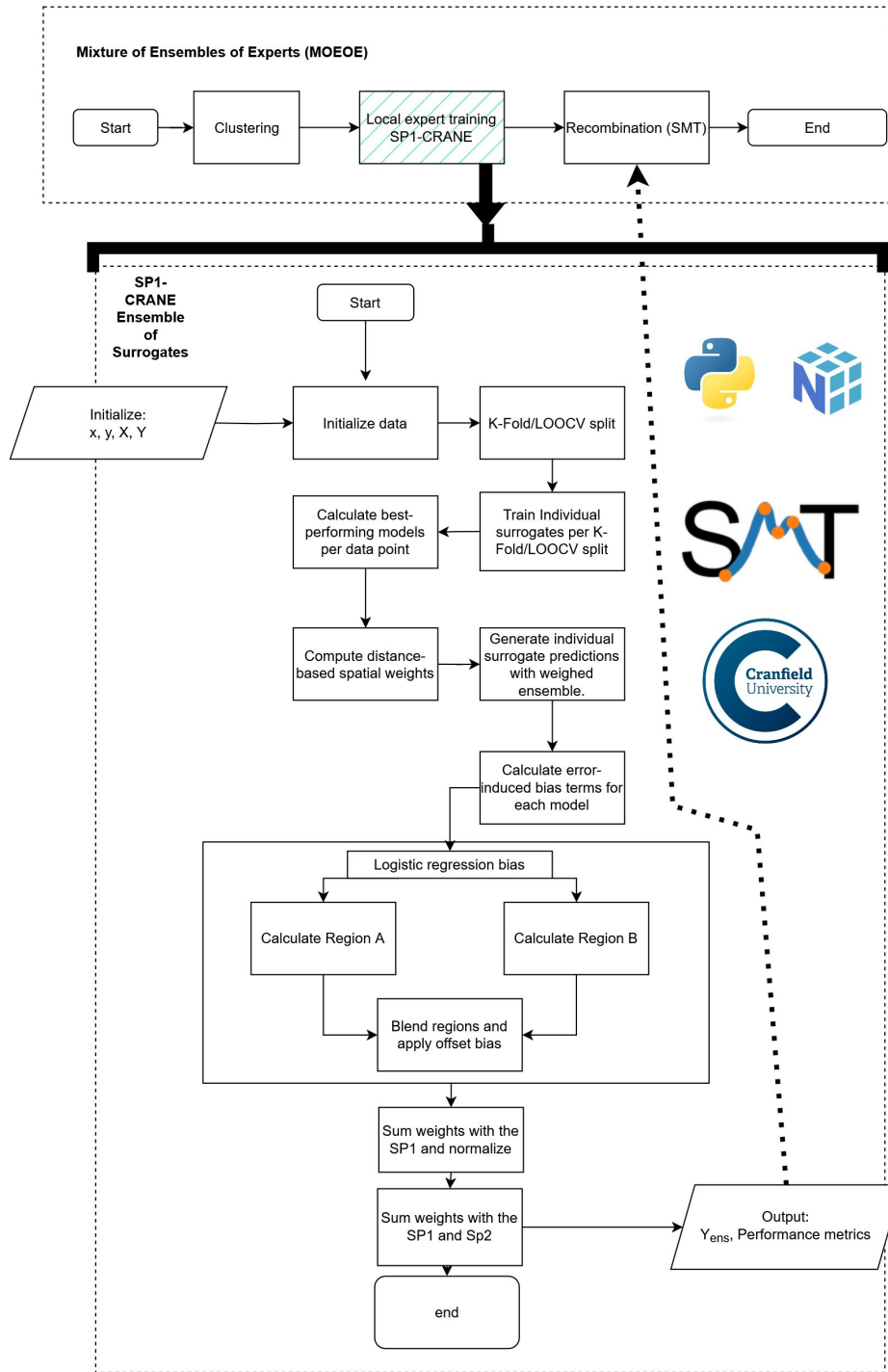


Figure 4.9: Operational workflow of the SPCrane framework implementing the Mixture of Ensembles of Experts (MOEOE) methodology. The top section illustrates the high-level process from clustering through local expert training (SP1-CRANE) to final recombination using the Surrogate Modeling Toolbox. The detailed implementation of SP1-CRANE is shown in the lower section, demonstrating the complete surrogate ensemble construction process from initialization to output generation.

regional predictions with appropriate offset bias application. This approach enables the framework to identify and leverage transition boundaries where one surrogate model demonstrates superior performance over others in specific regions of the parameter space. The workflow proceeds through subsequent normalization and summation steps to produce the final ensemble output with associated performance metrics. Regarding the future of SPCrane, the methodology shows considerable promise for further development in several directions. Automated transition boundary detection in n-dimensional parameter spaces represents a natural extension that would eliminate the need for exhaustive sampling while preserving the ability to identify critical regions where model performance characteristics shift. Integration of adaptive hyperparameter optimization for constituent surrogate models could dynamically adjust model complexity based on local data characteristics, further improving prediction accuracy in regions with complex response surfaces. Additionally, SPCrane demonstrates potential for integration with broader optimization frameworks, particularly for expensive black-box optimization problems where function evaluations are computationally costly. By providing more accurate surrogate models with quantified uncertainty, as suggested by recent research on uncertainty quantification methods like Deep Ensembles, Monte-Carlo Dropout, and Stochastic Variational Inference, SPCrane could significantly enhance the efficiency of optimization algorithms in engineering design, materials science, and other domains characterized by computationally expensive simulations. As computational demands continue to grow across scientific and engineering disciplines, frameworks like SPCrane will become increasingly valuable tools for navigating the challenges of complex system modeling and optimization.

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Chapter 5

Substituting A320 Brakes With Electric Machines for Maximized Impact of Landing Gear Drive System

As the aviation industry accelerates its shift toward electrification to combat climate change, opportunities arise to replace conventional hydraulic systems with more efficient, regenerative alternatives. This work proposes a novel concept for replacing traditional friction-based aircraft braking systems with electric machines, focusing on a multistage yokeless and segmented armature (YASA) topology integrated with a mechanical backup for safety compliance. An electromagnetic-thermal co-design approach is used to develop the system. Initial electromagnetic modeling employs a quasi-3D transient formulation validated against static 3D simulations, achieving an active material torque density of 120 Nm/kg at approximately 50 A/mm RMS current density. Thermal analysis incorporates a novel cooling method optimized for cruise altitude conditions. Analytical load models are developed and iteratively refined through material characterization of FeCoV and NdFeB alloys, balancing high torque capability with weight constraints. The final design supports braking performance equivalent to Airbus autobrake setting LOW and Boeing settings “1” and “2”, demonstrating the viability of regenerative electric braking in commercial

aviation.

5.1 Introduction

The aerospace industry is growing unprecedentedly, and the projected number of civilian aircraft is expected to double by 2040 compared to 2020, raising many concerns about sustainability [21]. Professional bodies are taking action to reduce the environmental footprint of aviation, and for instance, the Flightpath 2050 vision proposed by Agency [65] requires emissions-free ground movement.

Both runway-fitted and onboard systems have been introduced to meet Flightpath's objective, including Taxibots at Schiphol and the WheelTug system [70]. Electric taxiing concepts are mature, and once every few years, the subject of electric taxiing receives attention when a new project is released. Nevertheless, none of the undertakings to date has revolutionized the ground movement of aircraft. This indicates that the advantages brought with this novel system have been rather shallow when compared with development and implementation costs. Therefore, a greater impact is needed to draw more attention from regulatory bodies and investors.

Onboard electric taxiing systems so far have been powered by an auxiliary power unit (APU), which generally consumes less fuel than idling main engines throughout the ground movement of the aircraft. However, the APU has limited peak electric power output, and any electric taxiing system that enables high acceleration requires a bespoke APU, which ramps up the cost. An increasing number of electrified systems, such as an electric environment control or ice protection system, stretch out the electric architecture of the aircraft, and accordingly, high-power supply, wiring, and storage are being implemented as a part of a more electric aircraft (MEA). A Boeing 787 Dreamliner, taken as an example, has a total electric power output equal to 1.45 MW [133]. An MEA gives an opportunity to look at taxiing systems from a new angle, and accordingly, researchers have investigated energy recovery throughout taxiing, hydrogen fuel cell power supply exclusively for electric taxiing,

and battery-powered alternatives [75].

An energy storage present onboard is a distinct opportunity to further extend the functionality of electric taxiing systems to electromagnetic, regenerative braking that would effectively replace friction braking throughout the daily operation of the aircraft. Modern aircraft use carbon-carbon brakes that have an outstanding weight parameter, which comes at the price of energy-intensive manufacturing [134]. The substitution would considerably reduce overhaul costs of landing gear components because electric machines offer longevity in contrast to friction brakes. Finally, the driven-wheels that are continuously coupled to power components would enable wheels pre-spinning prior to touchdown [135]. Thanks to high electric power output in motoring mode, they would aid in takeoff, which would lead to further fuel savings. Each advantage can be achieved with high power and torque electric machines. Nevertheless, aerospace applications are weight and safety critical, and it is crucial to assess whether a torque and power to weight ratio of an electric machine would enable net savings in fuel and consequently, emissions.

The present work investigates the electromagnetic and thermal feasibility of implementing electromagnetic braking in a single-aisle short-haul aircraft. The scientific contribution is as follows: (1) Definition of design constraints and impact on the operations of the aircraft, (2) Electromagnetic and thermal modeling and optimization of high torque density, multistage, axial-flux electric machine integrated into a landing gear drive system, and (3) a novel cooling approach for the proposed electric machine.

5.2 Application constraints and drive cycle

Maximizing energy efficiency of aircraft is a top priority for each aircraft manufacturer, resulting in an increasing number of systems being present onboard. However, higher complexity also equates to more failure points, which could compromise safety in modern aviation. To ensure safety, well thought out procedures are im-

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

plemented to minimize the risk of hazardous situations and involve redundancy that mitigates catastrophic incidents caused by single points of failure. These procedures also influence the landing of an aircraft, which commonly relies on the autobrake system to reduce the workload exerted on pilots and minimize the wear rate of landing gear components.

The autobrake system is a closed-loop control circuit that utilizes deceleration feedback from a flight computer unit and compares it with a predefined value. Depending on multiple factors listed in Table 5.1, the flight computer calculates an optimum autobrake setting. These values are then used in a dynamic model [136] to estimate the corresponding power and torque throughout landing.

The reference distances for both Airbus and Boeing include distance from fifteen meters above threshold (300 m of air distance). In the textbook conditions the landing distances can be contained within two km and it is improbable that landing distance will exceed 2.5 km throughout standard operation. The values increase dramatically if reduced braking action is reported and it corresponds to limited tractive effort capability between a runway and aircraft tyres. Theoretically, if autobrake is set and skidding is absent, the actual landing values should remain constant regardless of runway condition.

Table 5.1: Reference distances from quick references handbook for both, an A320 [19] and B737-800 [20].

		Autobrake	REF DIST (m) for 66T	WEIGHT corr		ALT corr	WIND corr	TEMP corr	SLOPE corr	REV corr
A320's				per 1T below 66T	per 1T above 66 T	per 1000ft AMSL	per 5kt TW	per 10\deg C above ISA	per 1% downslope	per thrust reverser operative
Operational Landing										
Distances (OLDs),	MED	1470	-20	+30	+80	+160	+40	+30	-40	
Configuration full	LOW	1970	-20	+40	+90	+180	-60	-30	-10	
B737's Normal										
Configuration						per 1000ft				
Landing				per 5T below 60T	per 5T above 60T	AMSL (up to 8000ft)	per 10kt HW/ TW	per 10\deg above/ below	per 1% downslope/ upslope	one rev/ no rev
Distances										
Flaps 40										
Dry runway	2	1912	-134	+140	+55	-90 / +315	+50/-49	+29/-26	+35/+35	
	1	2115	-160	+166	+65	-104 / +370	+61/-59	+59/-50	+155/+206	
Medium reported braking action	2	2254	-160	+167	+64	-114/ +408	+58/62	+57/-51	+87/ +213	

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

In practice, it is safety critical to increase a safety margin if risk of skidding occurs to avoid runway excursion. Finally, a runway condition may change along its whole distance and pilots may decide to set up a higher autobrake setting to further increase the safe envelope. Figure 5.10 (a) and (b) show the autobrake interface unit for Airbus and Boeing accordingly. The setting from Airbus tends to have a higher deceleration rate where LOW setting equals to $2.0 \frac{m}{s^2}$ ($1.7 \frac{m}{s^2}$ before) and MED equals to $3.0 \frac{m}{s^2}$ deceleration rate. Boeing comprise one extra step while the lower levels rates tend to be very low where “1” and “2” equates to 1.2 and $1.5 \frac{m}{s^2}$ respectively.

Once knowing the deceleration rates and OLDs, it is important to benchmark it with available runway lengths. This was assessed for the three greatest air transportation markets; European countries in Figure 5.10(c), the US in Figure 5.10(d) and China. The investigation focused only on short-haul operations with occasional mid-haul flights over the period of seven consecutive days: (1) N8619F; B738, (2) HALXD; A321, (3) 9HQDT; B737-8, (4) B2945; B737-3 and (5) B1318; B738. These aircraft had flown to seventy-two different destinations of which only 3% had runway lengths lesser than 2.1 km and length for 8% was smaller than 2.4 km. The shortest airports often have a larger one in proximity and this is the case for Chicago MDW, New York LGA, London LTN and Liverpool LPL. Therefore, airlines would have an opportunity to alter destinations if the landing gear drive system is present. Such an alteration would incur costs to airlines however, it may be offset by regulatory bodies which would prioritize airlines that decided to implement the landing gear drive system during, for example, airport slot allocation.

The majority of flights can be executed with lower autobrake settings, the dynamic model was used for the landing gear drive system to estimate torque against speed [136]. Figure 5.10 (e) shows the resultant drive cycles for both landing and taxiing. An electric machine is subjected to fractional load during the latter in comparison to landing and therefore, optimization takes place to ensure that intermittent high power can be dissipated in generating mode because it is a much greater challenge.

An electric machine in the proposed application is subjected to an unconven-

5.2. APPLICATION CONSTRAINTS AND DRIVE CYCLE

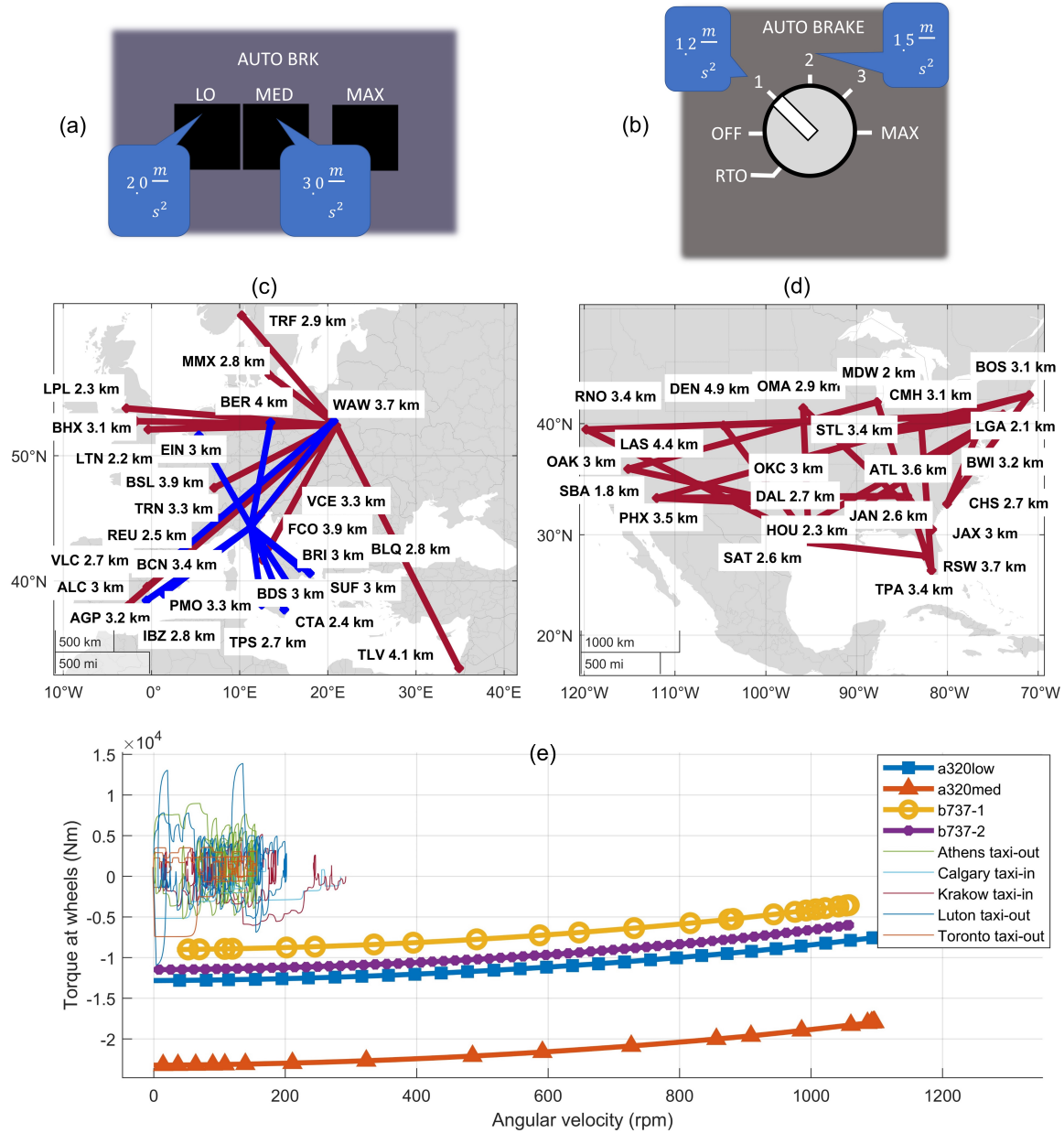


Figure 5.1: Design requirements formulation for electric machine: Airbus (a) and Boeing (b) autobrake panels together with given deceleration rates, (c) example runway lengths in Europe, (d) example runway lengths in the US and (e) drive cycles for both landing and taxiing.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

tional duty cycle. A cycle starts throughout taxiing-out and takeoff where the electric machine uses a fraction of peak performance to propel an aircraft during ground movement. When an aircraft is airborne, the power device is cooled to cruise altitude temperature to maximize its electromagnetic performance. Then, peak performance is exerted throughout the landing to safely decelerate an aircraft. There is also consideration for the pre-conditioning of the electric machines prior to landing providing considerable heat dissipation capacity throughout an operation cycle. Furthermore, a winding resistance will be reduced leading to smaller Joule heating and an improved B-H curve (second quadrant) of the permanent magnet (PM).

5.2.1 Electric machine and design requirements

The capability to replace friction brakes throughout the standard operation of an aircraft allows a saving of as much as eight million dollars corresponding to brake overhaul throughout the life cycle of aircraft. Simultaneously, an electric machine will undoubtedly be heavier than highly optimized carbon-carbon brake units that weigh as little as 40 kg in short-haul aircraft [137]. There is an emphasis on reducing the weight penalty of the proposed solution and therefore, only the highest performance materials are being considered during the development of an electric machine. Unlike in other applications, the materials are unconstrained by budget and consequently, the choice is made for the high-grade, N50H [138], NdFeB PMs and Fe-Co Vacoflux 48 lamination steel [139] for this application. The chosen PM grade offers outstanding magnetic flux density and coercivity while remaining working temperature up to 100 °C; any higher grade is limited to 80 °C. Similarly, the cobalt-iron soft-magnetic materials are known for superior hysteresis performance, permeability reaching eighteen thousand and the saturation flux density of 2.3 T. Due to the requirement of present superconducting materials for cryocooling, only copper is considered for winding. However, there is much novelty in manufacturing processes and additive manufacturing can result in maximizing the fill factor. Finally, a material selection for the housing is linked to titanium and aluminium alloys.

While titanium is generally better with its yield strength against weight metric, aluminium offers superior thermal conductivity which allows it to timely extract heat. This is especially important for high-current density applications and corresponding conduction between housing and windings. Each of the described materials ramps up the initial costs of the concept nonetheless, the longevity of electric machines will ultimately lead to remarkable savings by the end of the aircraft life cycle.

Besides material selection, the arrangement of PMs known as a Halbach array allows superior power and torque density to be achieved by removing the back iron [140]. Instead, the magnetic flux path is concentrated on one side of the array and runs through a continuous layer of PMs. These advantages are accrued at a price of considerably increased assembly complexity especially when high-strength magnets are used. They have to be assembled in proximity to each other while inducing high repelling forces. There is also an increased risk of demagnetization which can be mitigated by adding a small spacing between magnets.

Finally, a topology for the electric machine is selected to be a YASA primarily because it would be relatively easy to integrate inside the wheel and reuse the keys of a wheel rim. Secondly, this topology is known due to its geometry which further maximizes torque density of the proposed machine. Figure 5.2 shows the electric machine for the landing gear drive system demonstrator.

As can be seen in Fig. 5.2 (a), six stacks are used to match the torque constraints. Nevertheless, the stacking capability is limited by axial length, as illustrated in Fig. 5.2 (b), which shows the volumetric design space [141]. This limitation is managed by employing a high aspect ratio of outer diameter to axial length, reaching values of up to ten. The electric machine operates in motoring, generating, and braking modes. For a permanent magnet (PM) synchronous machine, both motoring and braking rely on external excitation, whereas in generating mode, the PMs provide the excitation source. The electromotive force (EMF) produced is proportional to the machines angular velocity, and at very low speeds, energy recovery becomes impractical due to the voltage difference between the electric machine and the storage system.

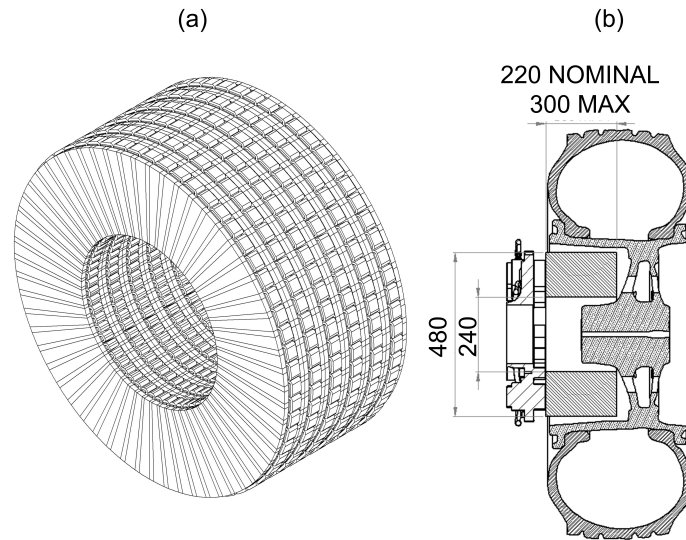


Figure 5.2: *Electric machine for the landing gear drive system; (a) demonstrator of assembled electric machine, (b) volumetric constraints associated with a short-haul aircraft landing gear.*

The added volume of the YASA electric braking system does not impose a significant penalty on the landing gear stowage. This is because the YASA unit replaces the existing carbon-carbon brake stack rather than supplementing it. The original torque tube and wheel assembly, including the keyed interface, is designed to withstand the high deceleration loads encountered during landing. The loads introduced during electric braking are of similar magnitude and orientation; therefore, no structural modifications to the torque path are required.

The high volumetric power and torque density of the axial-flux YASA topology make it well-suited for this configuration. If higher braking performance is desired to support regenerative operation under medium autobrake settings, the design can be scaled by modestly increasing the axial dimension rather than the overall diameter. This allows integration within the existing gear bay envelope without necessitating substantial alterations to the stowage volume or retraction geometry.

To ensure that an electric machine can seamlessly operate in the low angular speed regions, the high pole-segment combinations are considered reaching up to 58 poles and 60 segments. The higher count leads to a higher ratio between me-

5.3. ELECTROMAGNETIC DESIGN AND OPTIMIZATION OF YOKELESS AXIAL-FLUX MACHINE

chanical and electrical revolution and consequently, sufficient EMF for generating mode can be achieved with more ease at lower speeds throughout landing deceleration. Otherwise, the electric machine can decelerate an aircraft by braking (also known as plugging) which is similar to motoring mode, but phase offset equals 180 degree. The major drawback of plugging is the prohibitive amount of heat. In these circumstances, the remaining kinetic energy of an aircraft would be converted to heat inside an electric machine and therefore, it can only be applied at the end of landing deceleration in near standstill conditions.

Knowing that the device will be safety critical, the assumption is made that the magnetic flux path is independent for each segment and in addition, the number of phases was increased up to seven phases separated by stacks. If at any point a winding failure occurs in such a seven-phase, six-stack machine, the braking performance would be reduced by only 0.6% which would have a negligible impact on safe operation.

5.3 Electromagnetic design and optimization of yokeless axial-flux machine

The development of an electric machine for a landing cycle is a much greater engineering challenge than a drive for electric taxiing. Therefore, electromagnetic optimization takes place based on the drive cycle for the multiple autobrake settings. Figure 5.3 presents the genetic optimization algorithm used in the process. The design constraints were defined according to the assumptions given in the previous sections. Accordingly, it is estimated that the feasibility point can be described as torque demand t_{dem} equal 12 kNm, power demand P_{dem} equal 0.96 MW. The angular speed of the cycle in standard operation ω_{dem} is limited to approximately 1200 RPM however, the electric machine must remain intact in case of an overspeed landing. Aircraft tyre certification is used as a reference and accordingly, maximum speed equates to approximately 2000 RPM. The outer r_o and inner radii are derived from

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

preliminary design equations for a landing gear [137] and correspond to 240 and 120 mm respectively. Finally, the maximum mass $m_{\max}$ is not fixed because it is heavily dependent on aircraft operation and an electric machine weighing 300 kg would still be beneficial for aircraft which execute only short-haul flights. Nevertheless, the target of 160 kg maximum weight was set to ensure that the landing gear drive system remains applicable to a broad range of applications.

5.3. ELECTROMAGNETIC DESIGN AND OPTIMIZATION OF YOKELESS AXIAL-FLUX MACHINE

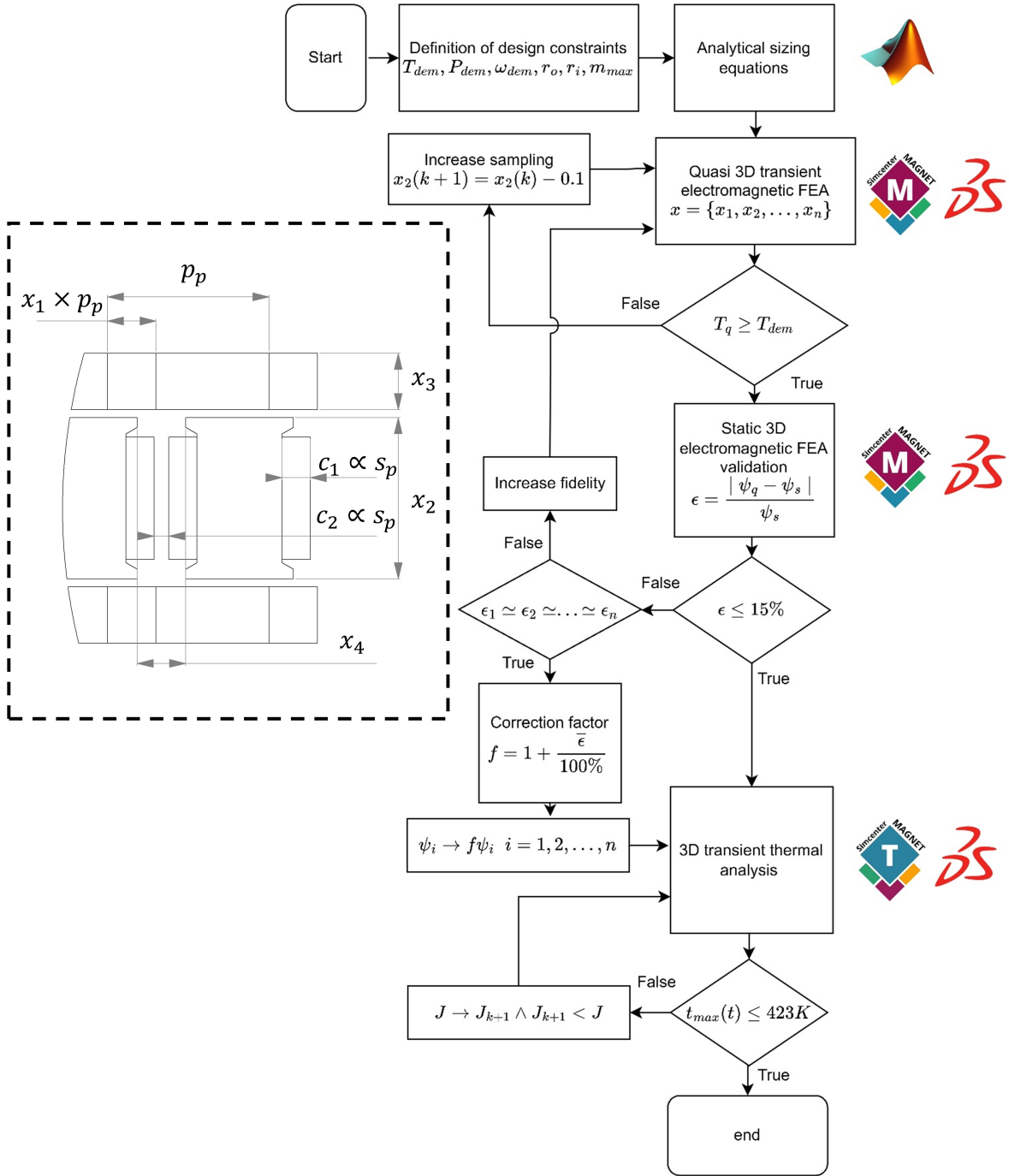


Figure 5.3: Optimization algorithm for the present work, including the optimization objectives, variables, validation and correction factor.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

Having the design constraints defined allows us to progress into analytical modelling which relies on the following sizing equation for power output [142]:

$$P_{out} = \frac{m}{m_1} \pi^2 \frac{(1 + k_d)(1 - k_d^2)}{8} k_{w1} n_s B_g A_s \eta \cos \varphi D_o^3 \frac{V_1}{E_f} \quad (5.1)$$

where the value of m represents the number of phases, m_1 denotes the number of phases for each stator, In case there are multiple stators, it can be assumed that each stator has an identical value of m_1 (i.e., the number of phases for each stator remains constant). k_d is the aspect ratio of outer diameter to axial length, k_{w1} is the fundamental winding factor, D_o is the outer diameter, n_s is the rotational speed in rev/s, B_g is the air gap flux density, A_s is the specific electric loading, η is the efficiency and $\cos \varphi$ is the generator power factor.

The PM thickness is calculated as:

$$l_{pm} = \frac{\frac{2K_r}{2+K_{rm}} \mu_r B_g g}{k_l B_r - B_g / C_\varphi} \quad (5.2)$$

where k_r is the reluctance factor of the steel path, which is typically in the range of 1; $k_r \leq 1.2$, k_{rm} is the reluctance factor to accommodate/ consider the reluctance of tangential arrangement of Halbach magnet, μ_r is the recoil permeability, g is the air gap, k_l is the leakage factor which is typically less than one, B_r is the residual flux density of PMs and C_φ is the PM concentration factor.

The length of segments is derived from:

$$l_s = \frac{I \pi D_o (1 + k_d)}{2 \sqrt{2} N_t k_{w1} J_{rms} k_f} \quad (5.3)$$

where I is the specific electrical loading, N_t is the number of turns, J_{rms} is the root mean square (rms) value of current density and k_f is the slot fill factor.

The analytical equations led to preliminary variable dimensions however, the finite element analysis was conducted for multiple variables to investigate the influence of the nonlinear magnetic performance of the components. Figure 5.4 (a) shows the

5.3. ELECTROMAGNETIC DESIGN AND OPTIMIZATION OF YOKELESS AXIAL-FLUX MACHINE

magnetic flux density for the quasi 3D model and that the knee point which induces nonlinearity from approximately 1.8 T onwards is reached. This phenomenon is further visible in Figure 5.4 (b) which indicates that the saturation phenomenon is more severe at lower radii. In a motoring mode, exceeding the knee point is highly undesired because exponentially more current must be passed through the coils to achieve a torque increase while the ohmic losses are proportional to the square of the current. In the generating mode, having the flux density in proximity to the knee point region indicates that there is a balance between the amounts of PMs and the core materials.

The geometry was optimized numerically according to the Halbach array proportion of axially-facing to side-facing components x_1 , the segment axial length (x_2), the PM axial length (x_3), the arc of the segment (x_4). Furthermore, the author investigated the influence of the varying number of segments and poles. Accordingly, the winding was scaled (c_1) and the housing (c_2) thicknesses changed proportionally to a number of segments.

The FEA assumptions were set and the tight stacking of multiple YASA machines together with the Halbach array arrangement of PMs have another distinctive advantage. The multiple stacks are arranged so the PMs located at the rotors of each stack tend to repel each other and thus, concentrate the magnetic flux on the stator sides with reduced leakage. This phenomenon was captured by neglecting the flux leakage in axial direction. However, the flux can still exit the machine in the radial direction and accordingly, in the full 3D model, the outer diameter of the airbox is 100 mm greater than the outer diameter of the geometry. These assumptions allowed us to manipulate the proportion of side- and axial-facing segments without concerns about flux concentration as shown in Figure 5.4. The best results were achieved for the generator when the ratio of axial-facing to the side-facing PM arc lengths is equal to 0.3 but this approach has to be validated for coil excitation in motoring mode.

In the electromagnetic design, the assumption of negligible axial flux leakage is a simplification aimed at focusing on dominant flux paths for initial optimization. While

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

the tight stacking of multiple YASA machine segments and the segmented Halbach array arrangement help to concentrate magnetic flux on the stator sides and reduce leakage along the axial direction, some axial flux leakage inevitably occurs at rotor ends and interfaces. This leakage can decrease the effective magnetic coupling, reduce torque density, and increase losses due to flux circulating outside the intended magnetic circuit. If axial leakage is more significant than anticipated due to manufacturing tolerances, assembly gaps, or nonlinear magnetic effects; this could lead to reduced machine efficiency and elevated thermal loading. The full 3D finite element analysis performed partly accounted for radial leakage but was limited in explicitly resolving all axial leakage flux. Therefore, future work includes detailed 3D modeling and experimental validation to quantify and mitigate axial leakage effects, potentially through design refinements such as optimized magnet segmentation, flux barriers, or additional magnetic shielding. Acknowledging and addressing this assumption is essential to ensure reliable high-performance operation in practical aerospace applications.

The electromagnetic modeling approach distinguishes clearly between Finite Element Method (FEM) as the mathematical formulation and Finite Element Analysis (FEA) as its practical implementation through software tools. For the optimization of the yokeless axial-flux electric machine, a FEM formulation was sourced from Siemens MAGNET software and used on transient quasi-3d model which was later validated against static 3D FEA results to balance accuracy and computational efficiency. The FEA utilized tetrahedral elements with adaptive mesh refinement, focusing fine meshing around regions of high magnetic flux density gradients such as air gaps and permanent magnets. A mesh convergence study was conducted by progressively refining the mesh until torque and flux linkage results varied by less than 1%, ensuring the robustness of the solution. The solver applied an implicit time integration scheme for transient simulations to capture dynamic electromagnetic behavior over the electrical cycle. The analysed geometry was parametrically varied using SolidWorks CAD models imported into Simcenter Magnet, which served as the FEA

5.3. ELECTROMAGNETIC DESIGN AND OPTIMIZATION OF YOKELESS AXIAL-FLUX MACHINE

tool for solving the coupled electromagnetic field equations. This careful workflow allowed for an accurate representation of nonlinear magnetic saturation and complex material anisotropies critical to the multistage YASA machines performance.

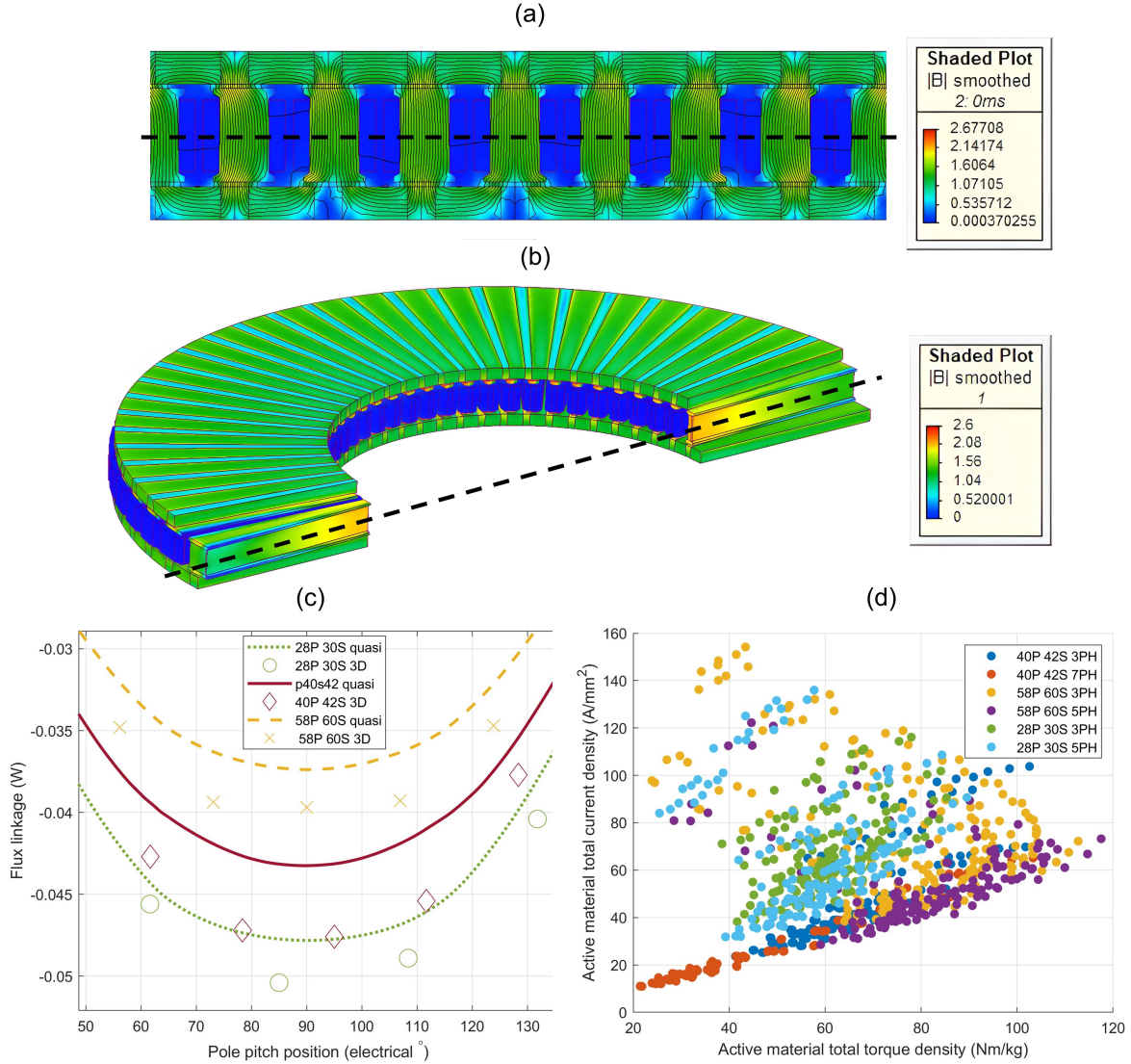


Figure 5.4: Electromagnetic FEA for the proposed electric machine: (a) quasi 3D and (b) 3D model magnetic flux paths and distribution of flux density; intermittent lines indicate the symmetry planes, (c) validation according to flux linkage, (d) Performance benchmark of all iterations showing the peak current density against the torque density.

The quasi 3D approach allowed us to minimize computing time to obtain the results however, this approach neglects the end effects at both radial ends of the ma-

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

chine. The model was sliced for selected iterations and the intermittent black line in both Figure 5.4 (a) and (b) illustrate these planes. To ensure the accuracy of results, the validation took place (see Fig. 5.4 (c)) the quasi 3D data with high-fidelity static 3D FEA by comparing the flux linkage at different electrical angles. The comparison reveal a small error after the peak value convergence check: $\varepsilon_{60s} = 6.2\%$, $\varepsilon_{42s} = 9.1\%$ and $\varepsilon_{30s} = 5.1\%$. Unusually, the peak values from 3D results were higher in each case. The most probable reason for this occurrence is the limited number of slices in quasi 3D analyses.

The simulation was conducted for nearly 600 different geometry and load setups. The iterative process for both Quasi-3D and 3D FEA was automated; the geometries were created in SolidWorks, which were later imported into Simcenter Magnet and solved. Then, the FEA data were fed into MATLAB and cleaned for analysis (Raw data available in Data Availability Statement). Figure 5.4 (d) shows a performance benchmark of active material total torque density against the root mean square current density. As expected, the higher number of poles and segments led to increased torque density. The flux saturation nonlinearity can be observed by assessing the best-case iterations.

The performance trends observed in Figure 5.4, illustrating the impact of increasing numbers of poles and segments, show consistent improvement in torque density due to enhanced flux linkage and reduced magnetic flux leakage. This behavior aligns well with industry benchmarks, such as the Emrax 348 in-wheel electric machine, which achieves a peak torque density of approximately 23 Nm/kg at current densities below 10 A/mm², whereas the proposed design reaches up to 120 Nm/kg active material torque density at 50 A/mm² current density. The higher pole-segment count in the proposed YASA topology enables increased electrical-to-mechanical revolution ratios, facilitating sufficient electromotive force generation at lower speeds critical to aircraft landing operations. The outcomes are aligned with the state-of-the-art for electric machines leveraging high-performance materials like NdFeB magnets and FeCoV alloys, innovative Halbach array configurations, and advanced cooling

methods.

To achieve the high torque density of 120 Nm/kg at 50 A/mm², several design trade-offs were deliberately made. The primary focus was on maximizing torque output per unit mass, which necessitated the use of high-performance materials such as N50H NdFeB permanent magnets and Fe-Co Vacoflux 48 lamination steel, both of which offer superior magnetic properties but at increased cost and complexity. The adoption of a Halbach array and a yokeless axial-flux (YASA) topology further enhanced torque density by concentrating the magnetic flux and minimizing the use of back iron, but this also increased the assembly complexity and risk of demagnetization. Additionally, the design prioritized a high aspect ratio (outer diameter to axial length) and a high pole-segment count, which improved torque density but may have led to higher eddy current and hysteresis losses, thus reducing overall efficiency compared to conventional designs. Finally, the design objective is to provide high performance for the period of approximately fifteen seconds meaning that more current density can be fed through the winding without overheating.

The transient results of magnetic flux change are presented in Figure 5.5 where nine steps across a whole pole pitch were taken into account. The machine was halved in axial direction according to the symmetry plane of magnetic path minimizing the computational cost of each simulation.

The change in flux density throughout a single pole pitch indicates that saturation is achieved at the stator tooth however, increasing its size leads to reduced performance due to increased flux leakage. In the worst case scenarios, when the axially-facing PMs and the stator teeth were large enough, the magnetic flux path circulated through a single rotor without penetrating through the core.

5.4 Thermal considerations

High performance machines generate a large amount of heat and thermal analysis must be executed to provide answers regarding the feasibility of an electric ma-

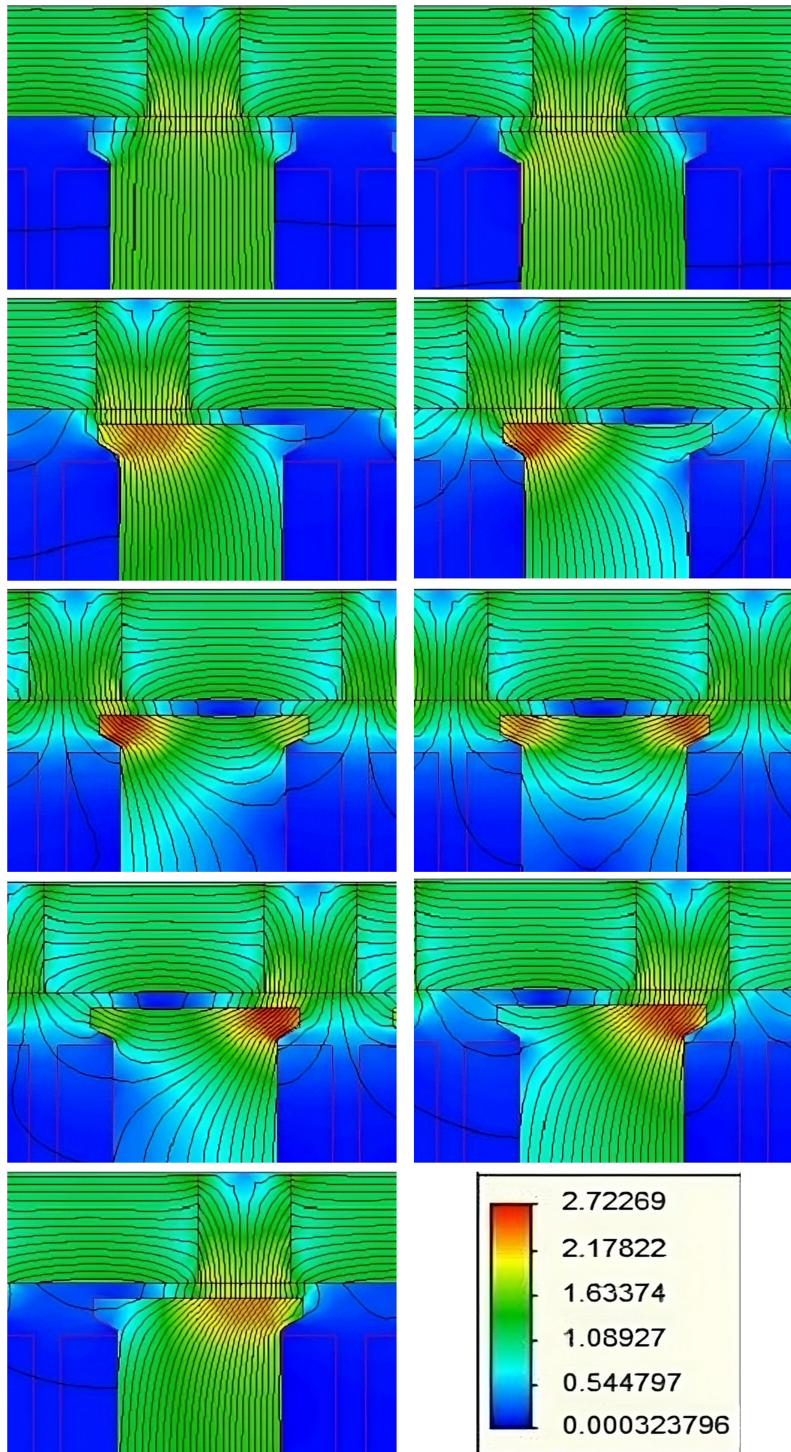


Figure 5.5: Magnetic flux density for nine steps of quasi 3D transient simulation at 1000 rpm.

chine for the landing gear drive system. This cycle differs from a standard automotive application due to its intermittent nature, and an electric machine is cooled prior to peak power application and has a considerable thermal capacity up to an overheating point. Contrary to internal combustion engines which require working temperature for safe operation, electric machines take advantage of low temperatures due to increased coercivity and higher flux density of PMs and reduced resistivity of copper.

A cruise altitude opens the possibility of further cooling down the electric machine prior to touchdown. This is applicable even to short-haul flights executed by A320s and B737s. Figure 5.6 (a) shows three flights in Europe that are shorter than one hour and in each case an aircraft reached an altitude that corresponds to International Standard Atmosphere's (ISA) temperature lower or equal to minus forty degrees Celsius. Utilizing this temperature by, for example, taking a small amount of air from NACA ducts would allow cooling the electric machines to as low as minus thirty degrees Celsius upon touchdown. As an outcome, the reduced Ohmic losses and increased electromagnetic performance would lead to even higher torque density throughout a landing.

Since the proposed method for the electric machine pre-cycle cooling requires more research regarding the concept feasibility, the conservative initial temperature of minus twenty degree Celsius in the semi-analytical model was used. Figure 5.6 (b) illustrates that the single segment was taken out of the inner stack because the highest temperature rise is expected in the middle of the motor and the assumption was made that an equal amount of heat is generated in each segment and pole of this multistage electric machine. Consequently, the author made an approximation that there are two symmetry planes (perfect insulators) in the axial direction flush to the PM outer faces and two additional symmetry planes equally spaced between two segments. The aluminium stator housing and the retaining sleeve components were added respectively to symmetry planes to increase the amount of heatsink material. Knowing that the landing cycle ends within thirty seconds, the assumption was set that the system is adiabatic.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

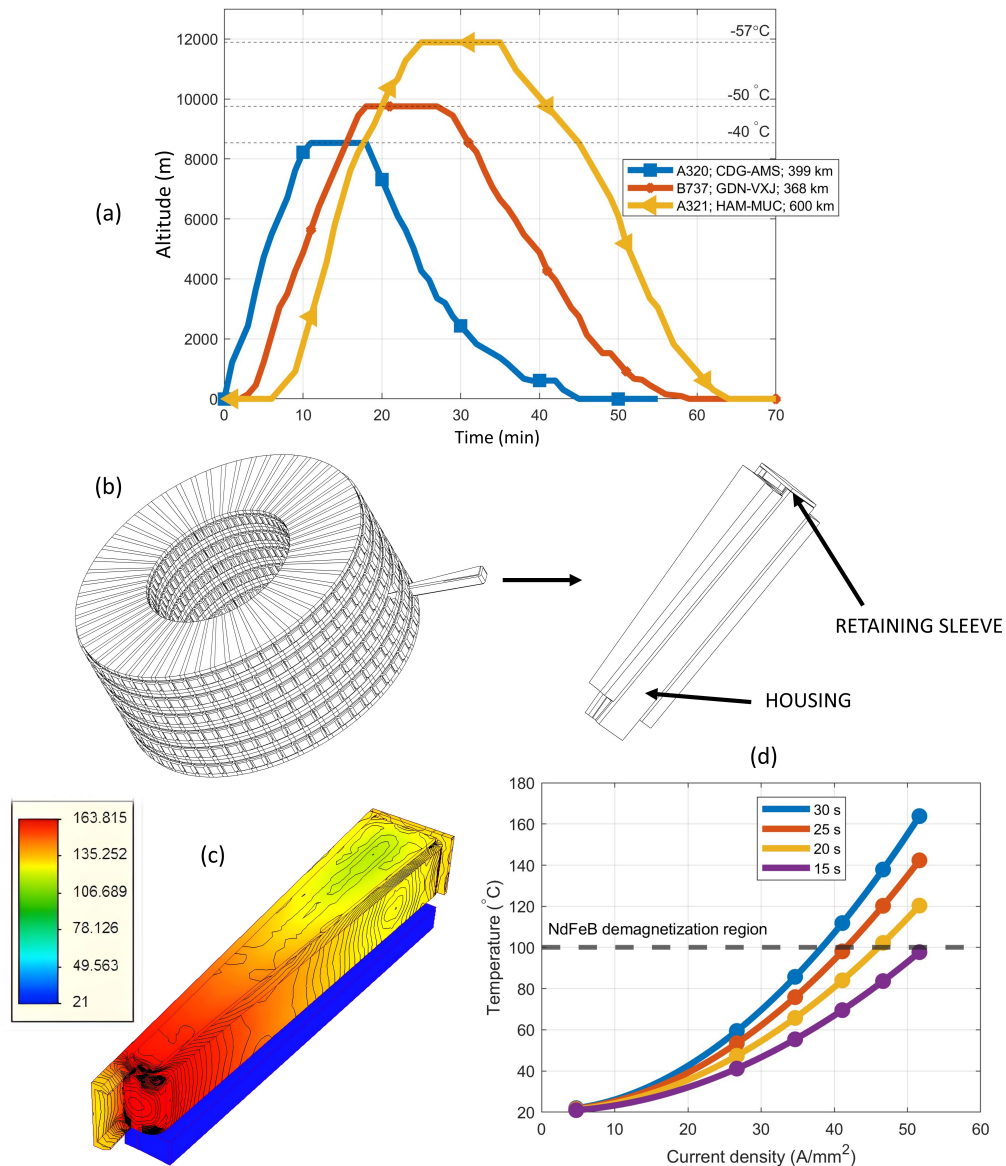


Figure 5.6: Thermal modelling of the electric machine: (a) Example short-haul flights that potentially permit cruise altitude cooling, (b) thermal simulation geometry initialization, (c) temperature shaded results for the highest current density simulated in Simcenter MAGNET Thermal, (d) Plot of temperature of winding against the current density at 15s, 20s, 25s, and 30s.

High torque and power density metrics require high current density which is an indication of high Joule losses which will be markedly higher than eddy currents, hysteresis and mechanical factors. The simulation reflects eddy current losses in the PMs and the stator core equal 2 and 0.9 W respectively. They were sourced from the quasi 3D electromagnetic FEA. The hysteresis losses equal 2.6 W were applied

in a similar manner. Finally, the ohmic losses were hand calculated because the quasi 3D approach skips the end windings. First, the mean length of winding was measured in the CAD software and then, the heat loss was calculated:

$$H(t) = I^2 \frac{\rho_r(t) l_{ws}}{\frac{\sigma_s}{N_t} \rho_c} \quad (5.4)$$

where I is the phase current density, ρ_r is the resistivity of copper, l_{ws} is the winding length per winding per segment, σ_s is the total winding cross section, N_t is the number of turns and ρ_c is the copper fill factor.

The simulation was conducted for different current densities up to $52 \frac{A}{mm^2}$ and Figure 5.6 (c) shows the transient results for the worst case scenario after the heating. The upper layer of PMs and a single side of housing were included in the simulation but removed from the figure to increase clarity. The highest recorded temperature equals 163 degree Celsius and as anticipated, the hot spot is present at the inner radius of the electric machine because the ratio of heat source to heatsink material decreases with the radius. The heat transfer between the core and the PMs was minimal due to a short period. Figure 5.6 (d) shows the plot of winding maximum temperature against the RMS current density after 15, 20, 25 and 30 s. The highlighted NdFeB demagnetization border indicates that the higher current densities will heat the winding and the core to temperatures exceeding the maximum safe temperature of the PMs above which they will demagnetize. While it is safe for the period of landing due to limited heat transfer through the airgap, the heat will be transferred at a later stage and may lead to irreversible demagnetization. The best possible mitigation is the cooling that allows controlling the temperature of the PMs after the landing. Besides the PMs temperature limitation, the winding material, iron core and housing can easily withstand the simulated temperatures. The insulation temperature rating is the primary limitation for these materials however, there are commercially available materials that sustain up to 400 degree Celsius. This simulation demonstrates that there is enough thermal capacity to sustain high current densities occurring during

the landing. However, the results are limited regarding the heat transfer and neglect the heat transfer resistivity of insulation varnish.

The presence of thermal hotspots near the inner radius, as indicated in the results, can significantly affect the long-term reliability and material integrity of the axial-flux electric machine because uneven heating causes localized thermal stresses that accelerate insulation degradation and increase the risk of winding or magnet demagnetization, especially for temperature-sensitive adhesive layers and permanent magnets; persistent exposure of these hotspots to elevated temperatures can trigger premature aging of insulation materials, reduce operational lifespan, and compromise structural stability due to thermal expansion mismatches between different materials, while efficient thermal management in axial-flux machines must therefore address such inner radius hotspots through the optimization of cooling including direct stator and rotor cooling, enhanced thermal conduction paths, or strategically placed heat pipes as well as through the use of high-temperature materials, localized thermal sensors, and real-time condition monitoring, given that uneven heat distribution will also raise winding resistance, reduce electromagnetic performance and efficiency over time, and thus highlight the importance of comprehensive hotspot risk mitigation in support of reliable long-term machine operation.

5.5 Frictionless brakes emergency backup device

Commercial aircraft are continuously improved to reduce operational costs and environmental footprints. Electric taxiing systems offer these advantages for short-haul operations, and the boldest attempt was made by Lufthansa together with L-3 Communications [22]. They replaced the main landing gear's brake unit with a geared electric machine, claiming it could harvest up to half of the required braking energy. Nevertheless, as pointed out in AIR 6246 [22], the removal of the brake unit makes the system a demonstrator rather than a practical solution. To mitigate this problem, the concept is inspired by bridging the YASA electric machine topol-

ogy with the conventional carbon reinforced-carbon brake units utilized in commercial aircraft. The combination of these two technologies has led to a novel hybrid electromagnetic-friction brake concept. This brake concept operates similarly to an in-wheel, direct-drive electric machine, typical in the automotive industry. However, in emergency situations such as RTO, the electric machine becomes a heatsink and acts in the same manner as a typical friction brake unit of aircraft. Consequently, the conventional brakes become redundant in this scenario, leading to further weight reduction.

The first fundamental question about idea's feasibility is linked to electromagnetic performance during standard operation. This was demonstrated in the previous work [136] that active material torque density reaches 120 Nm/kg at approximately 40 A/mm² RMS current density. Both numbers are considerably higher than other YASA machines and for example, Emrax 348 [143] offers peak torque density of 22.83 Nm/kg with current density lesser than 10 A/mm². This discrepancy is primarily caused by comparing the active material only versus the complete electric machine. However, we estimate that the finalized electric machine will have the torque density greater than 80 Nm/kg which is enabled by following factors: (a) usage of Halbach array of Permanent Magnets (PMs), (b) direct winding cooling enabled by additive printing technology and (c) thermal conditioning prior to a short-duration landing cycle, (d) reusing components of the landing gear such as a torque tube and (e) higher pole-segment number. Importantly, division between motoring and generating mode is required when assessing peak torque density. In the latter, the losses will add up to a total torque rather than subtract as in the motoring mode. The latest technology is also considered by startups where the Elaphe company [144] claims 100 Nm/kg active material torque density for their in-wheel electric machine whilst H3X [145] promises aerospace propulsion with torque density 53.6 Nm/kg including integrated

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

drives.

Thermal conditioning is considered to have the highest impact on the electro-magnetic performance of electric machine. This is enabled by a low temperature in a wheel well during cruise flight that averages -20 deg C. The temperature can be reduced further if a designated cooling system is used for thermal conditioning as outside temperature at cruise altitude could be as low as -60 deg C. There is considerable performance increase of the PMs linked to increased coercivity. One of the strongest PMs offered by Vaccumschmelze, VACODYM 722 DHR, have the temperature coefficients for remanence and coercivity of -0.12% and -0.67% per deg C, respectively. Whilst these values are specified for 20-100 deg C range, Hara et al. [146] demonstrated that the temperature coefficient remains nearly linear down to 120K. Similarly, low temperature reduces copper resistivity by 0.393% per deg C and there is substantial performance change between thermally conditioned electric machine with temperature equal -20 deg C and a conventional electric machine with working temperature of 40 deg C. This difference leads to armature resistivity reduced by a quarter and maximum energy product of Nd₂Fe₁₄B increased by a half.

Being aware of satisfactory electromagnetic parameters, the consecutive step is to assess feasibility of the proposed machine in emergency mode. The switching to this mode occurs by using conventional hydraulic brake pistons of an A320 as demonstrated in Figure 5.7. There are two design variants considered and Figure 5.7 (a) shows the 2x3 configuration which substitutes both conventional brake units of the landing gear leg with two triple-stacked electric machines. Alternatively, Figure 5.7 (b) shows the 1x6 setup where a single brake unit is retained whilst another is replaced by a six-stacked electric machine. During standard operation, the shear pins demonstrated in Figure 5.7 (c) separate the stators away from rotors maintaining the uniform airgap. No friction occurs in this condition and electric machine functions normally. This changes when the peak braking performance is required; force exerted by the hydraulic system breaks the shear pins and the rotors come into contact with the stators. Depending on a design configuration, transition from a regenerative

5.5. FRICTIONLESS BRAKES EMERGENCY BACKUP DEVICE

braking to a friction braking will be achieved at the MED or MAX autobrake setting (Fig. 5.7 (d)).

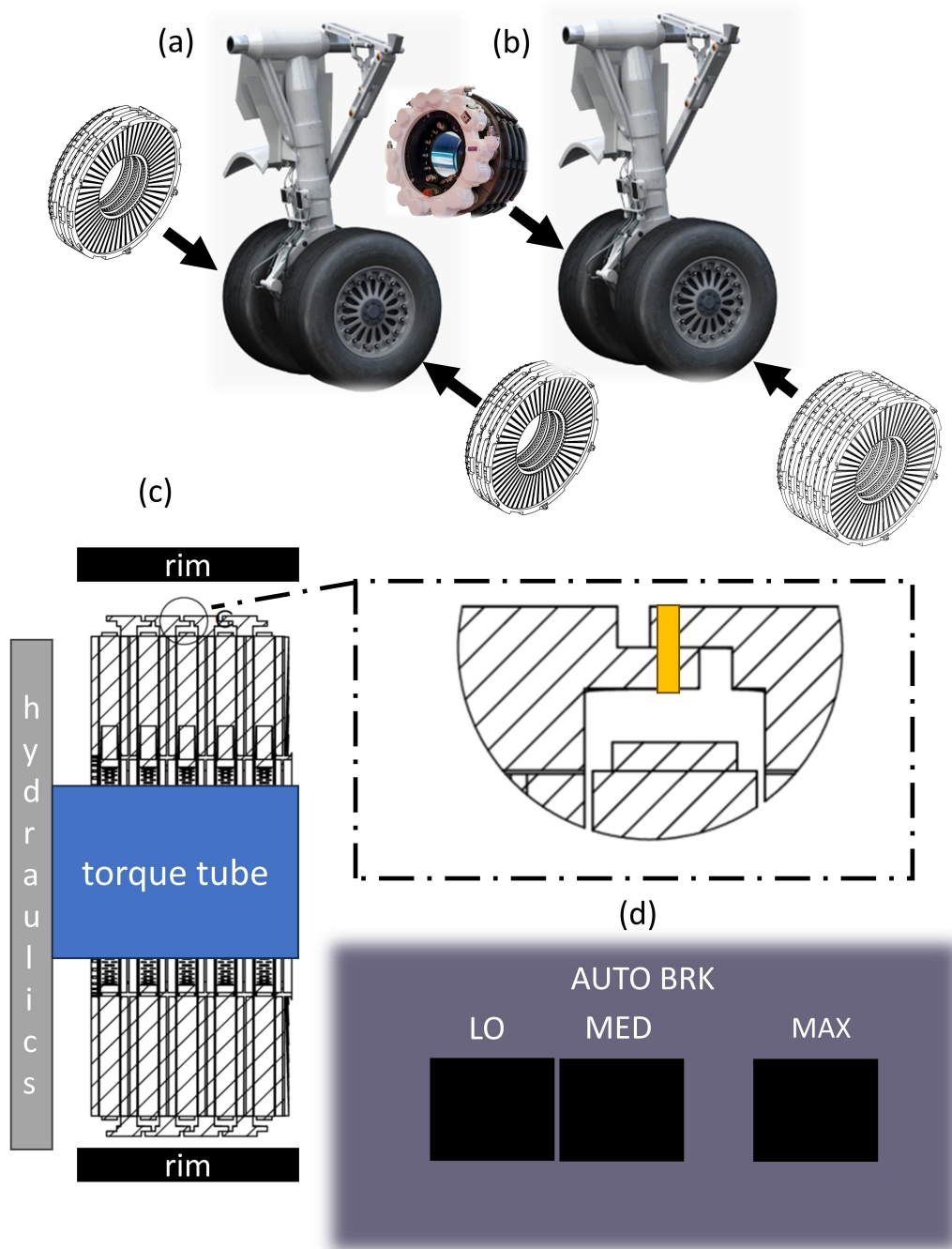


Figure 5.7: Hybrid electromagnetic-friction brake demonstrator: (a) 2x3 design configuration, (b) 1x6 hybrid design configuration, (c) shear pin concept and (d) autobrake settings

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

Table 5.2: *Braking modes for both proposed design configurations*

		AIRBUS AUTO BRK setting		
		LO	MED	MAX
design	2x3	regenerative	destructive	destructive
config- uration	1x6	regenerative/ hybrid (traction-dependent)	hybrid	destructive

Table 5.2 demonstrates which of the autobrake settings correspond to the regenerative and destructive braking depending on the design configuration. The 2x3 setup enables regenerative braking only for LO autobrake setting whilst 1x6 enables hybrid friction-regenerative autobraking at both LO and MED settings. Furthermore, solely regenerative braking in the LO setting is possible when the sufficient traction between tyre and pavement is available.

The highest performance electric machines rely on the Neodymium-Iron-Boron (Nd₂Fe₁₄B) alloy such as the VacoDym PMs [147] and the Cobalt-Iron-Vanadium (49Co49Fe2V) also known as the permendur or under the commercial names: Vacoflux [147] and Hiperco [148]. Whilst magnetic and mechanical properties are well explored from very low temperatures linked to superconductive machines and up to the Curie (demagnetization) point, there is limited literature available at elevated temperatures. For Nd₂Fe₁₄B material, there is a considerable gap between Curie temperature occurring at approximately two hundred degree Celsius and melting point that is beyond one thousand degree Celsius. The issue of lacking mechanical and thermal knowledge about given materials must be resolved before claiming feasibility of the given concept.

Learning more about mechanical and thermal properties of the magnetic materials for the emergency friction braking application falls in line with development of brake disc and pads. Kim et al. [149] defined a list of mechanical properties that affect the performance of disc brakes and they enlisted: (a) Diffusivity (thermal conductance), (b) abrasion strength, (c) Hardness, (d) fatigue life. Similarly, Choudhary

et al. [150] assessed different materials for disc brake design and they enlisted: (a) Youngs Modulus, (b) Density, (c) Poissons ratio, (d) Yield strength, (e) thermal conductivity and (f) specific heat. Maleque et al. [151] provided performance metrics for different brake disc materials and they factored: (a) compressive strength, (b) friction coefficient, (c) wear resistance, (d) thermal capacity and (e) specific gravity. In the automotive industry, Society of Automotive Engineers (SAE) [152] provides the standard for gray iron castings used in, among others, brake discs and they enlist tensile and transverse strength, and hardness.

Commercial aircraft rely on carbon fiber reinforced brakes (C/C) since the maiden flight of Concorde and there is an increasing interest in the carbon fiber reinforced silicon carbide (C/SiC) materials offering higher thermal stability [153]. These materials, similarly to the sintered Nd₂Fe₁₄B, can be described as brittle [154]. Generally, the sintered materials are commonly used in automotive brake pads whilst a very common material for discs is cast iron due to its cost effectiveness [155].

5.6 Material Characterization: Literature Review

Proposing the novel application for the magnetic materials requires thorough understanding of their properties. Both Nd₂Fe₁₄B and 49Fe49Co2V materials were first proposed in 20th century and are well characterized for standard applications. This section benchmarks these against the conventional braking materials and Figure 5.8 demonstrates the mechanical and thermal properties at room temperature.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

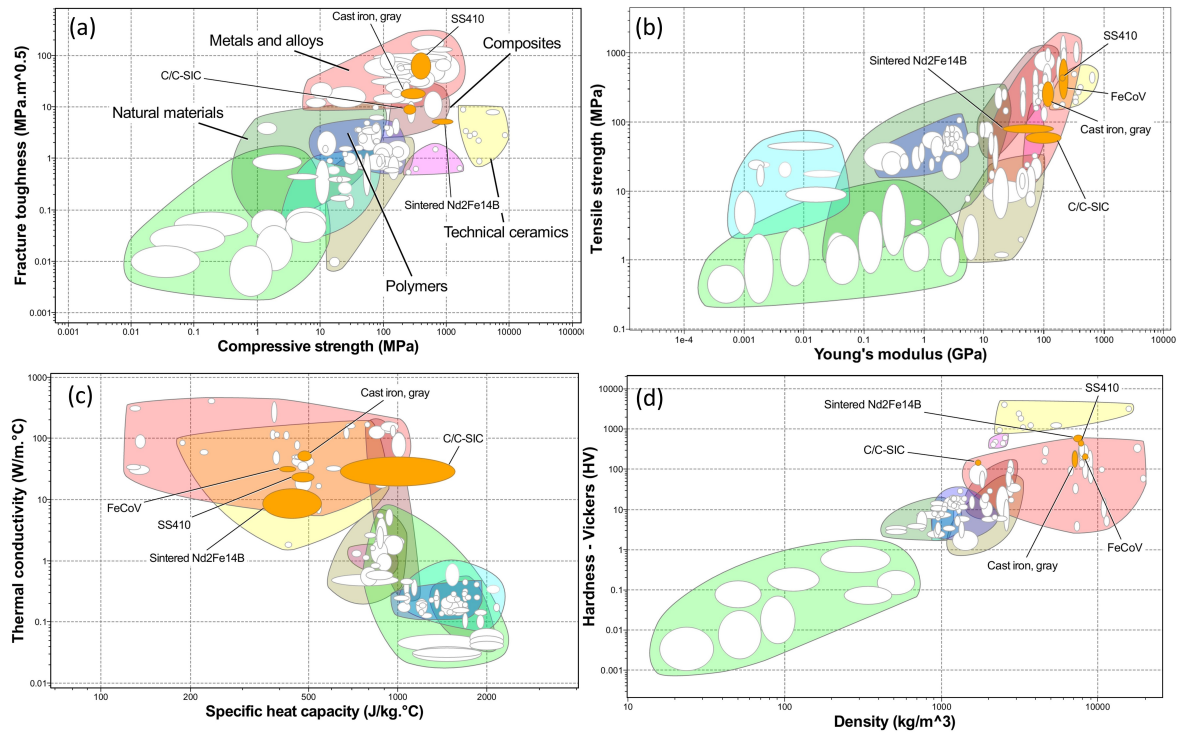


Figure 5.8: Preliminary material benchmark featuring conventional brake and magnetic materials: (a) Fracture toughness vs compressive strength, (b) Tensile strength vs Young's modulus, (c) Thermal conductivity vs specific heat capacity and (d) Hardness-Vickers vs density

Table 5.3: *Properties comparison between the magnetic materials and the conventional brake unit materials*

Property	Nd2Fe14B	49Co49Fe2V	C/C-C/SiC	Cast iron [156]	SS [156]
Fracture toughness (MPa.m ^{0.5})	2.52-5.8 [157, 158]	-	3.5-11 [159, 160, 161]	14.8-22.6	36-114
Compressive strength (MPa)	600-1250 [157]	-	210-320 [162]	194-456	275-550
Tensile strength (MPa)	78.48 [163]	220-400 [164]	66 [162]	169-381	400-480
Young's modulus (GPa)	140-190 [157]	200-250 [164]	50-100 [165]	94-140	190-210
Thermal conductivity (W/m C)	5-15 [157]	28-33 [164]	5-34 [166]	43-62	20-28
Specific heat capacity (J/kg C)	252-580 [157]	481-1000 [167]	640-1550 [162, 165]	460-508	440-520
Coefficient of thermal expansion (10 ⁻⁶ /K)	4-9 / -2-0 [157]	9.4-9.7 [164]	0-8 [162]	11-13	10.8-16.5
Hardness - Vickers (HV)	500-700 [157]	180-220 [164]	140-160 [162]	113-285	400-500
Density (kg/m ³)	8400 [157]	8120 [164]	1680-1720 [162]	6940-7230	7650-7850

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

Figure 5.8 (a) together with Table 5.3 demonstrate that the Nd2Fe14B material tends to have the doubled compressive strength in comparison to C/SiC however, the ratio is reversed for the fracture toughness. The latter property is of lower importance because the PMs are unlikely to have any defects prior to a single braking cycle unlike the conventional brakes which must withstand as many as two thousand landings. 49Co49Fe2V alloy is skipped in this graph due to lack of compressive strength data. This material is normally used as a very thin sheet metal of thickness smaller than 0.35 mm and therefore, it is unpractical to measure compression strength unless for a laminated assembly. Figure 5.8 (b) shows that tensile strength of a 49Co49Fe2V could reach values of the SS410 alloy. The Nd2Fe14B tensile strength and Young's modulus are comparable to C/SiC material. Thermal properties are shown in Figure 5.8 (c) and it is demonstrated that Nd2Fe14B has the thermal conductivity five times lower than the C/SiC. This disproportion could be compensated with much lower thickness; e.g., the PMs could have the thickness of 7mm whereas the conventional brakes reach 25 mm. Finally, Figure 5.8 (d) shows that C/SiC has much lower density and any magnetic material will induce weight penalty similar to the standard steel brakes. Both sintered Nd2Fe14B PMs and 49Co49Fe2V alloys are acknowledged for their intrinsic brittleness, a characteristic similarly observed in C/C and C/SiC brake rotors. Figure 5.9 benchmarks Split Hopkinson Pressure Bar (SHPB) dynamic compression data involving the comparison of Nd2Fe14B data sourced from two unrelated publications [7, 8] against the C/C [9] and C/SiC [10] data. There is a considerable difference between values obtained by Li et al. [7] and Loeffler et al. [8]. Despite similarities in the laboratory's equipment and procedure, the sintered Nd2Fe14B samples were procured from different suppliers and this is the most likely reason for the discrepancy. The latter authors averaged the values of 1200 MPa for all the iterations with strain rates varying from quasi-static up to 200 s^{-1} .

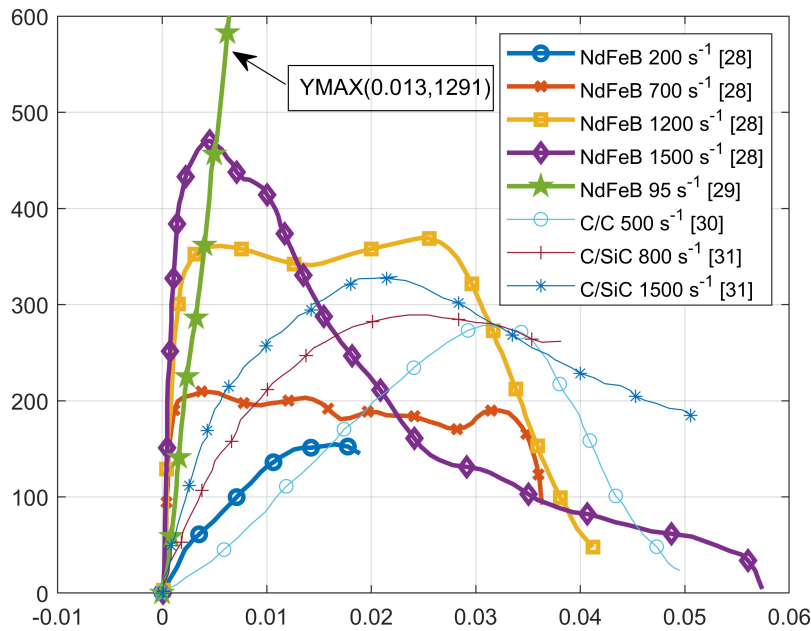


Figure 5.9: Dynamic compression testing of Nd₂Fe₁₄B [[7, 8], C/C [9] and C/SiC [10] materials at varying strain rates

The proposed brake unit will reach temperatures exceeding 600 degrees Celsius and accordingly, the material characteristics at elevated temperatures are needed. Morishita et al. [11] assessed heat capacity of Nd₂Fe₁₄B alloy up to 630 degree Celsius and the values are presented in Figure 5.10 (a). The heat capacity spike typical for Curie point is visible at around three hundred degree Celsius and beyond, the value remains greater than 550 J/kg/k. [168] reviewed the Hardness Vickers parameter up to 750 degrees Celsius and they observed reaching half of its initial value at 450C and dropping to just 10% at 650C. At approximately 600C, melting of a Nd-rich grain-boundary phase was observed. This behavior aligns with documented compression-induced crystallographic alignment of Nd₂Fe₁₄B magnets near 700 C.

Song and Sanborn [148] conducted tensile testing at 100 degree Celsius for a 49Vo49Fe2V alloy with the commercial name Hiperco 50A which is similar to Vacoflux 48. They discovered that the specimen yield strength decreased slightly at the maximum temperature and there was no necking observed. Ren et al. [12] char-

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

acterized the same material up to 800 degrees Celsius and Figure 5.10 (b) shows the yield strength and Young's modulus derived from Figure 5.10 (c) and Figure 5.10 (d).

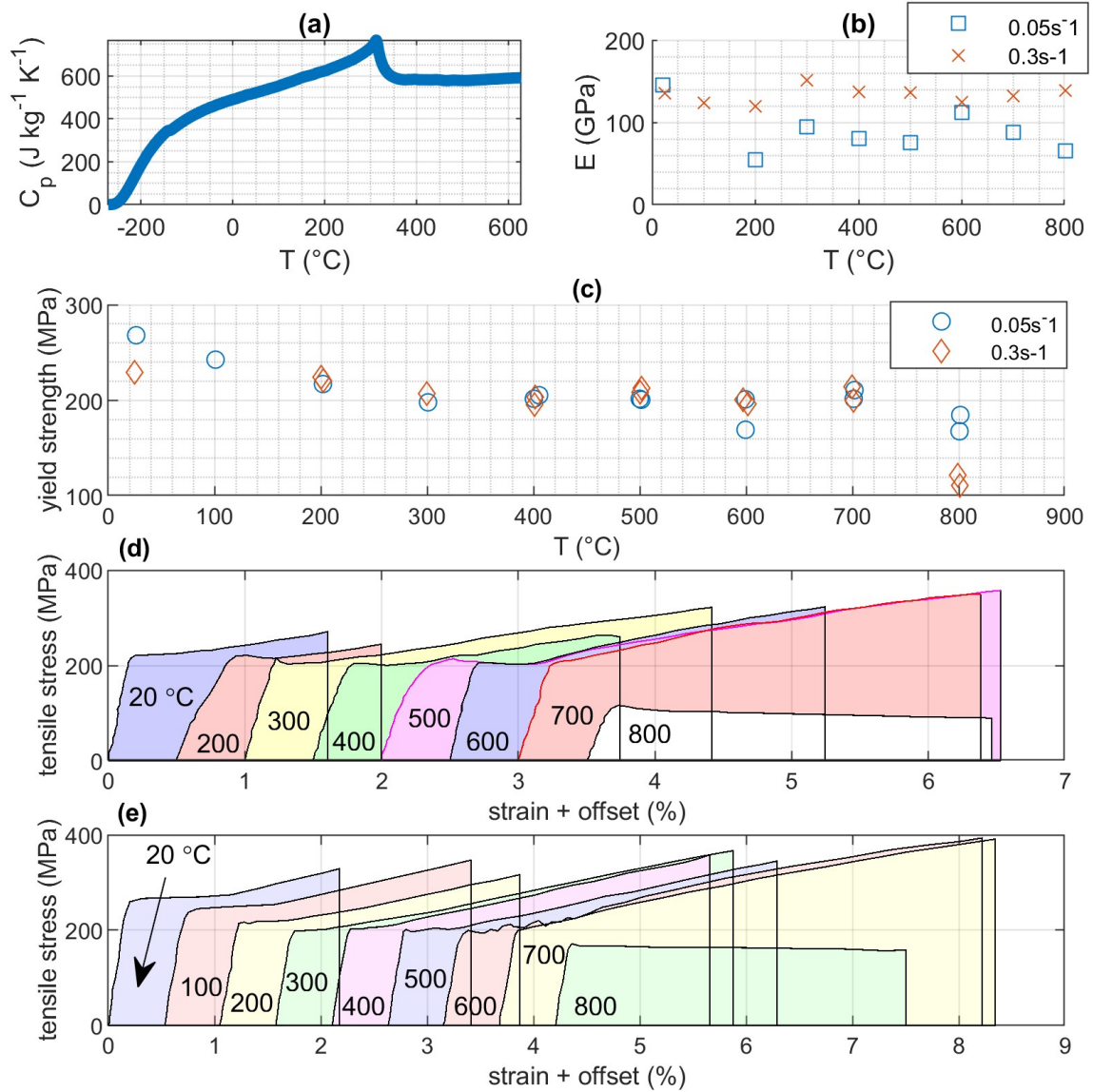


Figure 5.10: $\text{Nd}_2\text{Fe}_{14}\text{B}$ and $49\text{Co}49\text{Fe}2\text{V}$ characteristics at elevated temperatures: (a) specific heat capacity of $\text{Nd}_2\text{Fe}_{14}\text{B}$ [11], (b) $49\text{Co}49\text{Fe}2\text{V}$'s Young's modulus [12], (c) $49\text{Co}49\text{Fe}2\text{V}$ yield strength [12] (c) tensile testing at 0.83 %/min strain rate of $49\text{Co}49\text{Fe}2\text{V}$ [12] and (d) tensile testing at 5%/min strain rate of $49\text{Co}49\text{Fe}2\text{V}$ [12]

Both, Song and Sanborn [148] and Ren et al. [12] observed that the 49Co49Fe2V material displays viscoelastic behaviour at elevated temperatures and this property tends to magnify respectively to the strain rate. The material retains its mechanical strength up to 700 degrees Celsius and above this value, the rapid decrease in yield strength is observed at 800 degrees Celsius.

5.7 Preliminary Calculus for Mechanical And Thermal Loads

As introduced in Section 5.5, the proposed design will act in emergency mode as a typical friction brake unit of aircraft. Therefore, the loads can be calculated in the same manner and this section follows Schmidt's [137] procedure. It is assumed that the RTO is executed at Maximum Take-Off Weight (MTOW) of 77,000 kg and speed of 72 m/s. There are four wheels with brake units fitted and design point assumes 3.5 m/s^2 constant deceleration exerted solely by brake units. The kinetic friction coefficient μ_k is conservatively set to 0.3 whilst noting that carbon-carbon brakes could exceed 0.5. The wheel radius correspond to conventional 46x17R20 tyres and equals 0.508.

The calculus starts with estimating how much force applied by the hydraulic system in case of an RTO and equals $T_w = \frac{m_{ac} a_{dp}}{4} r_w = 34.227 \text{ kNm}$. This value is then compared against the friction coefficient between tyre and ground which is 0.45 for a dry pavement [137]. In this case, the coefficient of friction required equals $\mu_{tr} = \frac{\frac{T_w}{r_w}}{m_{ac} * 0.95 / 4 * g} = 0.3757$ which is within the threshold.

The torque estimates enable calculating the pressure required from the hydraulic system. The contact area and effective radius are sourced from the CAD model which was previously used for the electromagnetic optimization and are equal to $96,341 \text{ mm}^2$ and 189.02 mm respectively. Depending on the combination traced from Figure 5.7, there are either six or twelve friction gaps denoted as n_g . Hydraulic force required can be obtained $F_h = \frac{T}{r_{eff} \mu_k} \frac{1}{n_g}$ and equals 105 kN for six and 52.44 kN

for twelve friction gaps.

Unlike the thoroughly evaluated brake discs and pads, this design consists of multiple differently shaped components with complex stress distribution. Accordingly, the pressure was calculated at points where the highest loads are expected. Under assumption that force is equally distributed the evaluation of the narrowest (Fig. 5.11), 1268 mm^2 , cross-section of the design which is the mid-part of stator core. This leads to the pressure equal 1.4 MPa and 0.602 MPa respectively. This value is negligible when considering both Nd2Fe14B and 49Co49Fe2V materials properties.

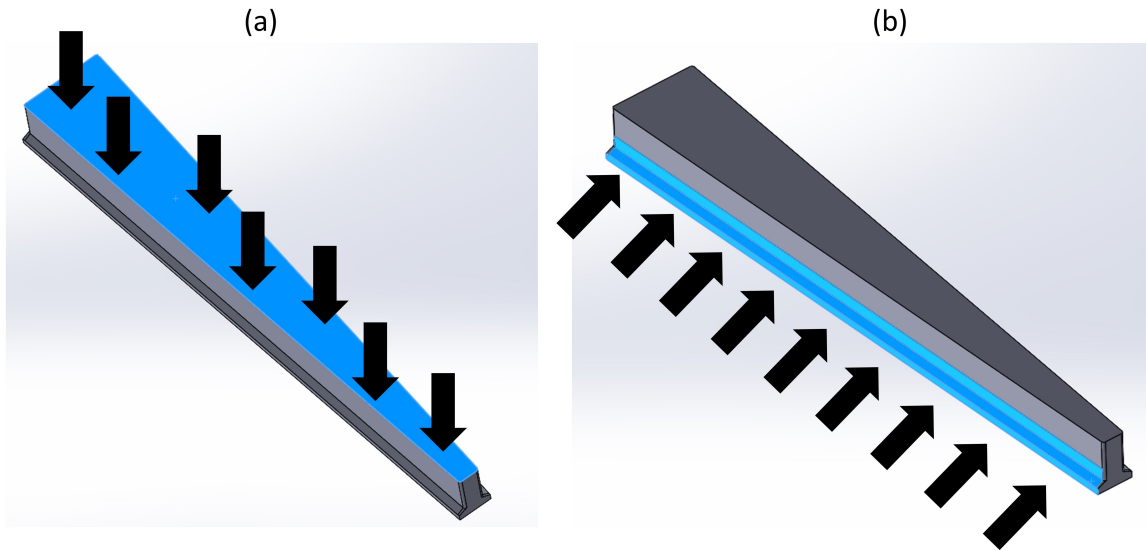


Figure 5.11: Loads applied to the stator's core during friction braking: (a) compressive load exerted by hydraulic cylinders and (b) compressive load at the contact with housing.

Another load is applied perpendicularly to the previous as shown in Figure 5.11 (b). The blue colour indicates where the housing comes into contact with a core. The effective area equals 520 mm^2 and resultant pressures are 1.02 and 0.442 MPa depending on the design configuration.

Heatsink capacity is one of the most important parameters when discussing feasibility of the concept. The kinetic energy that has to be dissipated in each wheel is derived from $E_k = 1/2 m V^2$ and equals 13.86 kWh for an A320 at Maximum Take-Off Weight (MTOW) (ref) at 72 m/s. Table 5.4 shows the weight and specific heat

5.7. PRELIMINARY CALCULUS FOR MECHANICAL AND THERMAL LOADS

capacity of heatsink materials.

Table 5.4: *Heatsink material available per single friction gap*

Component	Average specific heat capacity $C_p \left[\frac{J}{kg \cdot K} \right]$	Material	Number per stack	Weight (g)
Stator core	420	49Co49Fe2V	60	6443.95
PM	400	Nd2Fe14B	58	7665.59
Coil	385	Cu	60	4045.94

These parameters are used in estimating the temperature increase under assumption of uniform heat distribution:

$$\begin{cases} \Delta T = \frac{KE}{n_{fg}} \times \frac{1}{\Sigma C} \\ \Sigma C = C_{sc} + C_{pm} + C_c \\ C_i = m_i n_{qi} C_{pi} \end{cases} \quad (5.5)$$

The temperature gradient depends on whether four or two brake units are substituted and equals 1134 and 557 degrees Celsius respectively. The latter value is compared against the designed lumped-parameter thermal network presented in Figure 5.12 (a). The MATLAB/Simulink model for the lumped-parameter thermal network can be found in Appendix J. The author assumes that each of twelve friction gaps in the unit is subjected to 404 kW of heat flux and that the 0.4 G resultant deceleration leads to a full stop after 18.34 seconds. To simplify the thermal network, only the single PM that has an angle of 4.34 degrees and the single core was taken. Under assumption of even heat flux distribution between all components, the single PM take 4.34/360 of heat passed to a rotor and the core absorbs 1/60 of stator's heat because there are sixty segments. This model consists of twenty seven nodes where seven are designated for the PM, ten for the core, three replicate housing and the remaining seven are for the coil. They are placed at one mm axial increment and in the

radial center of each cross-section. The model's heat resistances take into account the surface roughness at each component connection and the 0.0275 mm layer of enamel surrounding the coil's copper. The heat distribution between stator and rotor can be manipulated by changing thermal conductivity of the thin, 0.1 mm, friction lining layer on top of the PMs. The simulations were performed for the conductivity values from 0.1 to 2 W/m/k. Figure 5.12 (b) shows that the temperature gradient between the first two nodes does not exceed seventy degrees Celsius and can be reduced to approximately 25 degrees Celsius. This indicates that the component will be subjected to a maximum of 0.00049 tensile elongation which is acceptable. Figure 5.12 (c) indicates that the peak temperature of the first PM's node remains below 600 degrees Celsius meaning that none of the neodymium-rich grains will transition to liquid. Similar analysis was conducted for the core as demonstrated in Figure 5.12 (d) and (e). The resultant temperature gradients and the maximum temperature of first node indicate that the 49Fe49Co2V material have satisfactory properties for this application.

Fatigue life remains of low importance and should be focused only on the low-cycle stress failure. Knowing that the friction braking is destructive for the electric machine and the brake unit will be overhauled after each friction braking, there is a demand only for a single thermal cycle and therefore, a thermal fatigue cracks and creep phenomenon are not envisaged.

5.8 Experimental Nd₂Fe₁₄B and 49Co49Fe₂V material characterization

Additional characterization of 49Co49Fe₂V and Nd₂Fe₁₄B materials is necessary when assessing feasibility of the concept. Despite low structural loads, friction braking application induces high heat flux. The preliminary calculus indicates thermal suitability however, it is heavily simplified and a detailed numerical analysis is required taking into account materials' nonlinearities. The materials used in electric

5.8. EXPERIMENTAL ND2FE14B AND 49CO49FE2V MATERIAL CHARACTERIZATION

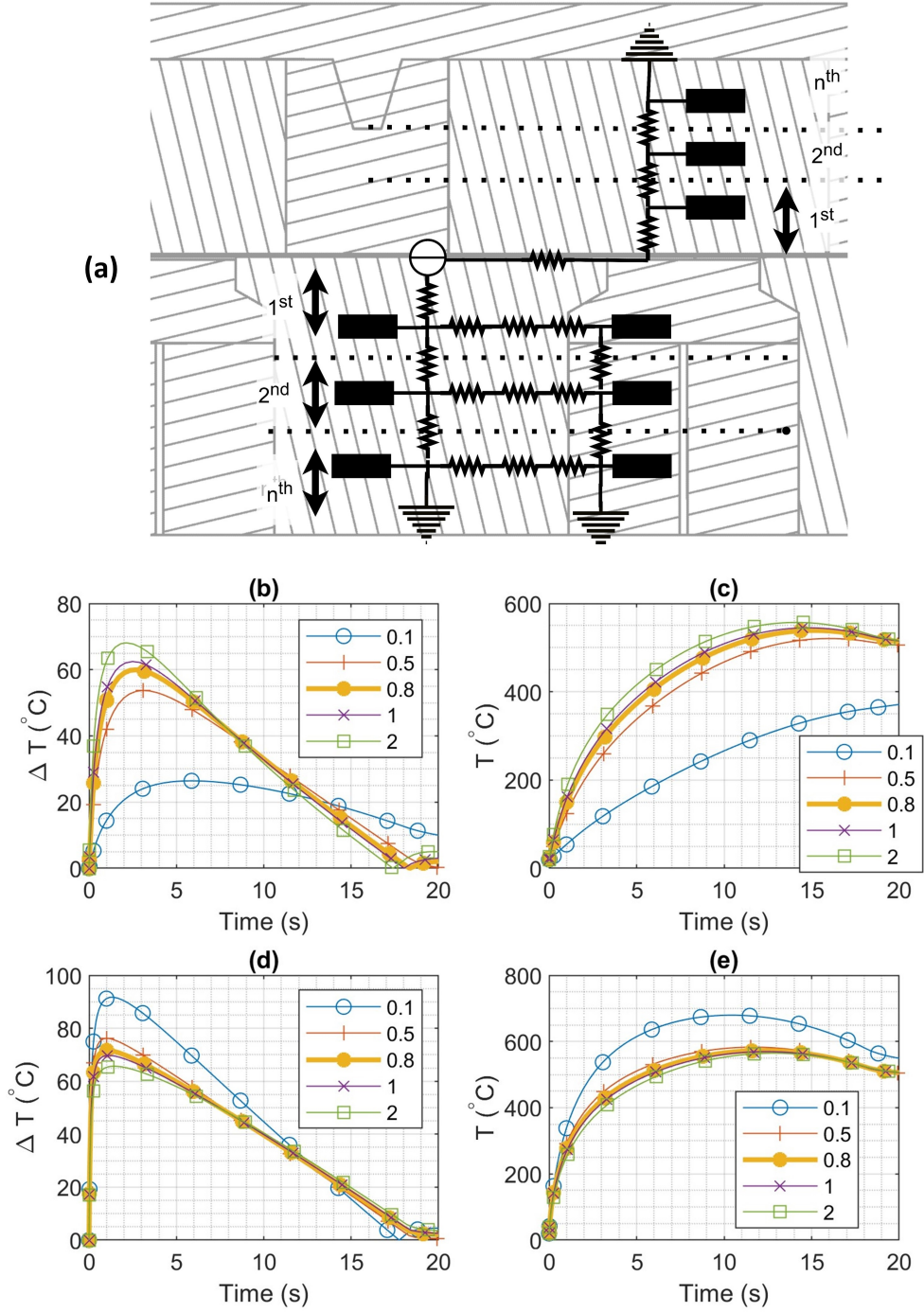


Figure 5.12: lumped-parameter thermal network for the single stator and the single PM: (a) sketch of the network, (b) temperature gradient between the first two nodes in the PM, (c) temperature of the first node in the PM during landing, (d) temperature gradient between the first two nodes in the core and (e) temperature of the first core's node during landing.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

machines are thoroughly characterised regarding magnetic and mechanical properties up to the Curie point of PMs at which they lose magnetic properties. The proposed concept however requires temperatures reaching as much as 1100 degree Celsius depending on the setup (Fig. 5.7). Accordingly, the key parameters have to be known: (a) Compressive strength, (b) modulus of elasticity, (c) Poisson's ratio, (d) thermal conductivity, (e) specific heat capacity and (f) coefficient of thermal expansion. These characteristics are crucial for accurate mechanical and thermal study of the concept.

Table 5.5: *Unknown properties and the corresponding characterization process*

Material/ Property at varying temperatures	Nd2Fe14B	49Co49Fe2V	Characterization process and lab instrument	Sample shape
Thermal conductivity	No	No	Laser flash analyzer	dia. 12.7 mm
Specific heat capacity	No	No	Differential scanning calorimetry / simultaneous thermal analyzer	dia. 5 mm
Coefficient of thermal expansion	No	No	Thermomechanical analyzer	9x2 mm
Compressive strength	No	No	Universal testing machine w/ environmental chamber	dia. 12.7 x 38.1/ Appendix H.1
Young's modulus	No	No	Universal testing machine w/ environmental chamber	dia. 12.7 x 38.1/ Appendix H.1
Poisson's ratio	No	No	Universal testing machine w/ environmental chamber	dia. 12.7 x 38.1/ Appendix H.1

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

Whilst literature provides partial characteristics of the materials, broader study is needed to demonstrate feasibility. Lack of available data was also confirmed by the sales department of magnetic materials supplier, Vacuumschmelze. This company is willing to provide the samples through the smaller company, the Swiss LCD Lasercut AG and stands out with the consistent quality of components. The trace of 49Fe49Co2V samples order can be found in Appendix H.1. In the past, they supplied magnetic materials for the Safran-Honeywell's e-taxiing project.

The characterization process was divided to structural and thermal analyses due to the resources availability. Cranfield University hosts the THERMMAT lab which has the appropriate equipment: (a) Differential Scanning Calorimetry (DSC) for thermal diffusivity, (b) Laser Flash Analyser (LFA) for thermal conductivity and (c) Simultaneous Thermal Analyser (SDT) for specific heat capacity measurements at elevated temperatures. Mechanical testing requires an Universal Testing Machine (UTM) with an environmental chamber and measurement optometry which can be found in: (a) Bristol University, (b) Strathclyde University, (c) Warsaw University of Technology and (d) Swansea Smart Lab. Table 5.5 demonstrates the characteristics of interest, corresponding literature availability and the experimental process required to characterize the materials.

5.8.1 Thermal Characterization via Laser Flash Analysis, Differential Scanning Calorimetry and Thermomechanical Analyzer

Thermal conductivity measurements of NdFeB and FeCoV alloys were conducted using the Laser Flash Analysis (LFA) method on DLF 1200 equipment as depicted in Figure 5.13(a), adhering to ASTM E1461 standard procedures. This technique involves measuring the thermal diffusivity of a material by applying a high-intensity short-duration laser pulse to one face of a thin disc-shaped sample and monitoring the resulting temperature rise on the opposite face. The thermal conductivity

5.8. EXPERIMENTAL ND₂FE₁₄B AND 49CO₄₉FE₂V MATERIAL CHARACTERIZATION

is subsequently calculated from the measured thermal diffusivity, specific heat capacity, and density of the sample material. This approach provides crucial data for understanding the heat transfer capabilities of these magnetic materials, which is essential for designing efficient thermal management strategies in applications where temperature control is critical. Prior to measurements, the samples require meticulous preparation to ensure accurate results, with thin discs featuring parallel faces being created with dimensions appropriate for the sample holders of the laser flash apparatus.

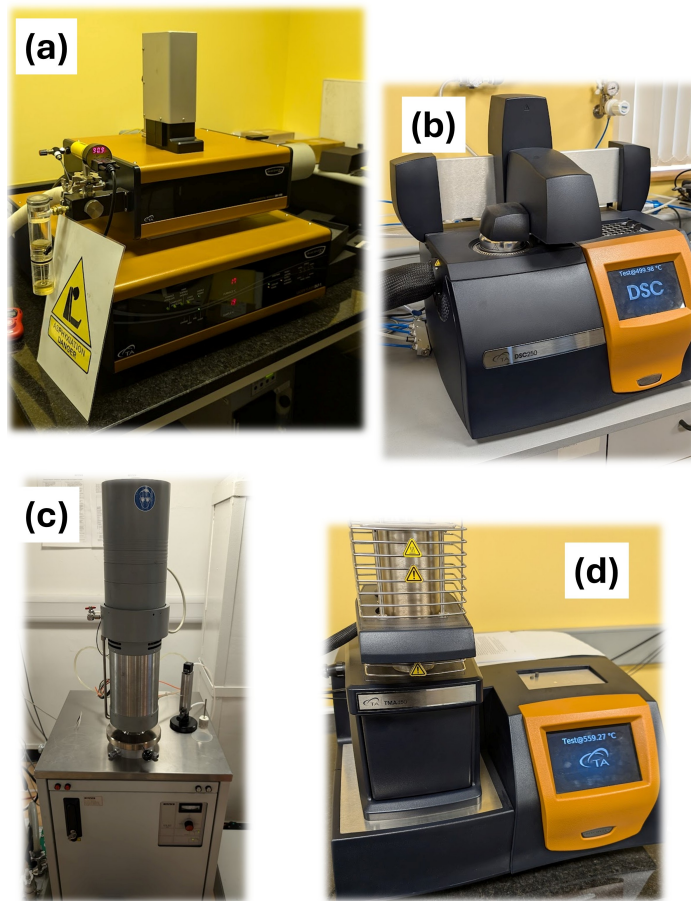


Figure 5.13: Laboratory instruments used for thermal characterization of NdFeB and FeCoV: (a) TA Instruments; DLF 1200; THERMMAT (b) TA Instruments; DSC 2500; THERMMAT, (c) Netzsch; LFA 427; AMRL and (d) TA Instruments; TMA 450; THERMMAT

Sample preparation for LFA testing involved creating appropriate disc specimens

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

as shown in Figure 5.14(b), where a specialized sample tray designed to accommodate three specimens simultaneously allowed for efficient testing procedures. For the NdFeB samples, the measurement process proceeded without significant complications since the specimens possessed sufficient thickness to prevent laser penetration, which is essential for accurate thermal diffusivity determination. These samples were coated with a thin layer of graphite spray on both faces to enhance laser energy absorption on the front surface and improve infrared emission on the rear surface for temperature detection. The thermal diffusivity was measured over a temperature range relevant to the application conditions of the magnetic material, with multiple measurements taken at each temperature point to ensure reproducibility of results. The attention to sample preparation details, including surface treatment and thickness considerations, is fundamental to obtaining reliable thermal diffusivity measurements through the LFA technique.

The measurement of FeCoV samples presented considerable challenges due to their limited thickness of 0.254 mm, which allowed partial penetration of the laser flash through the material. This penetration violates a fundamental assumption of the laser flash method, which requires all energy to be absorbed at the front surface of the sample. Initial attempts to measure these thin FeCoV sheets using the TA Instruments DLF1200 apparatus at THERMMAT facility yielded inaccurate results as the equipment could not sufficiently reduce the laser flash intensity to prevent penetration through the sample. To overcome this limitation, multiple FeCoV sheets were stacked together as illustrated in Figure 5.14(e) to increase the effective thickness. However, this approach initially failed to produce reliable measurements, likely due to thermal contact resistance between the stacked sheets, resulting in thermal conductivity values that deviated significantly from reference data. The measurement challenges were ultimately resolved by employing the Netzsch LFA 427 system available at Advance Material Research Laboratory (AMRL) facility, shown in Figure 5.13(c). This more advanced instrument offered greater flexibility in controlling the laser power settings, allowing for the reduction of laser intensity to a level that pre-

5.8. EXPERIMENTAL ND₂FE₁₄B AND 49CO₄₉FE₂V MATERIAL CHARACTERIZATION

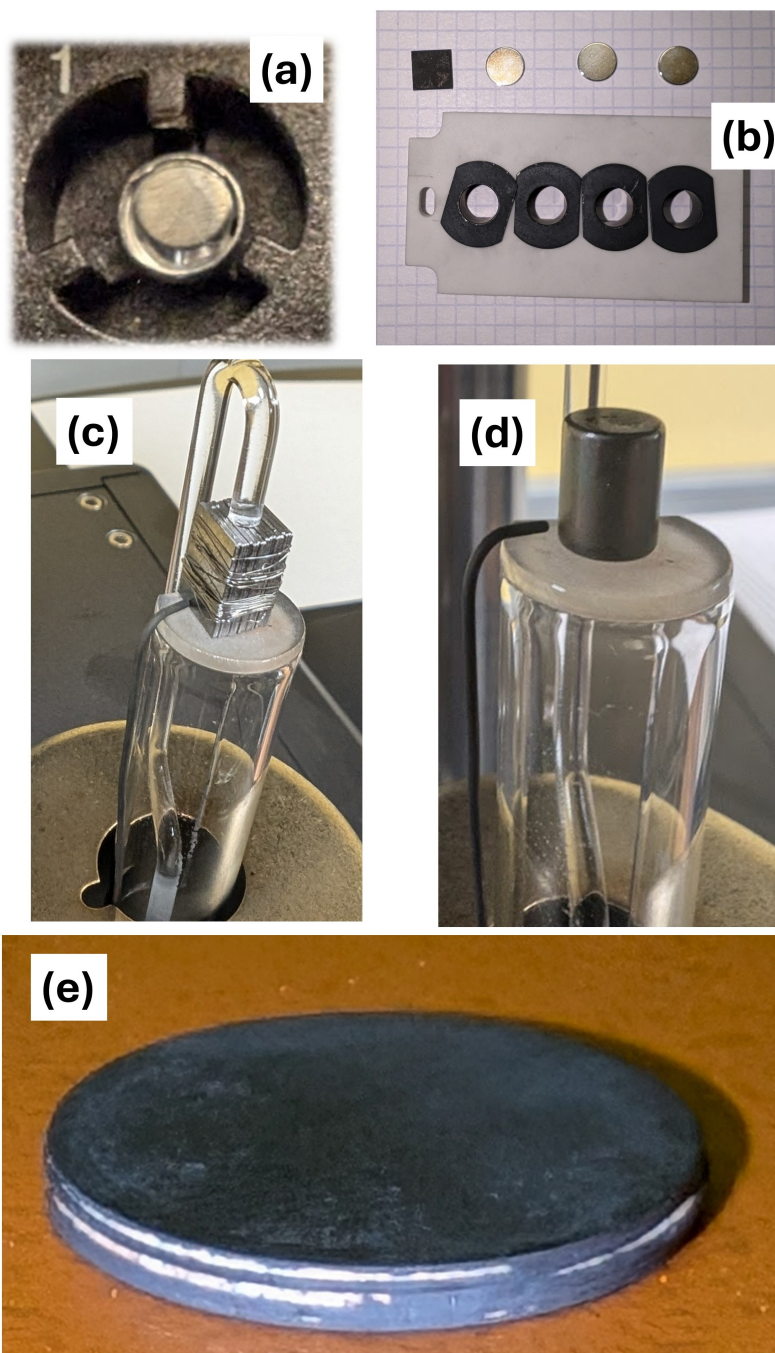


Figure 5.14: Samples used in thermal characterization: (a) the DSC pan filled with NdFeB sample, (b) LFA samples and the tray allowing to test three samples at once (c) the TMA sample made of stacked FeCoV sheets, (d) the TMA sample of NdFeB materials and (e) the stack FeCoV sheets for the LFA

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

vented penetration through the thin FeCoV samples while still providing sufficient energy for accurate thermal diffusivity measurement.

The LFA results for both materials are presented in Figure 5.15, which displays thermal conductivity as a function of temperature for FeCoV samples in Figure 5.15(a) and NdFeB samples in Figure 5.15(b). These results demonstrate the successful application of the adapted LFA methodology to measure thermal conductivity in both standard-thickness NdFeB and thin FeCoV samples. The thermal conductivity profiles reveal how these materials respond to temperature variations, providing essential information for predicting thermal behavior in applications where these magnetic materials are subjected to varying thermal conditions. The data obtained through the refined LFA approach serves as a reliable foundation for thermal modeling and simulation of devices incorporating these magnetic materials.

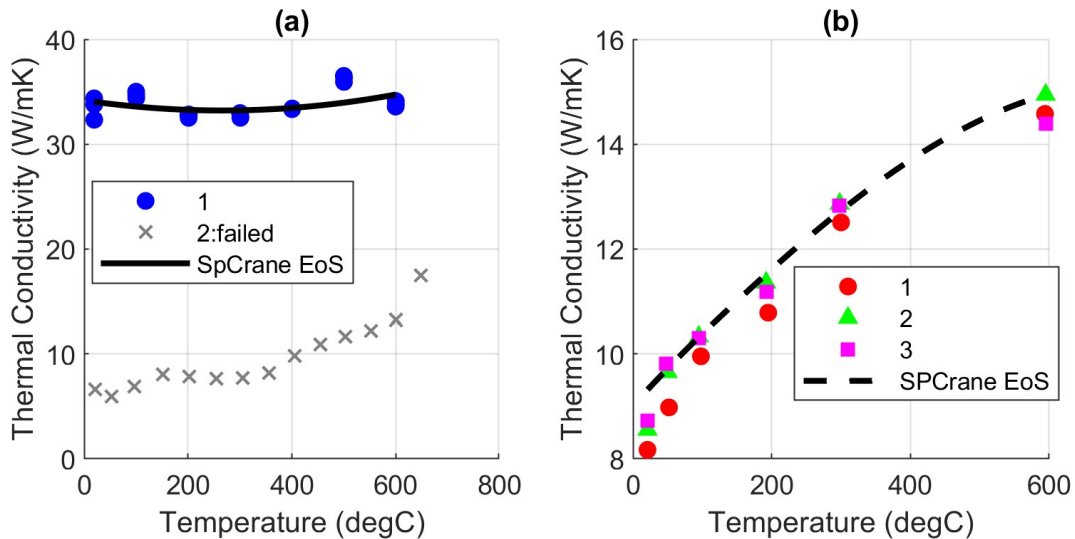


Figure 5.15: The LFA results displaying thermal conductivity for: (a) FeCoV samples and (b) NdFeB samples.

The specific heat capacity is a thermodynamic property critical for understanding thermal behavior of magnetic materials like NdFeB and FeCoV. Differential Scanning Calorimetry (DSC) was utilized to precisely measure the specific heat capacity of these materials according to the ASTM E1269-11 standard, which provides a systematic approach for determining accurate and reproducible results. The DSC mea-

5.8. EXPERIMENTAL ND₂FE₁₄B AND 49CO₄₉FE₂V MATERIAL CHARACTERIZATION

surements were performed using the TA Instruments DSC 2500 equipment located at the THERMMAT facility, as depicted in Figure 5.13(b). This property quantifies the amount of heat energy required to raise the temperature of a unit mass of material by one degree, serving as an essential parameter for heat transfer calculations and thermal management strategies in applications utilizing these magnetic materials. The precise determination of specific heat capacity complements the thermal diffusivity measurements from LFA, enabling a comprehensive thermal characterization of the materials under investigation.

The determination of specific heat capacity by DSC relies on the measurement of differential heat flow to a sample and reference material as they are subjected to controlled temperature programs. The ASTM E1269 standard methodology employs a three-step measurement process consisting of a baseline run with empty crucibles, a calibration measurement using a synthetic sapphire (α -aluminum oxide) reference material, and finally the sample measurement. This sequence is critical as accurate specific heat capacity results are only achieved when all three runs are carried out under identical experimental conditions. Sample preparation followed a meticulous protocol to ensure measurement accuracy. Aluminum pans were carefully selected and weighed to minimize mass differences between sample and reference holders, as even small imbalances can introduce systematic errors. For the FeCoV samples, a specimen weighing 40.72 mg was placed in a pan with a combined pan-lid mass of 28.40 mg. Similarly, the NdFeB samples were prepared with weights ranging from 143.74 to 145.42 mg in pans with lid weights between 28.38 and 28.46 mg. The reference pan was prepared identically but left empty (28.30 mg pan-lid weight). Synthetic sapphire, used as the calibration standard, was similarly encapsulated. All pans were hermetically sealed to prevent mass loss during heating and to ensure good thermal contact between the sample and pan, as shown in Figure 5.14(a).

The experimental procedure for DSC measurements began with purging the DSC cell with high-purity nitrogen at a flow rate of 50 mL/min to create an inert atmosphere and improve heat transfer. Following the ASTM E1269 standard protocol,

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

three successive runs were performed in the sequence: baseline (empty pans), sapphire standard, and sample (either FeCoV or NdFeB). Each measurement was conducted using identical temperature profiles, heating rates, and gas flow conditions. The samples were equilibrated at the lower temperature limit, held isothermally for several minutes to establish thermal equilibrium, and then heated at a constant rate of 20C/min to the upper temperature limit. This heating rate was selected as a compromise between the need for thermal equilibrium within the samples and reasonable experimental durations. Data processing was performed using the TA Instruments software, which applies the mathematical formulation specified in ASTM E1269-11 to calculate the specific heat capacity. This calculation involves determining the vertical displacement between the sample and empty pan curves, normalized by the heating rate and sample mass, and then correcting this value using the sapphire standard data. The specific heat capacity (C_p) was computed using the equation: $C_{p\text{sample}} = \left(\frac{W_{\text{sample}}}{W_{\text{sapphire}}} \right) \times \left(\frac{\Delta H_{\text{sample}}}{\Delta H_{\text{sapphire}}} \right) \times C_{p\text{sapphire}}$, where W represents the weight and H represents the differential heat flow.

The DSC results for the specific heat capacity measurements are presented in Figure 5.16, with Figure 5.16(a) showing the specific heat capacity as a function of temperature for FeCoV samples and Figure 5.16(b) displaying the corresponding data for NdFeB samples. These results provide quantitative insights into the thermal energy storage capabilities of these magnetic materials across a range of temperatures. The specific heat capacity data reveals how the materials' ability to absorb and store thermal energy changes with temperature, which is crucial information for thermal design considerations in applications where these materials operate under varying thermal conditions. When combined with the thermal conductivity data from LFA measurements, the specific heat capacity results enable a more complete understanding of the thermal response characteristics of these magnetic materials.

5.8. EXPERIMENTAL ND₂FE₁₄B AND 49CO₄₉FE₂V MATERIAL CHARACTERIZATION

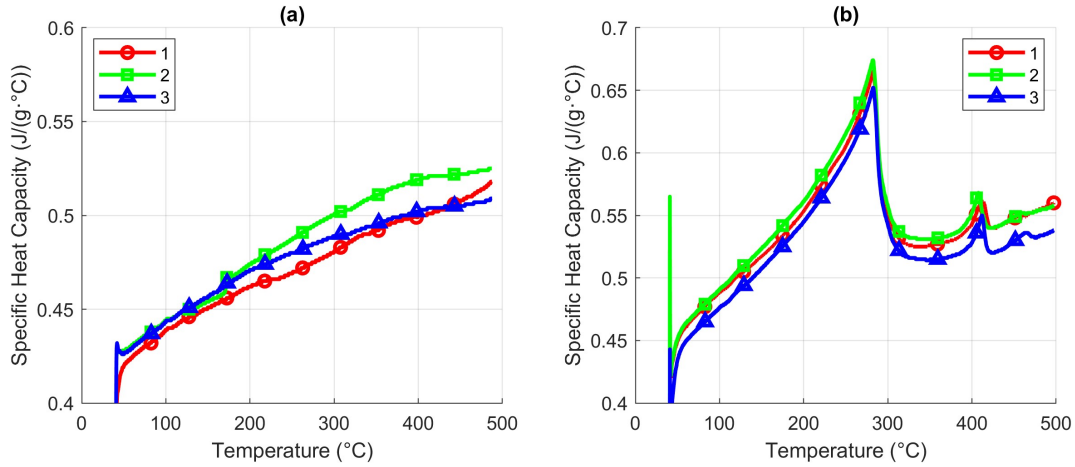


Figure 5.16: The DSC results displaying specific heat capacity for: (a) FeCoV samples and (b) NdFeB samples

Thermomechanical characterization of NdFeB and FeCoV alloys was performed using a TA Instruments TMA 450 system at the THERMMAT facility, as depicted in Figure 5.13(d). This technique quantifies the coefficient of thermal expansion (CTE) by measuring dimensional changes in response to controlled temperature profiles, adhering to ASTM E831 and E228 standards. The CTE is a critical parameter for mechanical design considerations, as it influences dimensional stability, thermal stress development, and potential failures in components subjected to temperature variations. In applications where NdFeB and FeCoV alloys are integrated with other materials, understanding their thermal expansion behavior is essential for predicting and mitigating thermal stresses at material interfaces. The TMA measurements complement the thermal transport and storage properties determined through LFA and DSC, providing a comprehensive thermal characterization package for these magnetic materials.

The FeCoV material, available only in 0.254 mm sheets, required a novel sample preparation approach for TMA testing. Multiple laminations were stacked and mechanically secured using AISI 316L stainless steel wire of 0.1 mm diameter, as illustrated in Figure 5.14(c). This method minimized interfacial gaps and ensured uniform thermal strain distribution across the composite structure. The NdFeB samples,

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

shown in Figure 5.14(d), were machined to 92 mm dimensions to fit the TMA quartz sample holder. The sample preparation techniques developed for both materials addressed the challenges associated with their form factors and enabled reliable CTE measurements despite the limitations of the available material geometries. The experimental procedure involved placing the prepared samples in the TMA apparatus, ensuring proper alignment within the measurement cell, and subjecting them to controlled temperature ramps while monitoring dimensional changes with high-precision displacement sensors. Calibration with reference materials of known thermal expansion behavior was performed to ensure accuracy of the measurements.

The TMA results displaying coefficient of thermal expansion as a function of temperature are presented in Figure 5.17, with Figure 5.17(a) showing results for FeCoV samples and Figure 5.17(b) presenting data for NdFeB samples.

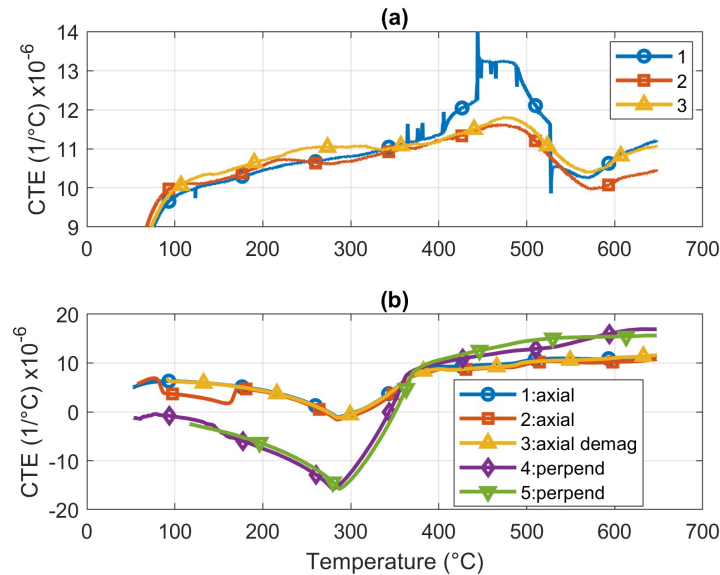


Figure 5.17: The TMA results displaying coefficient of thermal expansion as a function of temperature for: (a) FeCoV samples and (b) NdFeB samples.

These results reveal the temperature-dependent expansion characteristics of both magnetic materials, providing designers with essential information for predicting dimensional changes and potential thermal stresses in applications incorporating these materials. The CTE profiles indicate how the materials respond dimensionally to tem-

perature fluctuations, with implications for applications requiring precise dimensional stability or where these materials interface with components having different expansion coefficients. The comprehensive thermal characterization achieved through the combined application of LFA, DSC, and TMA techniques provides a robust foundation for thermal modeling and design optimization in systems utilizing NdFeB and FeCoV magnetic materials. The methodological approaches developed to address the specific challenges of sample preparation and measurement, particularly for thin FeCoV sheets, contribute valuable procedural knowledge to the field of thermal characterization of magnetic materials with non-standard geometries. Future work could explore the anisotropic thermal properties of these materials, as well as the effects of processing variations on their thermal behavior, further enhancing the understanding of their thermal performance in practical applications.

5.8.2 Mechanical Characterization via Servohydraulic Testing

The mechanical characterization of magnetic core materials presents unique challenges due to their distinctive physical properties and geometric constraints. In this study, comprehensive testing protocols were developed to accurately assess the mechanical behavior of NdFeB and FeCoV alloys under various temperature conditions. The sample geometry for mechanical testing was carefully considered based on material characteristics and testing requirements. For FeCoV samples, which measured only 0.35 mm in thickness, specialized fixtures were necessary to prevent buckling during compression testing. Standardized specimens measuring 15.3 x 63.5 mm were prepared according to ASTM standards for reliable data acquisition and comparison with established material databases.

Mechanical testing was conducted using Instron 5959 (50 kN capacity) and Instron 8801 (100 kN capacity) servohydraulic testing frames, both equipped with environmental chambers to facilitate temperature-controlled experiments (Appendix F, as shown in Figure 5.18). These systems provided precise load control and displacement measurement capabilities essential for characterizing the high-stiffness mag-

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

netic materials. The environmental chambers enabled testing across a temperature range representative of operational conditions for aerospace magnetic components, with particular focus on room temperature and elevated temperature (200 C) performance characteristics (Appendix G).

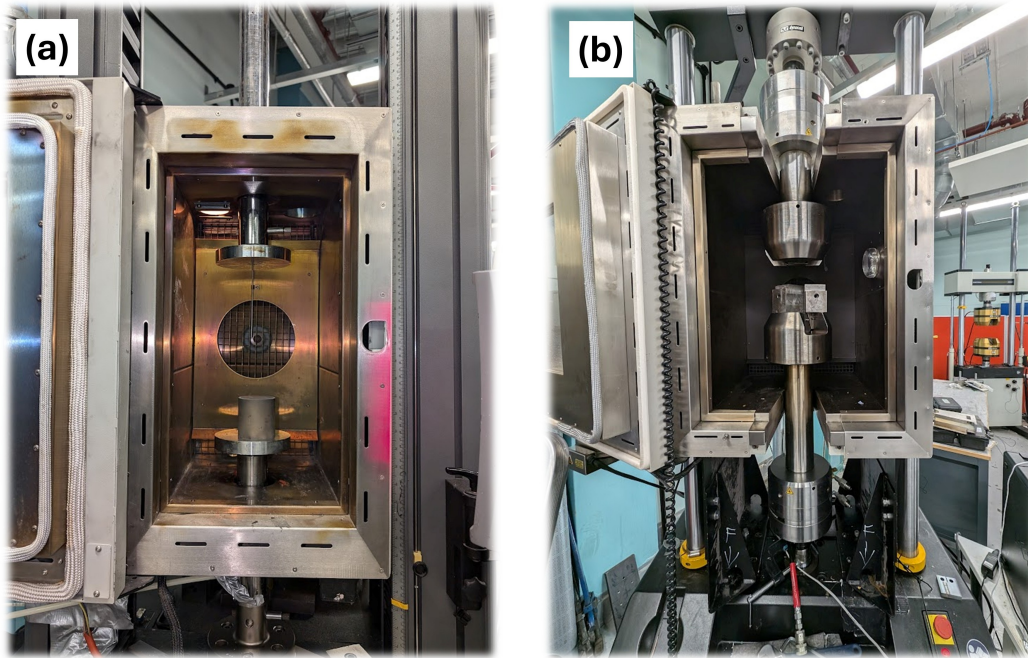


Figure 5.18: Servohydraulic machinery used during the mechanical characterization with environmental chambers fitted: (a) Instron 5959 50 kN and (b) Instron 8801 100 kN

A custom compression testing jig was designed and manufactured to address the unique challenges presented by the thin FeCoV specimens. The jig design, illustrated in Figure 5.19, incorporated spherical-seated platens and lateral support mechanisms to prevent premature buckling during compression loading. This design featured multiple steel balls positioned at 1.81 mm intervals between centers, effectively supporting the thin samples while allowing for controlled deformation up to approximately 4% elongation. The samples extended 0.7 mm beyond the supporting structure, permitting a strain of 1.1% during testing while maintaining alignment and preventing edge effects that could compromise measurement accuracy.

The jig assembly consisted of five precision-machined components that worked

5.8. EXPERIMENTAL ND2FE14B AND 49CO49FE2V MATERIAL CHARACTERIZATION

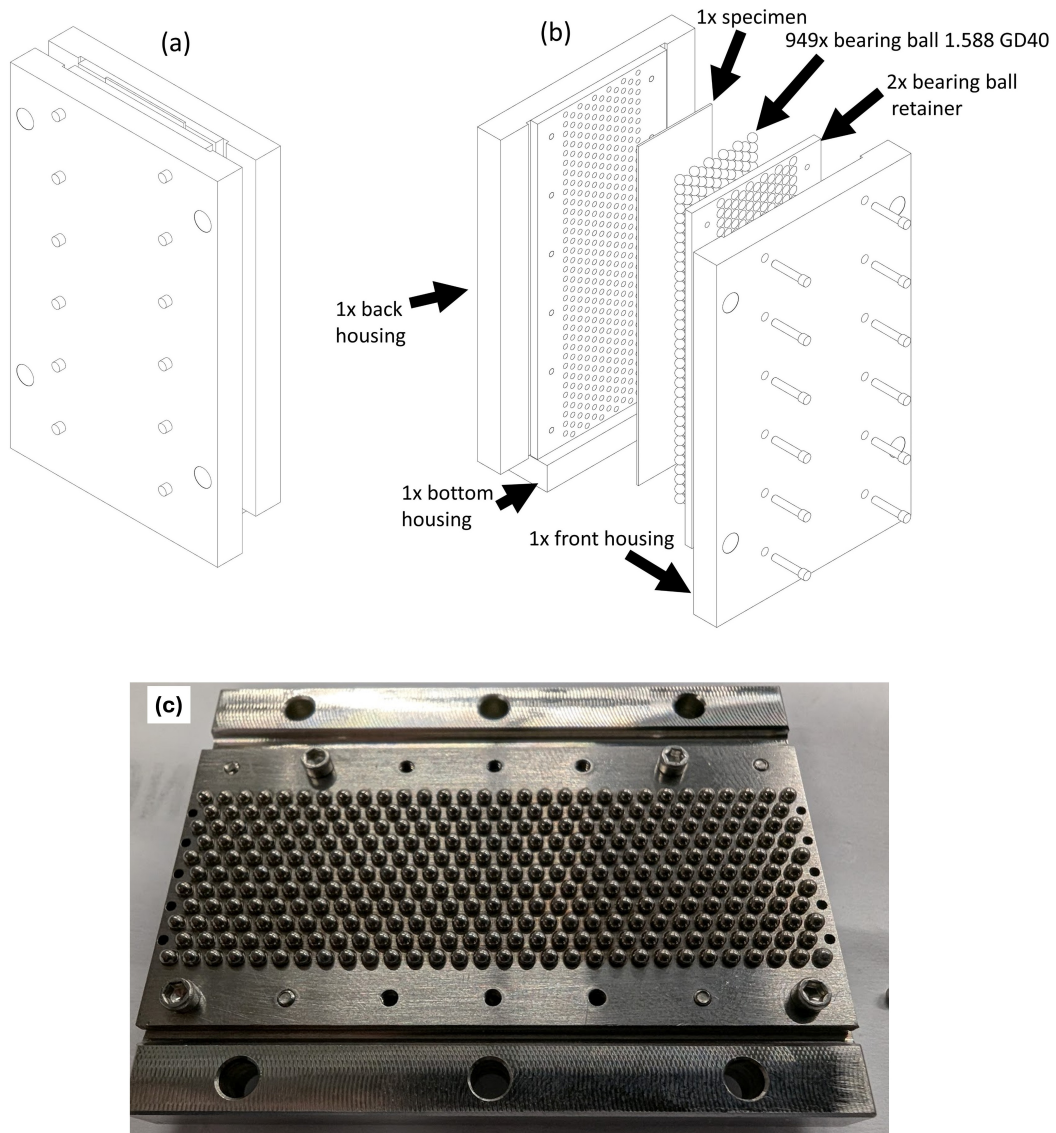


Figure 5.19: Design of the jigs enabling compressive testing of the materials according to ASTM E209-18: (a) ISO view of the assembly, (b) exploded and annotated view of the assembly and (c) the picture of manufactured and assembled parts.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

in concert to provide consistent boundary conditions during compression testing. As shown in Figure 5.19, the exploded view reveals the thoughtful integration of components designed to maintain sample alignment throughout the loading process. Additional information about the jigs can be found in Appendix I. This approach aligns with methodologies proposed by Papirno (1962) for testing thin sheet materials under compressive loading. The manufactured jigs were fabricated from high-strength tool steel to minimize compliance effects during testing and ensure dimensional stability across multiple test cycles.

Strain measurement posed a significant challenge, particularly for the brittle Nd-FeB specimens. A non-contact video extensometry system was implemented for strain monitoring, as depicted in Figure 5.20. The system utilized high-contrast speckle patterns applied to the specimen surfaces, allowing optical tracking of deformation patterns without influencing the mechanical response of the test specimens. For the FeCoV samples, this approach proved effective in capturing strain values up to 4% with high precision. Figure 5.20 illustrates the complete measurement setup, including the relative positioning of the video extensometer, environmental chamber, and sample fixtures within the testing apparatus.

The extreme stiffness of NdFeB specimens, with Young's modulus exceeding 150 GPa, coupled with their brittle nature and fracture strains below 0.2%, necessitated alternative measurement approaches. While the video extensometer provided excellent results for the more ductile FeCoV specimens, the limited deformation range and resolution constraints made it suboptimal for NdFeB testing. Consequently, high-resolution linear variable differential transformers (LVDTs) were directly coupled to the test fixtures to provide the requisite measurement precision for NdFeB specimens. This hybrid approach enabled accurate mechanical characterization across the diverse material portfolio.

Elevated temperature testing revealed significant temperature-dependent behavior in both materials. The NdFeB specimens exhibited a 15-20% reduction in compressive strength when tested at 200C compared to room temperature values, as

5.8. EXPERIMENTAL ND₂FE₁₄B AND 49CO₄₉FE₂V MATERIAL CHARACTERIZATION

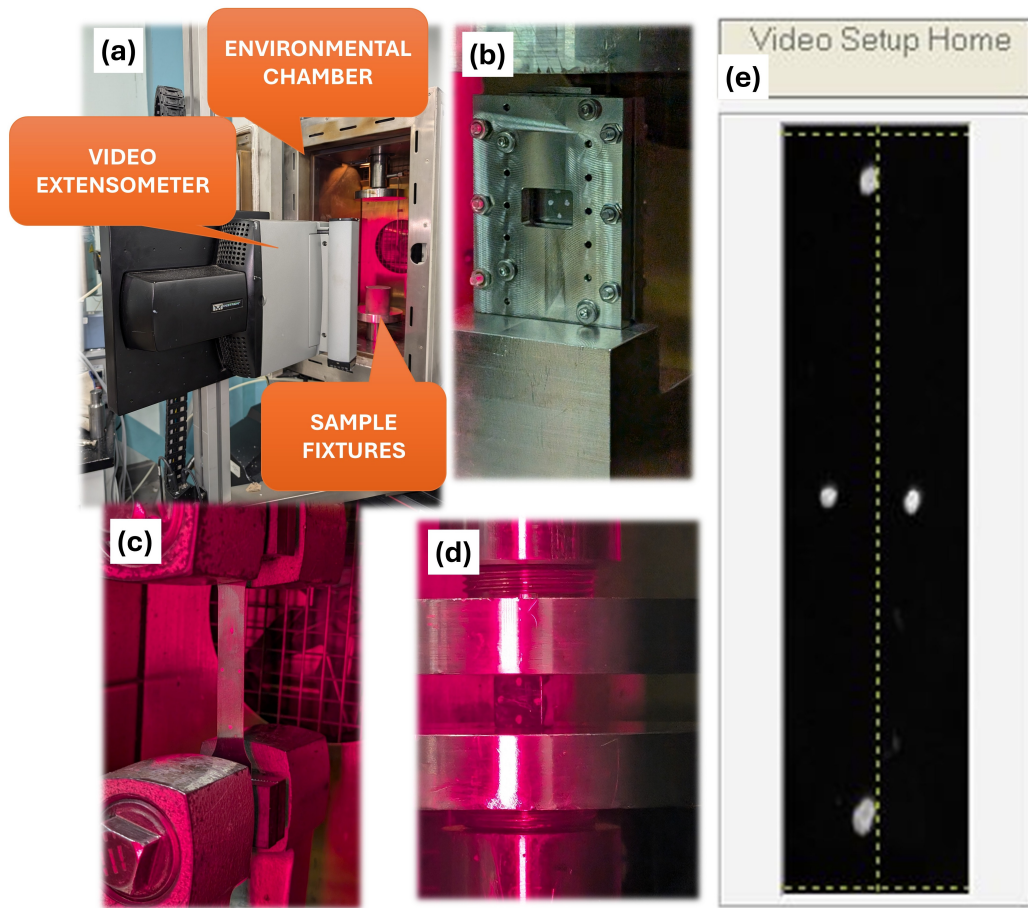


Figure 5.20: Video extensometer measurement system: (a) the annotated view of Instron 5959 pointing the video extensometer, environmental chamber and sample fixtures, (b) the speckled compression sample inside the jigs, (c) the speckled tensile sample, (d) the speckled compression NdFeB sample and (e) video extensometer interface in the GUI.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

documented in Figure 5.21. This temperature sensitivity represents a critical design consideration for applications operating in thermally variable environments.

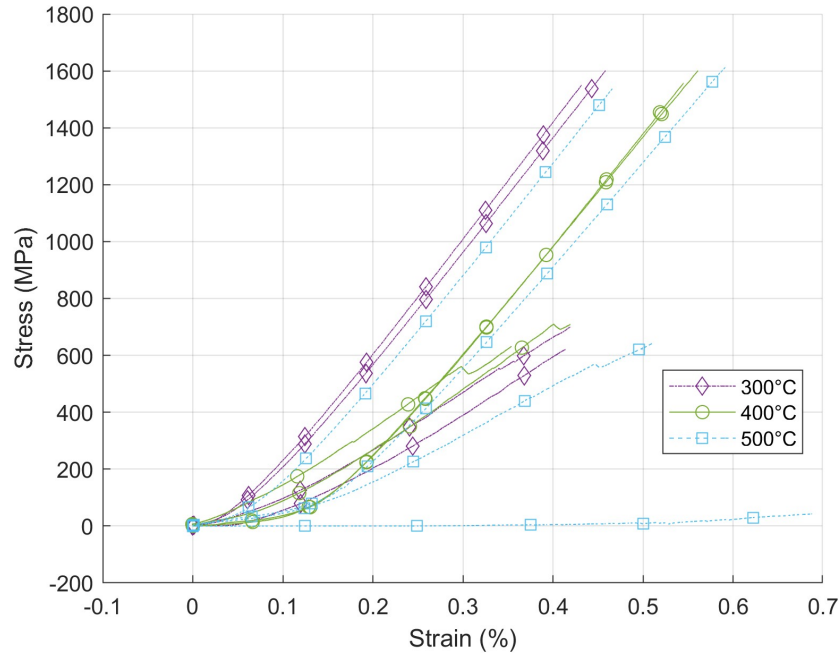


Figure 5.21: Stress vs strain of the NdFeB samples at elevated temperature. The strength of material remained constant over the temperature envelope, the stiffness reduced as temperature risen.

In contrast, the FeCoV alloys (5.22) maintained relatively consistent yield strength across the temperature range, though they demonstrated increased ductility at elevated temperatures. This behavioral difference highlights the importance of material-specific characterization for magnetic core applications.

The temperature-dependent mechanical response manifested visibly in the fracture surface morphology, as captured in Figure 5.23. Room temperature testing of FeCoV produced characteristic fracture patterns distinct from those observed at 200C, with the elevated temperature specimens showing evidence of increased plastic deformation prior to failure. Similarly, the NdFeB specimens displayed subtle but important differences in fracture behavior between room temperature and elevated temperature conditions. These microstructural observations provide valuable insights into the deformation mechanisms active under different thermal environments.

5.8. EXPERIMENTAL ND2FE14B AND 49CO49FE2V MATERIAL CHARACTERIZATION

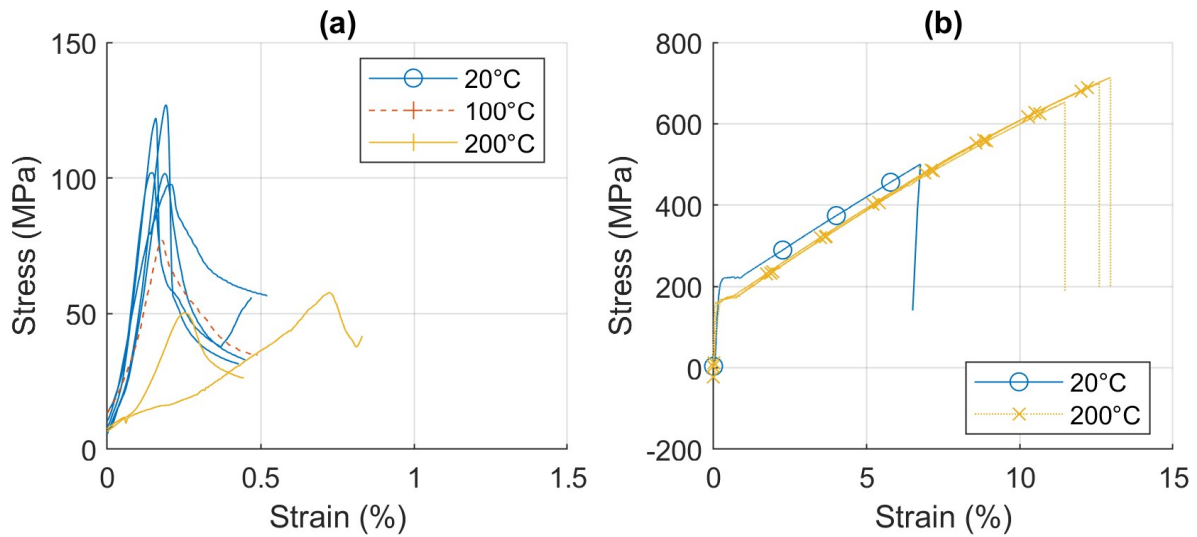


Figure 5.22: Stress vs strain curves (a) of the NdFeB samples at elevated temperature. (b) FeCoV samples; the strength of material remained constant over the temperature envelope, the stiffness reduced as temperature risen.

Post-test examination of the FeCoV samples, presented in Figure 5.24, revealed additional information about the material's response to mechanical loading. The initially smooth surface prior to testing contrasted with the evident grain structure visible after deformation, though notably without significant necking at the fracture location. Compression testing induced characteristic buckling modes, highlighting the importance of the specialized jig design in preventing premature instability during testing. These observations complement the quantitative stress-strain data in developing a comprehensive understanding of the materials' mechanical behavior.

Correlation analysis between the mechanical characterization results and thermal expansion data revealed important interdependencies between coefficient of thermal expansion (CTE) and the degradation of yield strength at elevated temperatures. This finding underscores the value of coupled thermomechanical analysis for materials operating in extreme environments, particularly in aerospace applications where concurrent thermal and mechanical loads are common. The comprehensive dataset acquired through these advanced characterization techniques provides critical input parameters for finite element modeling of magnetic component behavior under realistic operational conditions.

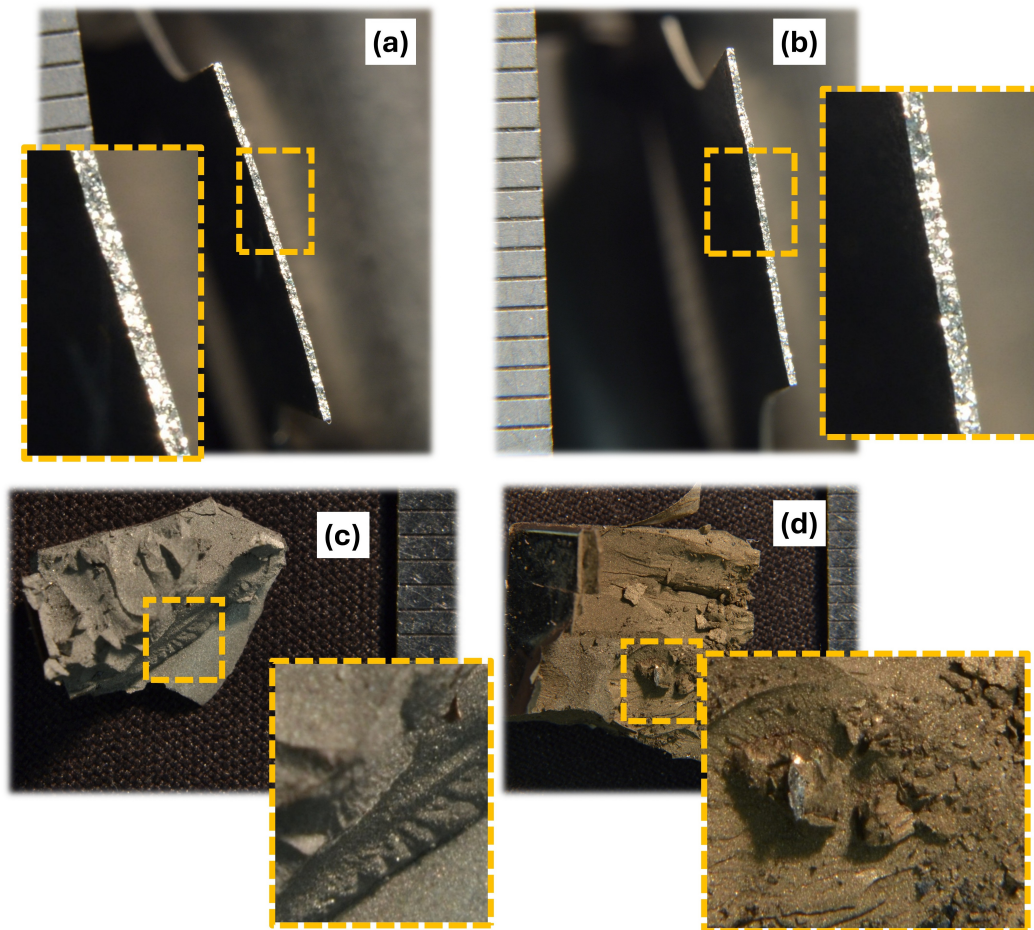


Figure 5.23: The macrograph illustrating the type of fracture for (a) *FecoV* at room temperature, (b) *FeCoV* at 200 degree Celsius, (c) *NdFeB* at room temperature and (d) *NdFeB* at 200 degree Celsius.

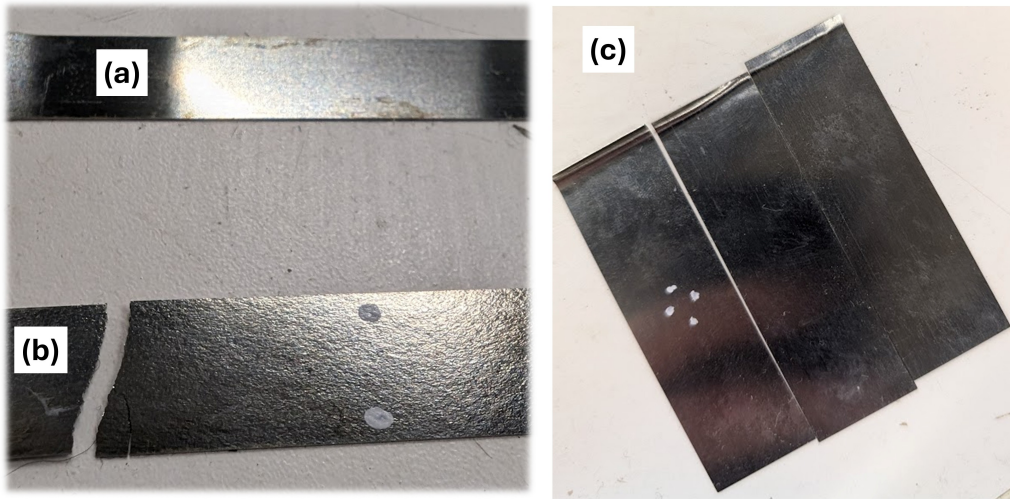


Figure 5.24: The $49\text{Fe}49\text{Co}2\text{V}$ samples after characterization showing (a) smooth surface prior to characterization, (b) the grain structure on the surface nevertheless, no necking at the fracture and (c) buckling mode in the compressive testing.

The mechanical testing program implemented in this study employed rigorous experimental protocols to generate reliable material property data across relevant temperature ranges. By addressing the unique challenges presented by thin FeCoV specimens and brittle NdFeB components through specialized fixturing and measurement techniques, the research established a robust foundation for thermomechanical analysis of magnetic core materials. These findings contribute directly to the design optimization of advanced magnetic components for extreme environment applications, where mechanical integrity must be maintained alongside magnetic performance across varying thermal conditions.

5.9 Revised Analytical Models for Fuel Savings and Heat Distribution

The conducted experiments and observed FeCoV and NdFeB properties enable higher-accuracy predictions. Accordingly, the author revises the analytical models from previous sections. Figure 5.25 presents a comprehensive analysis of fuel sav-

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

ings achieved by the Landing Gear Drive System compared to three conventional aircraft taxiing methods across varying mission parameters. The analysis examines the relationship between cumulative taxi time (horizontal axis, measured in seconds) and flight distance (vertical axis, measured in kilometers), with fuel savings represented through color gradients and contour lines (measured in kilograms).

The first subfigure (a) compares the Landing Gear Drive System against conventional twin-engine taxiing operations. The color gradient ranges from deep blue, representing negative fuel savings or increased consumption, to bright yellow, indicating substantial positive fuel savings of up to 800 kilograms. The distribution pattern demonstrates that for short taxi times and long flight distances, the Landing Gear Drive system results in negative fuel savings compared to twin-engine taxiing. This is due to the system's additional weight penalties affecting shorter flights more significantly.

Subfigure (b) evaluates the Landing Gear Drive System against single-engine taxiing operations, a method already recognized for improved efficiency compared to twin-engine taxiing. The color scale ranges from approximately -500 kilograms to +400 kilograms, with a noticeably different break-even contour line position compared to subfigure (a). This break-even threshold is positioned higher and further right, indicating that the Landing Gear Drive System requires longer taxi times and greater flight distances to overcome the efficiency of single-engine taxiing. This observation aligns with research indicating that single-engine taxiing alone can deliver significant fuel reductions compared to conventional operations.

The third subfigure (c) presents the most challenging comparison, evaluating LGDS against the Electric Green Taxiing System (EGTS). The scale of potential fuel savings is substantially reduced, ranging from approximately -100 kilograms to +150 kilograms, indicating much closer performance between these two advanced systems. The break-even contour line is positioned significantly higher in this graph, requiring considerably longer flight distances to achieve positive fuel savings. This visualization effectively demonstrates that electric taxiing systems already deliver sub-

5.9. REVISED ANALYTICAL MODELS FOR FUEL SAVINGS AND HEAT DISTRIBUTION

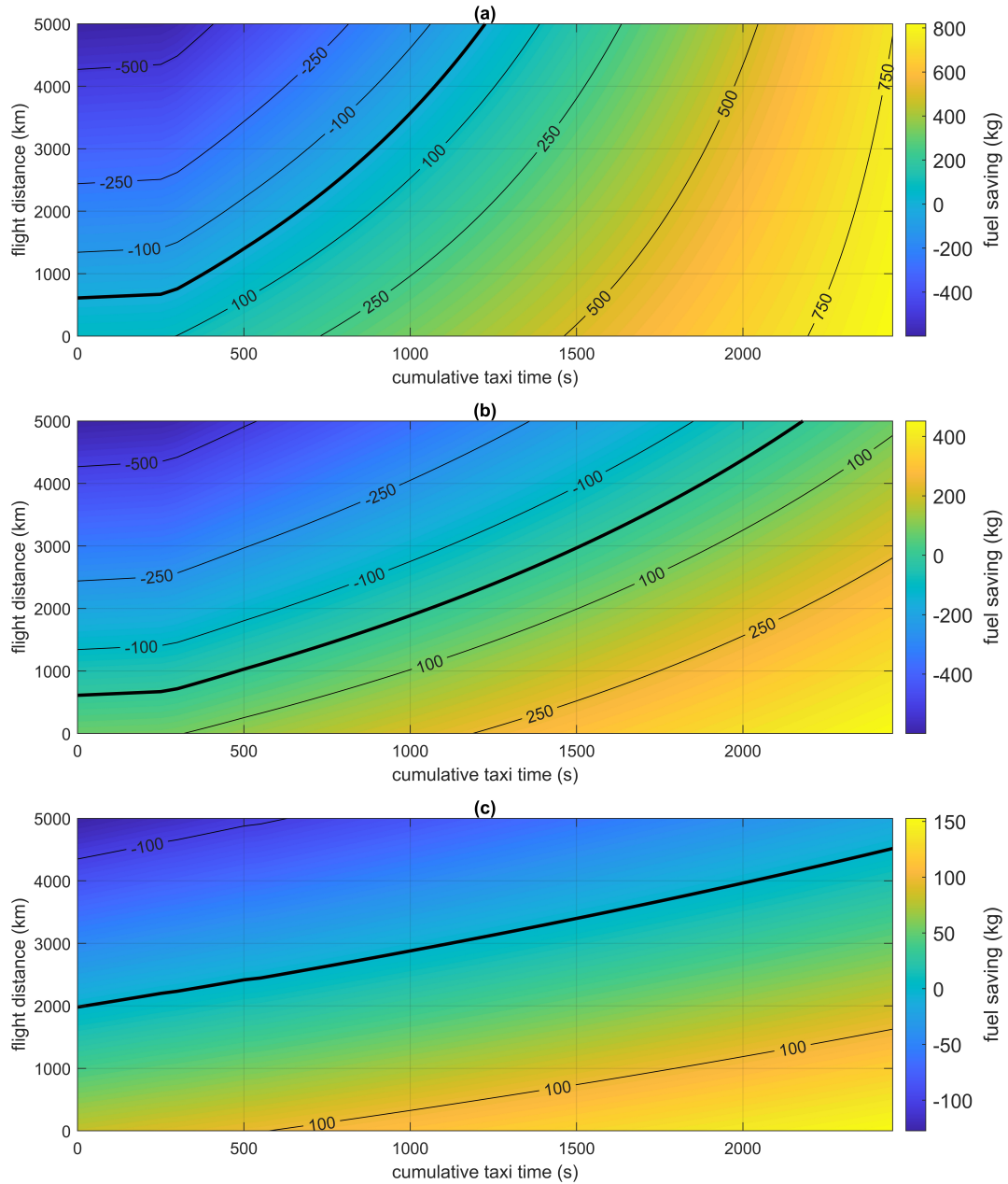


Figure 5.25: Revised fuel savings results for the Landing Gear Drive System that substitutes the friction brakes completely.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

stantial efficiency improvements, as documented in literature showing that electric taxiing can substantially reduce ground operations emissions and fuel consumption.

In case of emergency, the system shall retain same braking performance as the conventional friction brakes of aircraft and accordingly, the thermal performance of the mechanical backup device is assessed. 5.26 illustrates comprehensive thermal characteristics of a permanent magnet system during landing operations, with particular focus on temperature gradients and absolute temperatures at critical nodes in both the permanent magnet and core components. The data is presented across four distinct subfigures that collectively provide insight into the thermal dynamics of the system across a 20-second timeframe, representing a critical operational period during landing procedure.

The temperature gradient between the first two nodes in the permanent magnet, displayed in subfigure (a), reveals a characteristic transient thermal response with three distinct parametric conditions represented by values of 0.5, 0.8, and 1.0. All three conditions exhibit similar thermal behavior patterns, beginning near zero gradient, rapidly increasing to reach maximum values between 2-3 seconds, followed by a gradual decline toward thermal equilibrium at approximately 20 seconds. The maximum temperature gradient varies proportionally with the parametric value, with the 1.0 condition reaching approximately 55C, the 0.8 condition achieving approximately 50C, and the 0.5 condition peaking at approximately 45C. This pattern suggests that higher parametric values correspond to increased thermal stress within the permanent magnet material during the initial phase of landing operations.

Subfigure (b) depicts the absolute temperature of the first node in the permanent magnet during the landing operation, providing complementary information to the gradient data. The temperature profiles demonstrate rapid heating characteristics across all three parametric conditions, beginning near ambient temperature and increasing dramatically during the initial 10 seconds before approaching steady-state conditions. The magnitude hierarchy remains consistent with the gradient observations, where the 1.0 parameter condition reaches the highest steady-state tempera-

5.9. REVISED ANALYTICAL MODELS FOR FUEL SAVINGS AND HEAT DISTRIBUTION

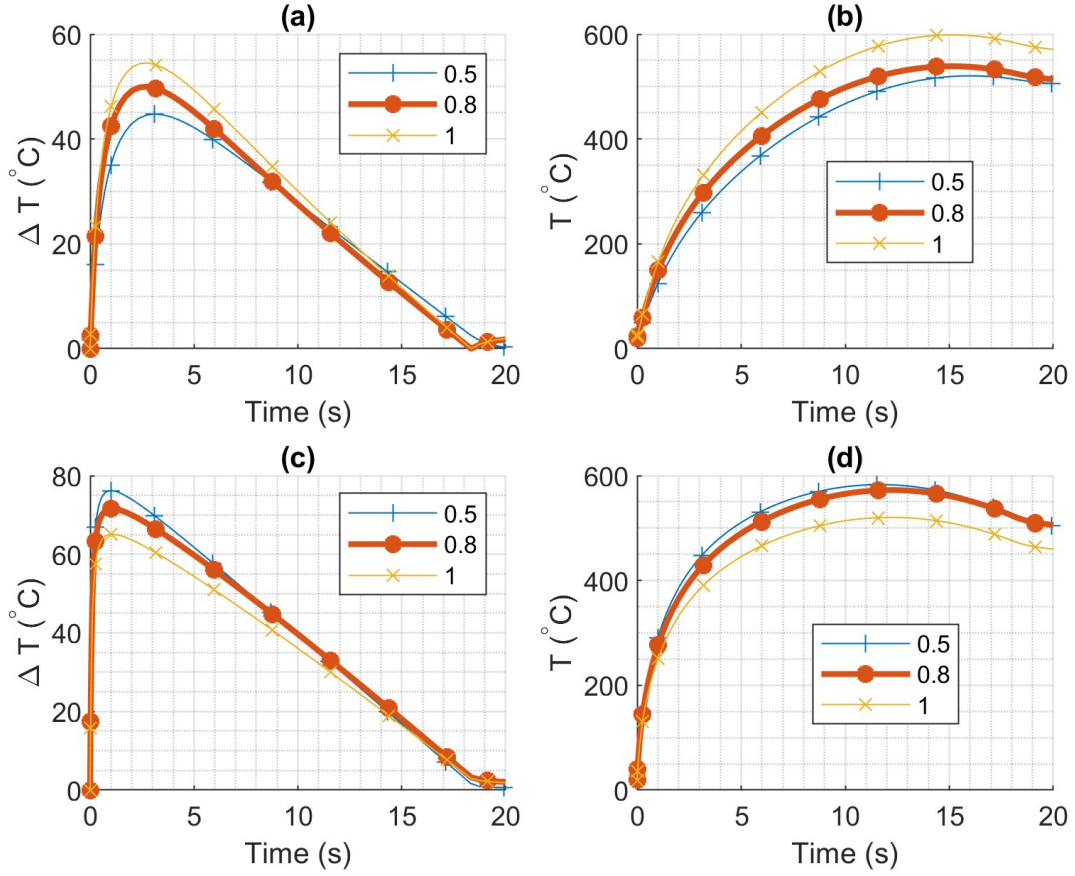


Figure 5.26: Revised lumped thermal network based on experimental data for FeCoV and NdFeB materials: (a) the temperature gradient between first and second node of the PM, (b) the temperature rise in the first node of the PM, (c) the temperature gradient between first and the second node of the stator and (d) the temperature rise in the first node of the stator.

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

ture of approximately 600C, followed by the 0.8 condition at approximately 540C, and the 0.5 condition at approximately 520C. Such elevated temperatures approaching 600C are significant for permanent magnet materials, as they substantially exceed the Curie temperature of most commercial permanent magnets, suggesting these measurements may represent a specialized high-temperature application or potentially a severe thermal condition requiring advanced cooling strategies.

In contrast to the permanent magnet behavior, subfigure (c) illustrates the temperature gradient between the first two nodes in the core component, demonstrating an inverse relationship between the parametric values and maximum temperature gradients. The 0.5 condition exhibits the highest peak gradient of approximately 75C, followed by the 0.8 condition at approximately 70C, and the 1.0 condition at approximately 65C. This inversion compared to the permanent magnet response suggests fundamentally different thermal transfer mechanisms or boundary conditions between the permanent magnet and core components. The general temporal pattern remains similar, with rapid gradient increase in the initial 1-2 seconds followed by a gradual decline toward equilibrium by 20 seconds, although the core exhibits slightly sharper initial response compared to the permanent magnet.

Subfigure (d) presents the absolute temperature profile of the first node in the core during landing, exhibiting a different thermal behavior pattern compared to the permanent magnet temperature. While all three parametric conditions demonstrate rapid temperature increases in the initial 10 seconds, they subsequently reach maximum values followed by a slight temperature decline in the later stages of the landing operation.

The parametric values (0.5, 0.8, and 1.0) represent variations in the thermal conductivity ratios between stator and rotor. The consistent crossover behavior between permanent magnet and core components indicates that optimization of thermal management strategies would require careful balancing of these parameters to minimize potential thermal stresses while maintaining operational performance. T

The data presented in this figure aligns with contemporary research on thermal

modeling of permanent magnet systems using lumped-parameter thermal networks (LPTN), where multiple thermal nodes are established to characterize heat transfer within complex electromechanical systems. The observed temporal temperature profiles during the 20-second landing period provide critical information for system designers to evaluate thermal management strategies, material selection criteria, and performance expectations under transient operating conditions. The magnitude of both the temperature gradients and absolute temperatures highlights the thermal challenges inherent in high-performance permanent magnet applications, particularly in aerospace or transportation systems where landing operations represent critical functional phases with significant thermal loading.

5.10 Conclusions

The thesis presented a novel approach for substituting conventional friction-based braking systems in commercial aircraft with electric machines, specifically focusing on a multistage yokeless and segmented armature (YASA) topology. The proposed solution aims not only to match the performance of current autobrake systems but also to recover kinetic energy, contributing to the overall electrification and sustainability of aviation.

The application constraints and typical drive cycle of the Airbus A320 were thoroughly analyzed, forming the foundation for the electric machine design requirements. Particular attention was given to the necessary braking torque, system volume constraints, and operational envelope, enabling a clear translation of aeronautical needs into engineering specifications.

The electromagnetic design and optimization phase utilized a quasi-3D transient approach, verified through static 3D simulations. This led to a design capable of delivering 120 Nm/kg active material torque density at approximately 50 A/mm RMS current density sufficient to decelerate an A320 under autobrake setting LOW (Airbus) or levels “1” and “2” (Boeing). A thermal study followed, incorporating a novel

CHAPTER 5. SUBSTITUTING A320 BRAKES WITH ELECTRIC MACHINES FOR MAXIMIZED IMPACT OF LANDING GEAR DRIVE SYSTEM

cruise altitude cooling approach, ensuring operational safety and reliability under extreme thermal gradients experienced during flight cycles.

To maintain compliance with aviation safety standards, a redundant friction-based mechanical braking system was also designed. This backup ensures aircraft deceleration in scenarios where the electric machine might be unavailable, preserving redundancy without significantly increasing system complexity or weight.

Material selection was informed by an extensive literature review and experimental testing. Candidate materials, particularly NdFe14B and FeCoV alloys, were characterized thermally and mechanically. Laser flash analysis and nanoindentation techniques revealed critical temperature-dependent behaviors that informed both the magnetic performance models and structural integrity assessments.

Based on these findings, the initial mechanical analytical models were revised to include experimentally validated properties. This adjustment allowed for more accurate stress and strain predictions under operational loading conditions and further improved the accuracy of torque-weight optimization calculations.

In conclusion, this work demonstrates that electric machines can feasibly replace traditional friction brakes on commercial aircraft both from a performance and thermal standpoint when supported by thoughtful design, novel cooling strategies, and a robust mechanical backup. The use of experimentally validated material data and revised mechanical models ensures that the design is grounded in practical engineering constraints. Future work may explore integrated power electronics, control strategies, and full-scale prototyping to move this concept toward certification and commercial application.

Chapter 6

Conclusions

This thesis has systematically addressed critical challenges in aviation sustainability through four interconnected research pillars, each contributing novel solutions to reduce energy waste, enhance system efficiency, and accelerate the industry's transition toward electrification. By integrating advanced energy recovery systems, electrified ground operations, intelligent optimization frameworks, and regenerative braking technologies, this work provides a cohesive blueprint for mitigating aviation's environmental impact while maintaining operational viability. The research not only demonstrates technological feasibility but also delivers a quantifiable contribution to the broader goals of decarbonization and sustainable growth within the aerospace sector.

The arresting gear energy recovery system demonstrated potential for converting otherwise wasted kinetic energy into usable electrical power. By achieving a validated conversion efficiency of 60% through optimized configurations and adaptive generator control, the system was shown capable of generating 70 kWh per landing for a medium-haul aircraft such as the A320. Scaled to a major hub like Heathrow Airport, this translates to approximately 17 GWh annually enough to power nearly 4,500 UK homes for a year. These results strongly support the objective of energy waste minimization, providing a measurable and deployable path for repurposing aircraft landing energy into airport power networks. The resulting energy recovery directly offsets fossil fuel consumption, potentially reducing 6,367 metric tons of coal or 5,667 m of diesel each year per major hub. Its scalability, including compatibility with aircraft up to A380-class weights, reinforces its practical viability as a near-term solution aligned with evolving green airport strategies.

The landing gear drive system addressed one of aviation's most pressing challenges: battery energy density constraints. The research demonstrated that integrating regenerative braking with a modular 200 kWh battery enables the recovery of 10% of landing energy, enabling 26 minutes of fully electric taxiing. This capability, coupled with the system's two-speed gear optimization, enhances energy utilization across a range of taxi conditions while achieving up to 7% fuel cost reduction for short-haul flights. The flexibility provided by modular 50 kWh battery segments allows integration with hybrid-electric and next-generation propulsion architectures, providing a credible bridge technology toward fully electrified ground operations and hybridized flight missions.

The SPCrane optimization framework enabled automated selection of the best pointwise surrogate model. By integrating Rust-accelerated Gaussian processes, the framework achieves rapid exploration of multidisciplinary design spaces, facilitating certification-oriented design iteration. This advancement not only supports the optimization goals of the systems studied in this thesis but also broadens application potential across the aerospace industry, where computational efficiency and precision are paramount for digital certification and design automation. The friction brake case study directly related to the thesis subject and it was demonstrated that the SPCrane could be used in the multi-objective FEA optimization problems.

The development of the YASA electric braking system further advanced the frontiers of electrified aircraft systems. Achieving a torque density of 120 Nm/kg and maintaining performance through severe thermal and mechanical stress conditions, this system matched the braking dynamics of current Airbus and Boeing autobrake standards while enabling regenerative energy capture. Laboratory analyses of Fe-CoV and NdFeB materials established their durability under peak performance operation and temperature gradients, confirming the practicality of sustained electric braking in commercial operations. The inclusion of a mechanical backup architecture ensures compliance with FAA and EASA safety standards, addressing one of the critical barriers to certification in aerospace regenerative braking technologies.

Taken collectively, these systems capture or repurpose wasted kinetic energy during short-haul cycles, supporting greenhouse gas emission reductions through large-scale deployment of energy recovery and electric taxiing. These claims, supported by both simulation and analyses, provide evidence that the technologies developed are not only experimentally validated but also economically viable and industrially scalable. The 7% reduction in fuel cost per short-haul flight enhances airline competitiveness, while airport-side energy recovery and grid integration create tangible financial incentives via feed-in tariffs and carbon credits. The modularity of these systems supports gradual fleet transition strategies, aligning with current asset management and retrofit cycles across global operators.

From a technological standpoint, this thesis bridges the gap between theoretical innovation and certifiable application. The arresting gears force-based dynamic model and braking systems experimentally validated material properties offer rigorous validation frameworks that anticipate the certification needs of emerging electric aircraft systems. By adopting a systems-level approach informed by both experimental and digital analysis, the thesis ensures that the proposed technologies are compatible with ongoing evolution in regulatory frameworks such as EASAs CS-25. The combination of model-based verification, experimental validation, and optimization logic confers both scientific credibility and engineering readiness.

Viewed within the wider research context, this work extends beyond technical innovation to present a cohesive methodology for sustainable systems engineering in aviation. It achieves quantifiable, real-world energy and emissions savings while defining a rigorous design and validation process adaptable to future electrified propulsion systems. The SPCrane optimization toolkit contributes methodological maturity to the digital transformation of aerospace design, while the material data derived from braking and generator systems support broader innovation in high-performance electric actuators. Collectively, these advances demonstrate that sustainability and certification readiness can coexist within the same design philosophy.

While the transition from prototype to operational deployment will require continued industrial collaboration and regulatory engagement, the analytic, computational, and experimental evidence presented provides high confidence in the projected performance and benefits of the proposed systems. Sensitivity analyses confirm that even under conservative assumptions, the energy and emission savings remain materially significant. Future work should focus on deploying system prototypes, performing long-duration testing under operational conditions, and exploring high-voltage power electronics and magnetic gear hybridization to further improve energy efficiency.

Ultimately, this thesis demonstrates that credible, high-impact progress toward sustainable aviation is already achievable through integrated engineering innovation. By uniting practical electrification technologies with robust analytical and experimental validation, it provides guidelines for near-term decarbonization while retaining the safety, economic, and operational imperatives of modern air transport. These contributions collectively chart a realistic course toward cleaner, quieter, and more energy-efficient aviation, a vision in which environmental stewardship, technological advancement, and regulatory feasibility advance together.

6.1 Future Work

Building on the foundational advancements demonstrated in this thesis, several strategic research trajectories emerge to advance sustainable aviation technologies from prototype validation to operational implementation. A critical next step involves elevating the yokeless segmented armature (YASA) braking system from analytical models to laboratory-validated prototypes through scaled testing with FeCoV stator stacks and NdFeB rotors. This experimental campaign must replicate extreme operational conditions, including Airbus A320's 2,200C/s heat flux rates during rejected takeoffs and 180-220C finish temperatures observed in active autobrake systems. Concurrent material durability testing across 50,000+ braking cycles will as-

sess rare-earth magnet stability, with success enabling full-scale certification under EASA CS-25 protocols.

The SPCrane optimization framework's capabilities can be extended through high-fidelity multi-domain simulations integrating ANSYS Mechanical, COMSOL Multiphysics, and Altair Flux solvers. This approach would address current limitations in arresting gear modeling by combining real-time structural health monitoring with NVH-EM-thermal co-simulations, potentially improving energy capture predictions by 12-18% through advanced kink wave analysis. Digital twin development could further enhance predictive capabilities by employing the framework's sigmoid-based transition logic to detect thermal runaway thresholds in braking systems.

Operational deployment ultimately requires rigorous compliance with aviation safety standards, necessitating comprehensive failure mode analyses. Common Cause Analysis of arresting gear grid interconnections and Fault Tree Analysis of multi-stack YASA configurations will quantify systemic risks, while FMECA validation must confirm the mechanical backup system's reliability target. Parallel integration studies should address electromagnetic compatibility challenges between regenerative systems and critical avionics during simultaneous energy recovery and instrument landing operations. Collectively, these efforts provide a clear development from laboratory prototypes to certified systems, aligning with ICAO's decarbonization targets through coordinated industry and academia partnerships over the next 5-7 years.

As the industry progresses toward hydrogen and full-electric propulsion, these intermediate technologies offer critical "bridge solutions" capable of reducing aviation's carbon footprint within existing infrastructure constraints. Their modular nature enables phased implementation, allowing airlines to maintain competitiveness while meeting tightening emissions regulations.

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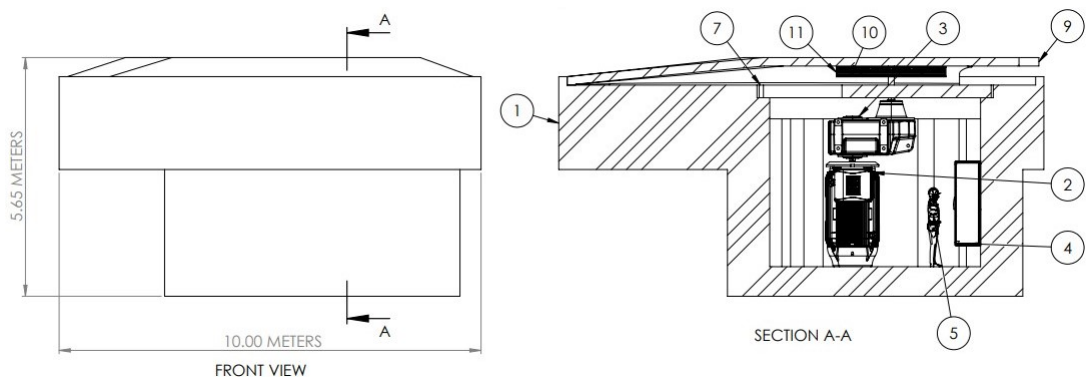
Appendix A

Illustration of the winding subsystem

Cross-section view of winding subsystem

BALLOON NO.	DESCRIPTION	QTY
1	FOUNDATION	1
2	MOTOR-GENERATOR	1
3	GEAR REDUCER	1
4	ELECTRICAL CABINET	1
5	SERVICE ENGINEER FOR SCALE	1
6	BOTTOM BEARING (NOT VISIBLE)	1
7	BLANKING PLATE	1
8	TOP BEARING (NOT VISIBLE)	1
9	SAFETY ENCLOSURE	1
10	WINDING DRUM	1
11	ARRESTING ROPE/TAPE	1

APPENDIX A. ILLUSTRATION OF THE WINDING SUBSYSTEM



Appendix B

Parameters of the rope

Rope parameters used in USS navy Mark 7 Mod 3 arresting gear systems

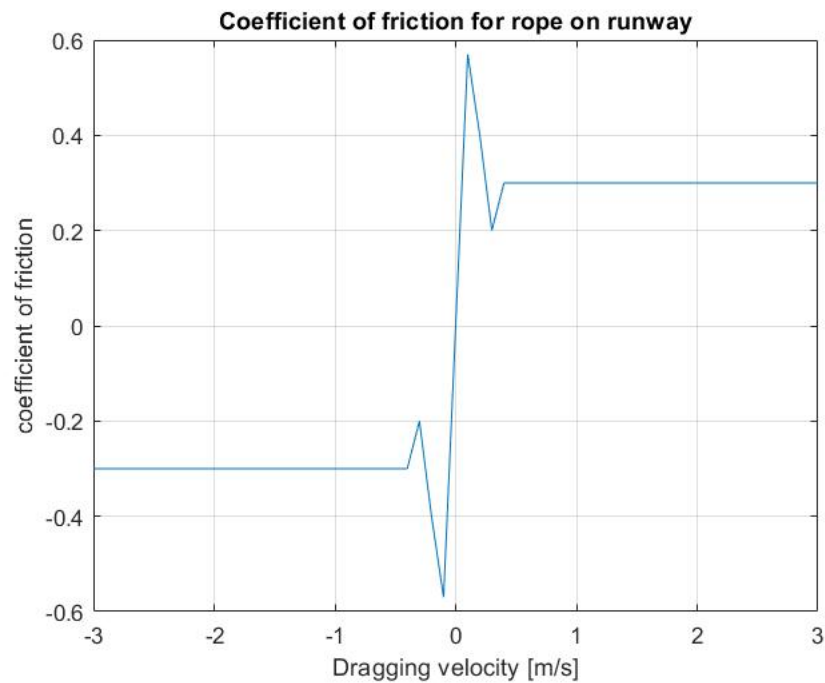
	Deck Pendant	Purchase Cable
Type	6x30 flat strand polyester core	6x31 flat strand polyester core
Diameter	36 mm	36 mm
Breaking strength	93 metric tons	98 metric tons

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Appendix C

Rope friction induced by contact with runway

Rope against a runway coefficient of friction



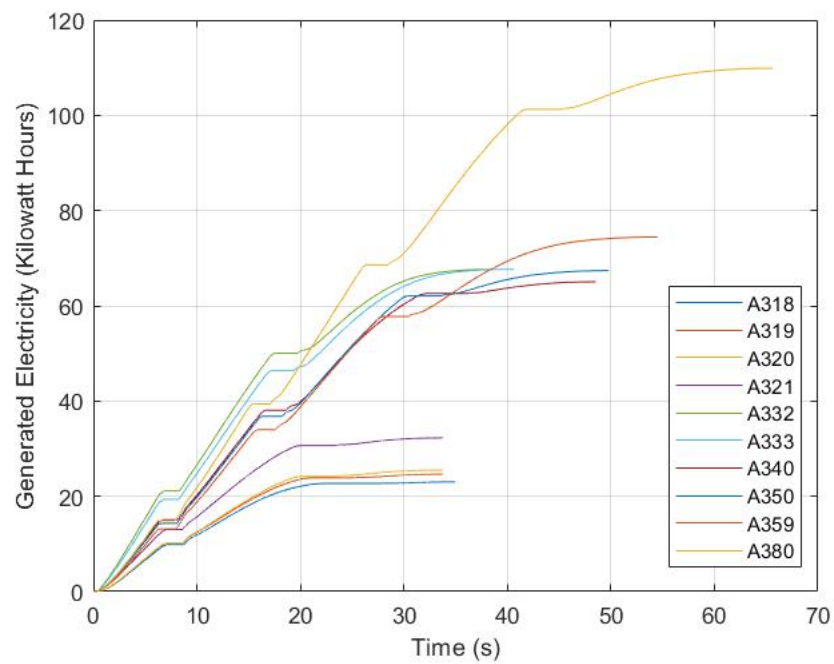
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Appendix D

Top-level energy transfer

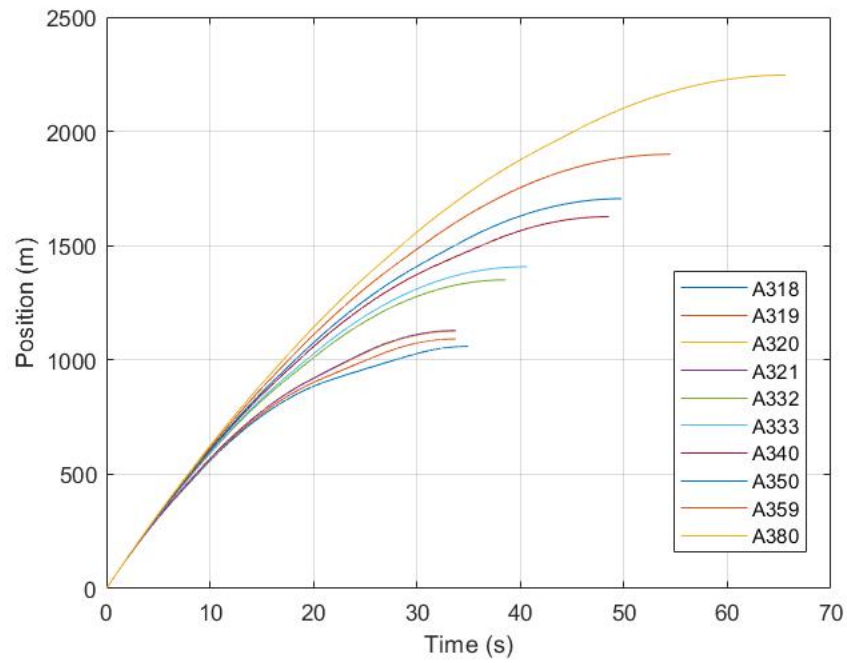
D.0.1

Generated Energy for all aircraft at gear ratio equal 3



D.0.2

Stopping distance for all aircraft at gear ratio equal 3



Appendix E

Production source code for SPCrane

```
1
2 """
3 INPUT:
4     X: Input variables [array (n,i) where n are breakpoints, i is number of variables]
5     Y: Objective values [array (n,1)]
6     xhat: Approximation input [array (j,i) where j are breakpoints, i is number of variables]
7     surrogate_models: [dictionary [SMTs_surrName : parameters]]
8     OPTIONAL
9         TYPE (REGRESSION/INTERPOLATION), DEFAULT: REGRESSION
10
11 OUTPUT:
12     yhat: predictions at given xhat [array (j,1)]
13     OPTIONAL
14         LOOCV
15         DOMINANT AT GIVEN LOOCV BREAKPOINT
16         ERRORS RMSE, R2, MAE, MAPE
17         TUNING METHODS
18
19
20
21 Authors: Jakub Deja <jakub.deja@cranfield.ac.uk>
22
23 """
24
25
26 import numpy as np
27 import math
28 import copy
29
30
31 from sklearn.model_selection import LeaveOneOut
32 from sklearn.model_selection import StratifiedKFold
33 from sklearn.model_selection import KFold
34 import importlib
35 from sklearn.metrics import mean_absolute_error, mean_squared_error
36
37 class EoS: #Class for ensemble of surrogates
38     def __init__ (self, x, y, xpred, yTrueTest, surrogate_model, n_splits, biasSFac):
39         """
40         Initialize the Ensemble of Surrogates (EoS) class.
41
42         This class implements an ensemble of surrogate models for prediction tasks.
```


APPENDIX E. PRODUCTION SOURCE CODE FOR SPCRANE

```
43     It validates input data, sets up the model framework, and prepares for training
44     and prediction operations.
45
46     Parameters
47     -----
48     x : numpy.ndarray
49         Training input data matrix, where rows are samples and columns are features.
50     y : numpy.ndarray
51         Training target values corresponding to the input data x.
52     xpred : numpy.ndarray
53         Prediction input data matrix with the same number of features as x.
54     yTrueTest : numpy.ndarray
55         True target values for the prediction set, used for evaluation.
56     surrogate_model : dict
57         Dictionary of surrogate models to be used in the ensemble.
58         Each key should be a string (model name) and each value should be a dictionary
59         of model parameters.
60     n_splits : int
61         Number of splits for cross-validation.
62     biasSFac : float
63         Bias scaling factor used in the ensemble.
64
65     Raises
66     -----
67     TypeError
68         If x, y, or xpred are not numpy arrays, or if surrogate_model is not a dictionary.
69     ValueError
70         If dimensions of inputs don't match or if surrogate_model has invalid structure.
71     """
72     try:
73         # Check if x, y, and xpred are numpy arrays
74         if not hasattr(x, "shape") or not isinstance(x, np.ndarray):
75             raise TypeError("x must be a numpy array.")
76
77         if not hasattr(y, "shape") or not isinstance(y, np.ndarray):
78             raise TypeError("y must be a numpy array.")
79
80         if not hasattr(xpred, "shape") or not isinstance(xpred, np.ndarray):
81             raise TypeError("xpred must be a numpy array.")
82
83         if not isinstance(surrogate_model, dict):
84             raise TypeError("surrogate_model must be a dictionary.")
85
86         # Check the dimensionality of x and y
87         if len(x) != len(y):
88             raise ValueError("The number of rows in x must match the number of rows in y.")
89
90
91         if x.shape[1] != xpred.shape[1]:
92             raise ValueError("The number of variables (columns) in x must match xpred.")
93
94         # Check that surrogate_model has valid keys and values
95         for key, value in surrogate_model.items():
96             if not isinstance(key, str):
97                 raise ValueError("Keys in surrogate_model must be strings representing model names.")
98             if not isinstance(value, dict):
99                 raise ValueError("Values in surrogate_model must be dictionaries of parameters.")
100
101         # If all checks pass, assign to class attributes
```

```

102     self.x = x
103     self.y = y
104     self.xpred = xpred
105     self.surrogate_model = surrogate_model
106     self.n_splits = n_splits
107     self.yTrueTest = yTrueTest
108     self.biasSFac = biasSFac
109
110
111     #Add noise
112     # Generate random noise (10% of each value in self.y)
113     self.noise = 0.00 * self.y * np.random.randn(*self.y.shape)
114
115     # Add noise to self.y
116     self.y = self.y + self.noise
117
118
119
120     except Exception as e:
121         print(f"Error initializing EoS: {e}")
122         raise
123
124 def _initialize_model(self, model_type, **kwargs):
125     """
126     Dynamically initialize a surrogate model from the SMT library.
127
128     This method imports the specified model class from the SMT (Surrogate
129     Modeling Toolbox) library and instantiates it with the provided parameters.
130
131     Parameters
132     -----
133     model_type : str
134         Name of the model class to import from smt.surrogate_models.
135     **kwargs : dict
136         Keyword arguments to pass to the model constructor.
137
138     Returns
139     -----
140     object
141         Instantiated surrogate model object.
142
143     Raises
144     -----
145     ValueError
146         If the specified model_type cannot be found in the SMT library
147         or if there's an error during model initialization.
148
149     Notes
150     -----
151     This method uses dynamic importing to allow flexibility in model selection
152     without having to import all possible models at the module level.
153     """
154     try:
155         # Attempt to dynamically import the model from the SMT library
156         module = importlib.import_module('smt.surrogate_models')
157         model_class = getattr(module, model_type) # Get the class by name
158
159         # Instantiate the model
160         return model_class(**kwargs)
161     except (ModuleNotFoundError, AttributeError) as e:

```

APPENDIX E. PRODUCTION SOURCE CODE FOR SPCRANE

```
161         # If the model cannot be found, raise an error and continue
162         raise ValueError(f"Unsupported model type: {model_type}. Error: {e}")
163     def _perform_kfold_split(self):
164         """
165         Performs k-fold cross-validation on the input data.
166
167         This method splits the dataset into k folds for cross-validation,
168         storing each train-test split for later use. The splits are
169         created using scikit-learn's KFold implementation with shuffling
170         enabled for randomization.
171
172         Parameters
173         -----
174         None
175
176         Uses self.n_splits, self.x, and self.y from instance variables.
177
178         Returns
179         -----
180         None
181
182         Results are stored in self.KFsplit and self.testindices.
183
184         Notes
185         -----
186         Each element in self.KFsplit is a tuple containing:
187         (X_train, y_train, X_test, y_test, test_index) where:
188         - X_train: Training input features
189         - y_train: Training target values
190         - X_test: Testing input features
191         - y_test: Testing target values
192         - test_index: Indices of test samples in the original dataset
193
194         The method uses a fixed random_state (3) for reproducibility.
195         """
196         kf = KFold(n_splits=self.n_splits, shuffle=True, random_state=3) # Shuffle for randomness
197
198         # Define an array to store all combinations of train-test splits
199         self.KFsplit = []
200         self.testindices = []
201
202         # Loop through each training/testing split
203         for train_index, test_index in kf.split(self.x):
204             # Split data into training and testing sets
205             X_train, X_test = self.x[train_index], self.x[test_index]
206             y_train, y_test = self.y[train_index], self.y[test_index]
207
208             # Store each combination as a tuple in the list
209             self.KFsplit.append((X_train, y_train, X_test, y_test, test_index))
210             self.testindices.append(test_index)
211
212     def _determine_best_model(self):
213         """
214         Determine the best surrogate model for each data point based on cross-validation.
215
216         This method evaluates all surrogate models specified in self.surrogate_model
217         across each K-fold split. It trains each model on the training data, makes
218         predictions on the test data, and computes the absolute error for each prediction.
219         The model with the lowest error for each data point is identified as the best model.
220
221         Parameters
222         -----
```

```

220     None
221     Uses instance variables including self.surrogate_model and self.KFsplit.
222
223     Returns
224     -----
225     None
226
227     Results are stored in several instance variables:
228     - self.ypredsorted: Sorted predictions from all models
229     - self.errorsorted: Sorted errors for all models
230     - self.best_model: List indicating which model performs best for each data point
231     - self.best_lowerror: Minimum error for each data point
232
233     Notes
234     -----
235     The method performs these key steps:
236     1. Trains each surrogate model on each fold of the data
237     2. Makes predictions and calculates absolute errors
238     3. Reshapes and sorts predictions and errors to match the original data order
239     4. Identifies the best-performing model for each data point
240
241     This implementation assumes that K-fold cross-validation has already been
242     performed via the distance_based_kfold method.
243     """
244     # Determine the number of models and iterations based on K-Fold splits
245     num_models = len(self.surrogate_model)
246     num_iterations = len(self.KFsplit) # Using K-Fold splits instead of LOOCV
247     num_entries = len(self.y) #
248     # Initialize arrays to store errors and function predictions
249     self.errors = np.zeros((num_entries, num_models))
250     self.xfuncs = np.zeros((num_entries, num_models))
251     self.yfuncs = np.zeros((num_entries, num_models))
252
253     self.alltestindices = []
254
255     self.allYpreds = []
256     self.allErrors = []
257
258     for model_idx, (model_name, model_params) in enumerate(self.surrogate_model.items()):
259         print(f"Initializing Model: {model_name} with params: {model_params}")
260         sm = self._initialize_model(model_name, **model_params)
261
262         # Loop through each train-test split
263         for i in range(num_iterations):
264             X_train, Y_train, X_test, Y_test, test_index = self.KFsplit[i] # Extract train-test sets
265             sm.set_training_values(X_train, Y_train)
266             sm.train()
267
268             # Predict values for multiple test points in K-Fold
269             self.y_pred = sm.predict_values(X_test) #
270             self.allYpreds.append(self.y_pred)
271
272             self.error = np.abs(self.y_pred - Y_test)
273             self.allErrors.append(self.error)
274
275     self.final_predictions = np.concatenate(self.allYpreds, axis=0)
276     self.final_errors = np.concatenate(self.allErrors, axis=0)
277
278

```

APPENDIX E. PRODUCTION SOURCE CODE FOR SPCRANE

```
279 self.y_predreshaped = self.final_predictions.reshape(len(self.final_predictions)//num_models,num_models)
280 self.errorreshaped = self.final_errors.reshape(num_models,len(self.final_errors)//num_models).T
281 self.alltestindices = [int(item) for tup in self.KFsplit for item in tup[4]]
282
283 self.sorted_indices = np.argsort(self.alltestindices)
284 self.ypredsorted= self.y_predreshaped[self.sorted_indices]
285 self.errorsorted = self.errorreshaped[self.sorted_indices]
286
287 self.best_model = np.argmin(self.errorsorted, axis=1).tolist()
288 self.best_lowerror = np.min(self.errorsorted, axis=1).tolist()
289 def _calculate_distance_penalties(self):
290     """
291     Calculate distance-based penalty matrix between training and prediction points.
292
293     This method computes the Euclidean distance between each training point in
294     self.x and each prediction point in self.xpred. It then creates a penalty
295     matrix with values inversely proportional to the squared distance,
296     normalized to the range [0,1]. Points with zero distance (identical points)
297     are handled as a special case with maximum penalty value.
298
299     Parameters
300     -----
301     None
302
303     Uses self.x and self.xpred from instance variables.
304
305     Returns
306     -----
307     None
308
309     Results are stored in:
310     - self.Ik: Matrix of normalized inverse squared distances (penalty matrix)
311     - self.euclidean_dist: Matrix of raw Euclidean distances
312
313     Notes
314     -----
315     The penalty calculation follows the formula:
316     Ik[j][i] = 1 / (||x[j] - xpred[i]||) for non-zero distances
317
318     Zero distances (identical points) are assigned a penalty value of 1, while
319     all other values are normalized to be less than 1, making identical points
320     have the highest influence in subsequent calculations.
321     """
322     num_j = len(self.x)
323     num_i = len(self.xpred)
324
325     # Initialize Ik as a NumPy array with zeros
326     self.Ik = np.zeros((num_j, num_i))
327     self.euclidean_dist = np.zeros((num_j, num_i))
328
329     # List to save indices where norm_value is 0
330     zero_norm_indices = []
331
332     for j in range(num_j):
333         for i in range(num_i):
334             norm_value = np.linalg.norm(self.x[j] - self.xpred[i])
335             self.euclidean_dist[j][i] = norm_value
336             if norm_value == 0:
337                 self.Ik[j][i] = 1 # Handle the singularity case explicitly
338                 zero_norm_indices.append((j, i))
339             else:
```

```

338         self.Ik[j][i] = 1 / (norm_value) ** 2
339
340     # Normalize the self.Ik array by its maximum value
341     max_value = np.max(self.Ik)
342     if max_value != 0: # Avoid division by zero
343         self.Ik /= max_value
344
345     # Replace values at saved indices with 1.1
346     for j, i in zero_norm_indices:
347         self.Ik[j][i] = 1
348
349 def _train_surrogate_models(self):
350     """
351     Train surrogate models and generate predictions for prediction points.
352
353     This method iterates through all specified surrogate models, trains each
354     model on the full training dataset, and generates predictions for all
355     points in the prediction set. The predictions from each model are stored
356     in a matrix for later use.
357
358     Parameters
359     -----
360     None
361
362     Uses instance variables including self.surrogate_model, self.x,
363     self.y, and self.xpred.
364
365     Returns
366     -----
367     None
368
369     Results are stored in self.yHatSur, a matrix where each column
370     contains predictions from a specific surrogate model, and each row
371     corresponds to a prediction point in self.xpred.
372
373     Notes
374     -----
375     The method follows these steps for each surrogate model:
376     1. Initialize the model with specified parameters
377     2. Train the model using all available training data
378     3. Generate predictions for all prediction points
379     4. Store predictions in the corresponding column of self.yHatSur
380
381     Debug information about shapes is printed during execution to verify
382     correct dimensionality of predictions.
383     """
384     num_models = len(self.surrogate_model)
385     num_iterations = len(self.xpred)
386
387     self.yHatSur = np.zeros((num_iterations, num_models))
388
389     for model_idx, (model_name, model_params) in enumerate(self.surrogate_model.items()):
390         print(f"Initializing Model: {model_name} with params: {model_params}")
391         sm = self._initialize_model(model_name, **model_params)
392
393         sm.set_training_values(self.x, self.y)
394         sm.train()
395
396         syfun = sm.predict_values(self.xpred)
397
398         self.yHatSur[:, model_idx] = syfun.reshape(-1)

```

APPENDIX E. PRODUCTION SOURCE CODE FOR SPCRANE

```
397         print(f"syfun shape: {syfun.shape}, self.yHatSur[:, {model_idx}].shape: {self.yHatSur[:, model_idx].shape}")
398     def _blend_surrogate_models(self):
399         """
400         Blend multiple surrogate models into a single ensemble prediction.
401
402         This method creates a weighted ensemble of surrogate models based on
403         which model performs best for similar training points. It uses the
404         distance-based influence matrix (self.Ik) combined with best model
405         indicators to calculate weights, then applies these weights to the
406         surrogate model predictions.
407
408         Parameters
409         -----
410         None
411
412         Uses instance variables including self.best_model, self.Ik,
413         self.num_surrogates, and self.yHatSur.
414
415         Returns
416         -----
417         None
418
419         Results are stored in self.yHatEns, which contains the blended predictions
420         for each prediction point.
421
422         Notes
423         -----
424         The blending process involves these key steps:
425         1. Create a one-hot encoding matrix (wei_ik) indicating the best model for each point
426         2. Multiply this encoding with the distance-based influence matrix (Ik)
427         3. Weight the surrogate predictions by these influence factors
428         4. Normalize and sum to produce the final ensemble prediction
429
430         This approach ensures that predictions from models that perform well on similar
431         training points have more influence on the final prediction.
432         """
433         #calculate W_{ik}, it is 0/1 boolean for the best model at data point
434         self.num_surrogates = range(len(self.surrogate_model.keys()))
435
436         self.wei_ik = np.zeros((len(self.num_surrogates), len(self.best_model)), dtype=int)
437
438         for i, key in enumerate(self.num_surrogates):
439             self.wei_ik[i] = [1 if x == key else 0 for x in self.best_model]
440
441         # Create an empty list to store the results
442         self.Wiks = []
443         self.wei_ik = self.wei_ik.T
444
445         #novelty
446         self.wei_cran = []
447         self.wei_cran_min = []
448         self.wei_cran_min = np.amin(self.errorsorted, axis=1)
449
450         # print("Shape of wei_ik:", self.wei_ik.shape)
451         # # Loop through each column of B
452         for i in range(self.wei_ik.shape[1]):
453             # Multiply rows of A with the corresponding column of B
454             Wik = self.Ik * self.wei_ik[:, i, np.newaxis]
455
456             self.Wiks.append(Wik)
```

```

456     self.sum_Wiks = np.sum(self.Wiks, axis=0)
457
458     #multiply self.Wiks times self.yHatSur
459     #columns of Wiks with value from row of syfuns
460     # Result storage (same structure as self.Wiks)
461     self.WSurr = []
462
463     for i, array in enumerate(self.Wiks): # Iterate over the arrays in self.Wiks
464         syfun_col = self.yHatSur[:, i] # Get the i-th column of self.yHatSur
465         new_array = np.zeros_like(array) # Placeholder for the modified array
466
467         for col_index in range(array.shape[1]): # Iterate over columns of the current array
468             # Element-wise multiplication: column of self.Wiks * syfun value
469             new_array[:, col_index] = array[:, col_index] * syfun_col[col_index]
470
471         self.WSurr.append(new_array)
472
473     ##### create a resultant model
474     #sum self.WSurr list one by one
475     self.unweighed_sum = np.sum(self.WSurr, axis=0)
476     #divide by resultant weights
477     self.yHatEns = np.sum(self.unweighed_sum, axis=0)/np.sum(self.sum_Wiks, axis=0)
478 def _calculate_performance (self):
479     #Calculate the performance metrics based on
480
481     for i in range(len(self.surrogate_model)):
482         key_at_index = list(self.surrogate_model.keys())[i]
483         print(f"The model's performance metrics: {key_at_index}")
484
485         mae = mean_absolute_error(self.yTrueTest, self.yHatSur[:,i])
486         mse = mean_squared_error(self.yTrueTest, self.yHatSur[:,i])
487         rmse = np.sqrt(mse)
488         mape = np.mean(np.abs((self.yTrueTest - self.yHatSur[:,i]) / self.yTrueTest)) * 100
489         print(f"MAE {np.format_float_scientific(mae, exp_digits=4,precision=3)}")
490         print(f"MSE {np.format_float_scientific(mse, exp_digits=4,precision=3)}")
491         print(f"RMSE {np.format_float_scientific(rmse, exp_digits=4,precision=3)}")
492         print(f"MAPE {np.format_float_scientific(mape, exp_digits=4,precision=3)}")
493
494
495
496     print("_____")
497     print("SPCrane")
498
499     mae = mean_absolute_error(self.yTrueTest, self.yHatEns)
500     mse = mean_squared_error(self.yTrueTest, self.yHatEns)
501     rmse = np.sqrt(mse)
502     mape = np.mean(np.abs((self.yTrueTest - self.yHatEns) / self.yTrueTest)) * 100
503     print(f"MAE {np.format_float_scientific(mae, exp_digits=4,precision=3)}")
504     print(f"MSE {np.format_float_scientific(mse, exp_digits=4,precision=3)}")
505     print(f"RMSE {np.format_float_scientific(rmse, exp_digits=4,precision=3)}")
506     print(f"MAPE {np.format_float_scientific(mape, exp_digits=4,precision=3)}")
507     print("_____")
508 def execute(self):
509
510     print("Running surrogate model calculations...")
511     self._perform_kfold_split()
512     print("Running surrogate model calculations...")
513     self._determine_best_model()
514     print("euclidean distance penalty calculation")

```


APPENDIX E. PRODUCTION SOURCE CODE FOR SPCRANE

```
515     self.__calculate_distance_penalties()
516     print("Calculating surrogate models for ensemble")
517     self.__train_surrogate_models()
518     print("Blending the model")
519     self.__blend_surrogate_models()
520     print("performance metrics")
521     self.__calculate_performance()
522     print("All methods executed successfully.")
523
524
525     return self.KFsplitted, self.errors, self.xfuncs, self.yHatSur, self.best_model, self.Ik, self.sum_Wiks, self.yHatEns
```

Appendix F

Redundant Thermal Measurement Throughout Mechanical Characterization

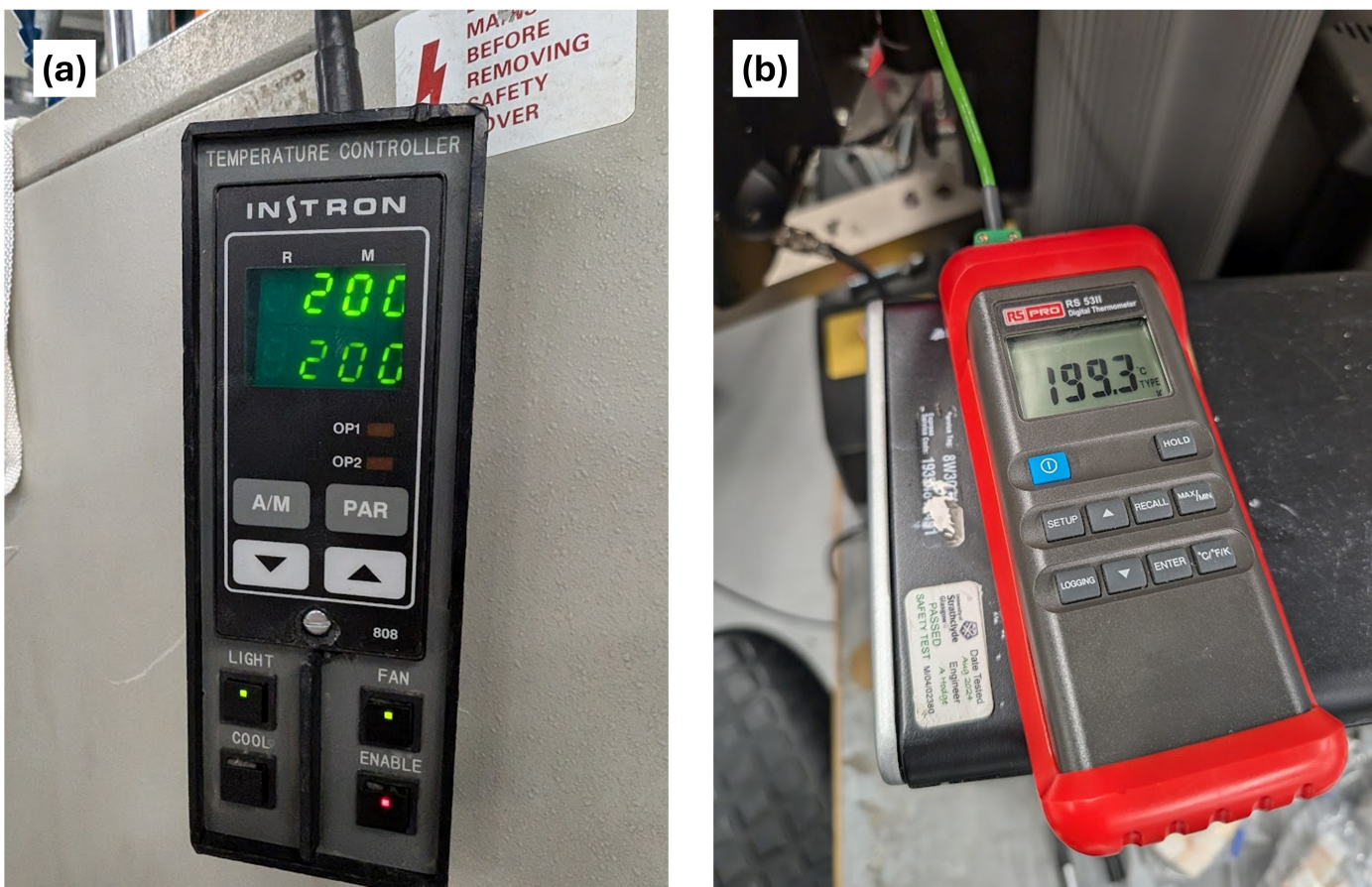


Figure F.1: Environmental Chamber Temperature control (a) Default thermocouple, (b) backup thermocouple

Appendix G

Mechanical Characterization Procedure and Samples

Table G.1: *FeCoV* testing procedure

ID	Sample	Type	Temperature	Strain rate (mm/min)	Comments
Fecov_1	63.70x19.50x0.254 F4	compressive	RT	6.3	The jigs ex, DIC, strain rate normalised 0.00165 (1/s)
Fecov_2	63.70x19.50x0.255 F4	compressive	RT	6.3	Clearance, noDIC?, strain rate normalised 0.00165 (1/s)
Fecov_3	63.70x19.50x0.256 F4	compressive	RT	3	Clearance, DIC, strain rate normalised 0.00078 (1/s)
Fecov_4	63.70x19.50x0.256 F4	compressive	RT	3	Clearance, noDIC, strain rate normalised 0.00078 (1/s)
Fecov_5	63.90x20x0.256 F6-mod	compressive	RT	3	Vice grip test, noDIC, strain rate normalised 0.00078 (1/s)
Fecov_6	63.70x20x0.256 F6-mod	compressive	RT	3	Vice grip test, DIC, strain rate normalised 0.00078 (1/s)
Fecov_7	dogbone F6	tensile	RT	1	Fractured in grip, n/a, strain rate normalised 0.00026 (1/s)
Fecov_8	dogbone F6	tensile	RT	1	Slipped in grip, n/a, strain rate normalised 0.00026 (1/s)
Fecov_9	dogbone F6	tensile	RT	1	Repeat above, n/a, strain rate normalised 0.00026 (1/s)
Fecov_10	63.70x19.50x0.256 F4	compressive	100	3	noDIC, strain rate normalised 0.00078 (1/s)
Fecov_11	63.7X19.50x0.256 F4	compressive	100	3	DIC, failure, strain rate normalised 0.00078 (1/s)
Fecov_12	63.7 F4	compressive	100	3	DIC, strain rate normalised 0.00078 (1/s)
Fecov_13	dogbone F6	tensile	200	1	Tensile on, n/a, strain rate normalised 0.00026 (1/s)
Fecov_14	dogbone F6	tensile	200	1	Tensile on, n/a, strain rate normalised 0.00026 (1/s)
Fecov_15	dogbone F6	tensile	200	1	Tensile on, n/a, strain rate normalised 0.00026 (1/s)
Fecov_16	63.70x19.50x0.254 F4	compression	200	3	Compression test, DIC, strain rate normalised 0.00078 (1/s)
Fecov_17	63.70x19.50x0.254 F4	compression	200	3	Compression test, DIC, strain rate normalised 0.00078 (1/s)
Fecov_18	63.70x19.50x0.254 F4	compression	200	3	Compression test, noDIC, strain rate normalised 0.00078 (1/s)
Fecov_19	dogbone	tensile	300	1	Save one sample (broken in gauge) for macro- and micrography
Fecov_20	dogbone	tensile	300	1	-
Fecov_21	dogbone	tensile	300	15 Hz	10k, 15 Hz cycles, max strain rate, 20N-100N
Fecov_22	jig	compressive	500	15 Hz	10k cycles, 15 Hz, max strain rate 10N-50N
Fecov_23	jig	compressive	500	15 Hz	10k cycles, 15 Hz, max strain rate 10N-50N
Fecov_24	jig	compressive	500	15 Hz	10k cycles, 15 Hz, max strain rate 10N-50N



Figure G.1: *Environmental Chamber Temperature control (a) Default thermocouple, (b) backup thermocouple*

Table G.2: *NdFeB testing procedure*

ID	Sample	Type	Temperature	Strain rate (mm/min)	Comments
Ndfeb_1	15x15x8	compressive	RT	0.1	-
Ndfeb_2	15x15x4	compressive	RT	0.1	-
Ndfeb_3	6diax8	compressive	RT	0.1	-
Ndfeb_4	15x15x8	compressive	RT	0.3	-
NdFeB_5	15x15x4	compressive	RT	0.3	-
Ndfeb_6	15x15x8	compressive	100	0.3	-
Ndfeb_7	15x15x8	compressive	100	0.3	-
Ndfeb_8	15x15x8	compressive	100	0.3	-
Ndfeb_9	15x15x4	compressive	100	0.3	-
Ndfeb_10	dia 6x8	compressive	100	0.3	-
Ndfeb_11	15x15x8	compressive	100	0.3	-
NdFeB12	15x15x8	compressive	200	0.3	-
NdFeB14	15x15x8	compressive	200	0.3	-
NdFeB15	15x15x4	compressive	200	0.3	-
NdFeB16	15x15x4	compressive	200	0.3	-
NdFeB17	dia 6x8	compressive	200	0.3	-
NdFeB18	dia6x8	compressive	200	0.3	-
Ndfeb_19	15x15x4	compressive	200	0.3	-
Ndfeb_20	15x15x4	compressive	200	0.3	-
Ndfeb_21	dia6x8	compressive	200	0.3	-
Ndfeb_22	dia6x8	compressive	200	0.3	-
Ndfeb_23	15x15x4	compressive	300	0.3	Save one 15x15x4 from 300 deg C for macro- and micrography
Ndfeb_24	15x15x4	compressive	300	0.3	Save one 15x15x4 from 300 deg C for macro- and micrography
Ndfeb_25	dia6x8	compressive	300	0.3	-
Ndfeb_26	dia6x8	compressive	300	0.3	-
Ndfeb_27	15x15x4	compressive	400	0.3	Save one 15x15x4 from 400 deg C for macro- and micrography
Ndfeb_28	15x15x4	compressive	400	0.3	Save one 15x15x4 from 400 deg C for macro- and micrography
Ndfeb_29	dia6x8	compressive	400	0.3	-
Ndfeb_30	dia6x8	compressive	400	0.3	-
Ndfeb_31	15x15x4	compressive	500	0.3	Save one 15x15x4 from 500 deg C for macro- and micrography
Ndfeb_32	15x15x4	compressive	500	0.3	Save one 15x15x4 from 500 deg C for macro- and micrography
Ndfeb_33	dia6x8	compressive	500	0.3	-
Ndfeb_34	dia6x8	compressive	500	0.3	-
Ndfeb_35	15x15x4	compressive	500	15 Hz	10k cycles, 15Hz, max strain rate 100N-800N
Ndfeb_36	15x15x4	compressive	500	15 Hz	10k cycles, 15Hz, max strain rate 100N-377N
Ndfeb_37	15x15x4	compressive	600	0.3	Save one 15x15x4 from 600 deg C for macro- and micrography
Ndfeb_38	15x15x4	compressive	600	0.3	Save one 15x15x4 from 600 deg C for macro- and micrography

Appendix H

FeCoV Procurement: LCD-Lasercut AG

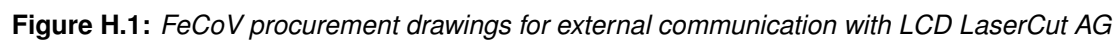
Quotation No. 241030/109/CW

Test lams (6 geometries) According to the attached drawing Laminations laser cut and bundled with adhesive tape Micro-joint on outside diameter Tolerances IT8/it8 but minimum tolerance range 0.04mm Magnetic steel Vacodur49 x 0.254 magnetically optimized annealed before lasercutting

Table H.1: *Bill of Materials: LCD LaserCut AG procurement*

ID	dims [mm]	quantity
F1	5	4
F2	12.7	4
F3	10x7	20
F4	63.7x19.5	20
F5	25x10	4
F6	ISO "dogbone"	20

Delivery time: 2 weeks ex works (delivery dates are valid after receipt of official order and DXF-files). Final inspection: Standard LCD LaserCut AG with signed customer drawing but without (3D)-measuring report. Base of prices: unpacked, ex works, without VAT, 30 days net This quote is based on our general terms and conditions We are certified according to ISO 9001:2015 and ISO 14001:2015 Validity of quote: 4 weeks



Appendix I

Jigs Procurement: MetalCube Sp. z o.o. and Xometry

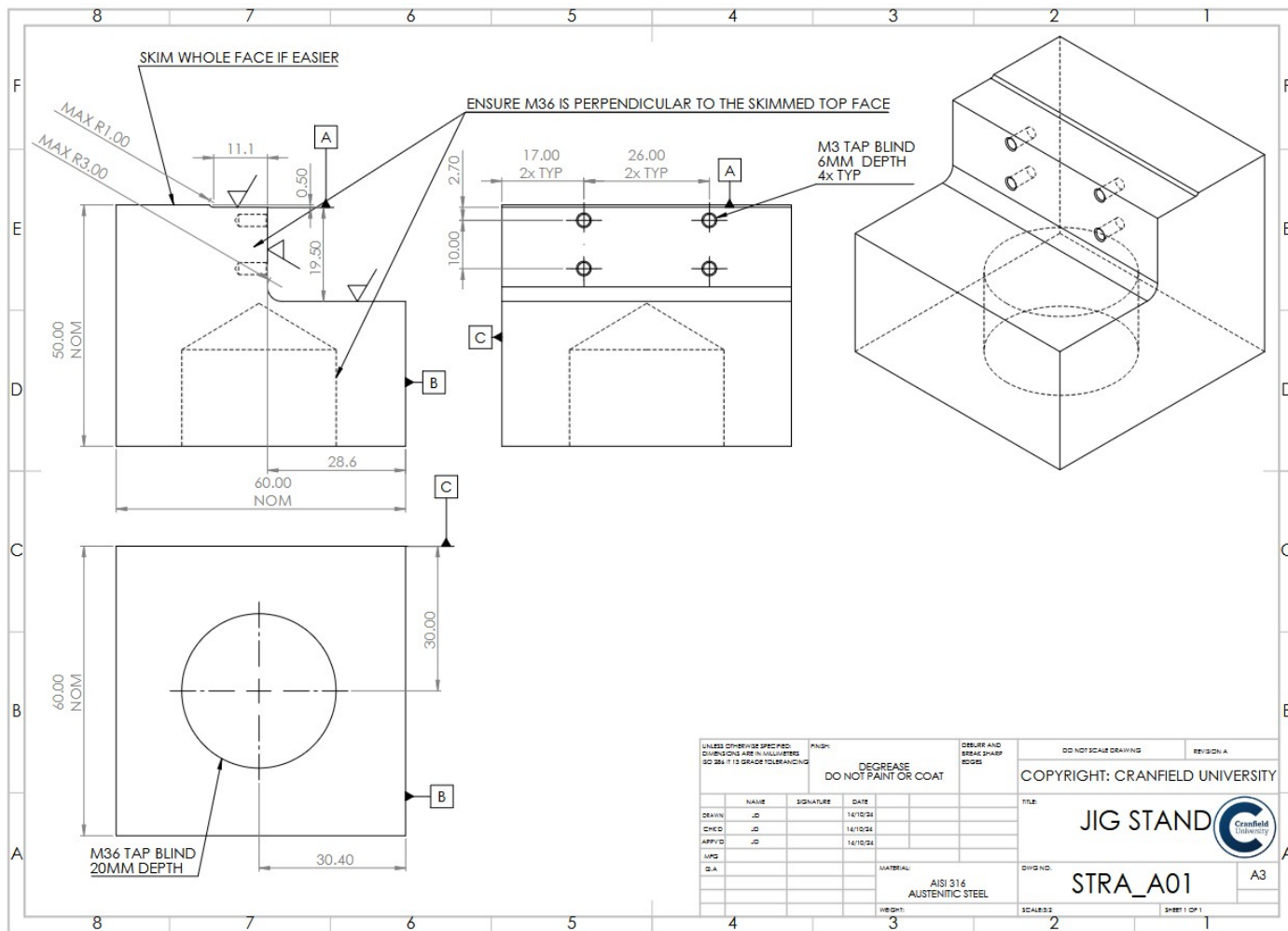


Figure I.1: Drawing of the part A01

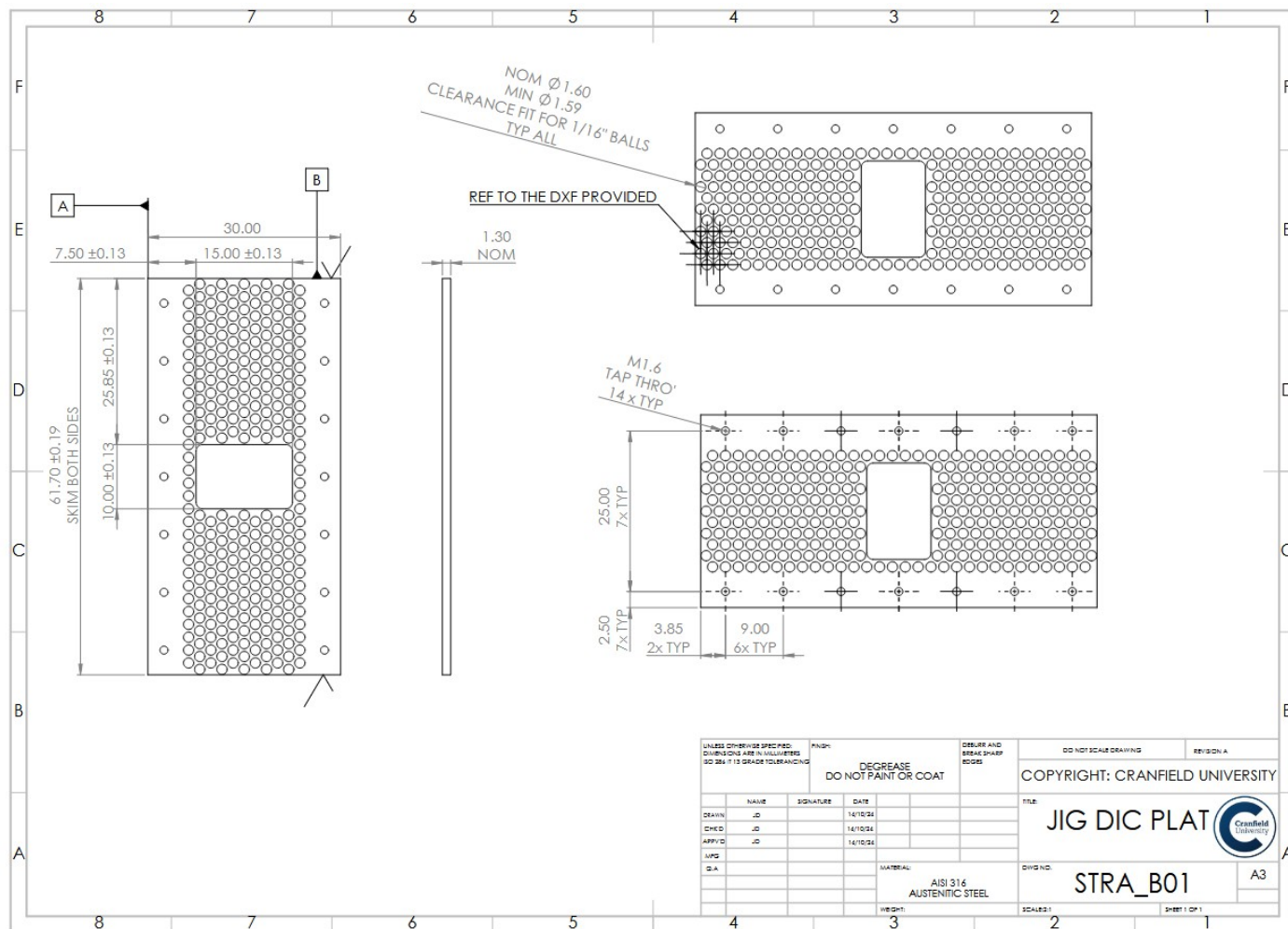


Figure I.2: Drawing of the part B01



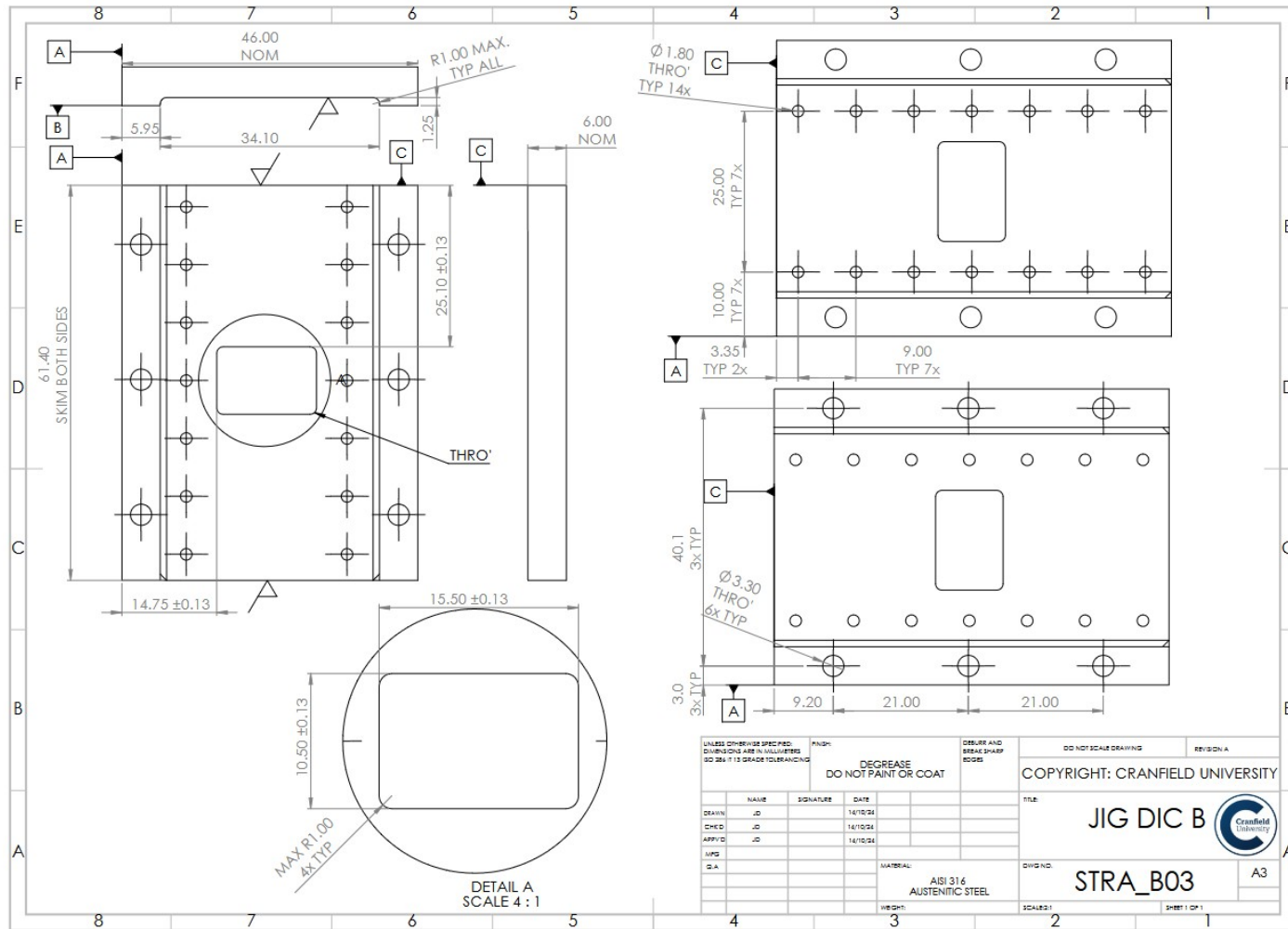


Figure I.4: Drawing of the part B03

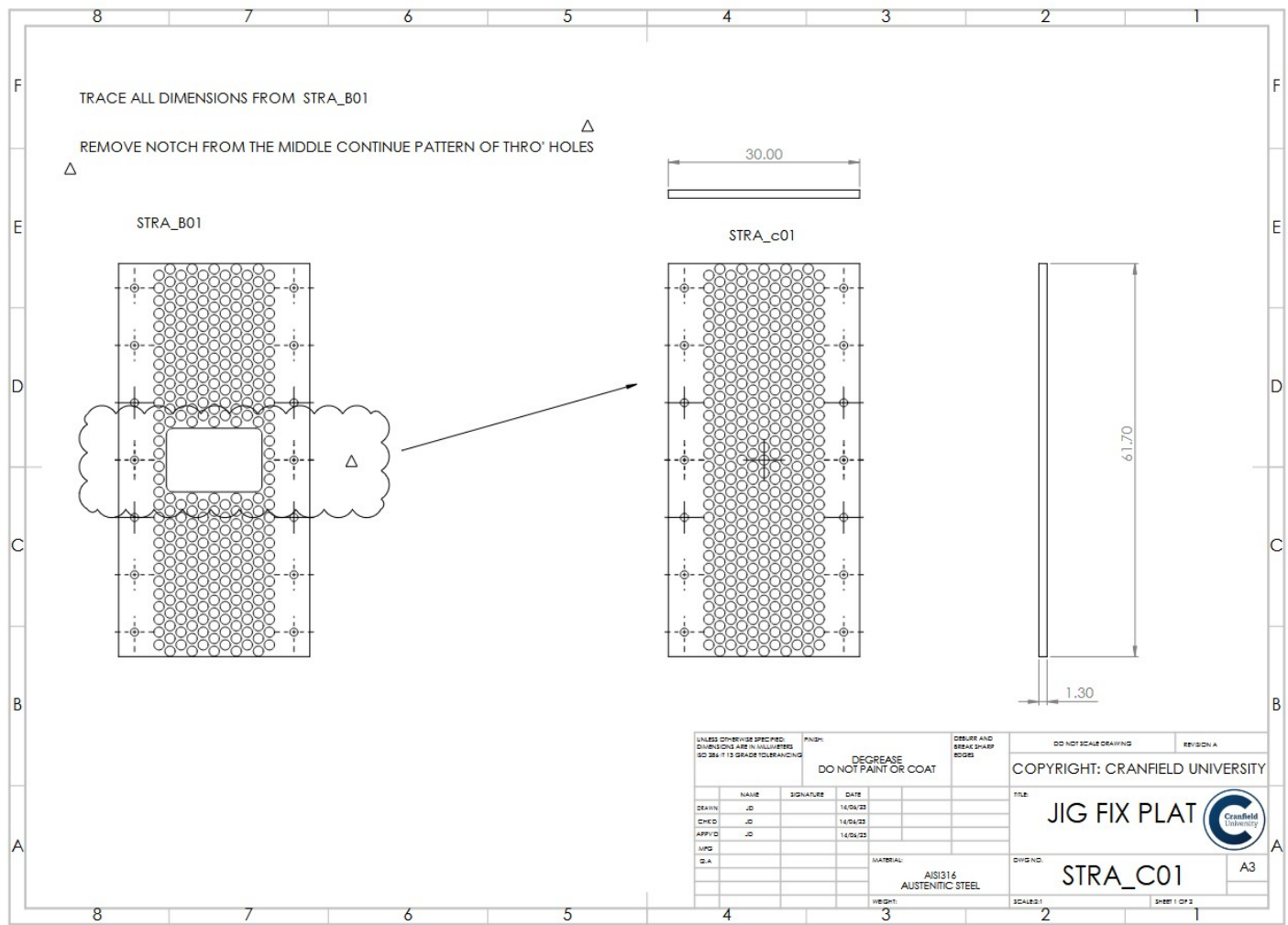


Figure I.5: Drawing of the part C01

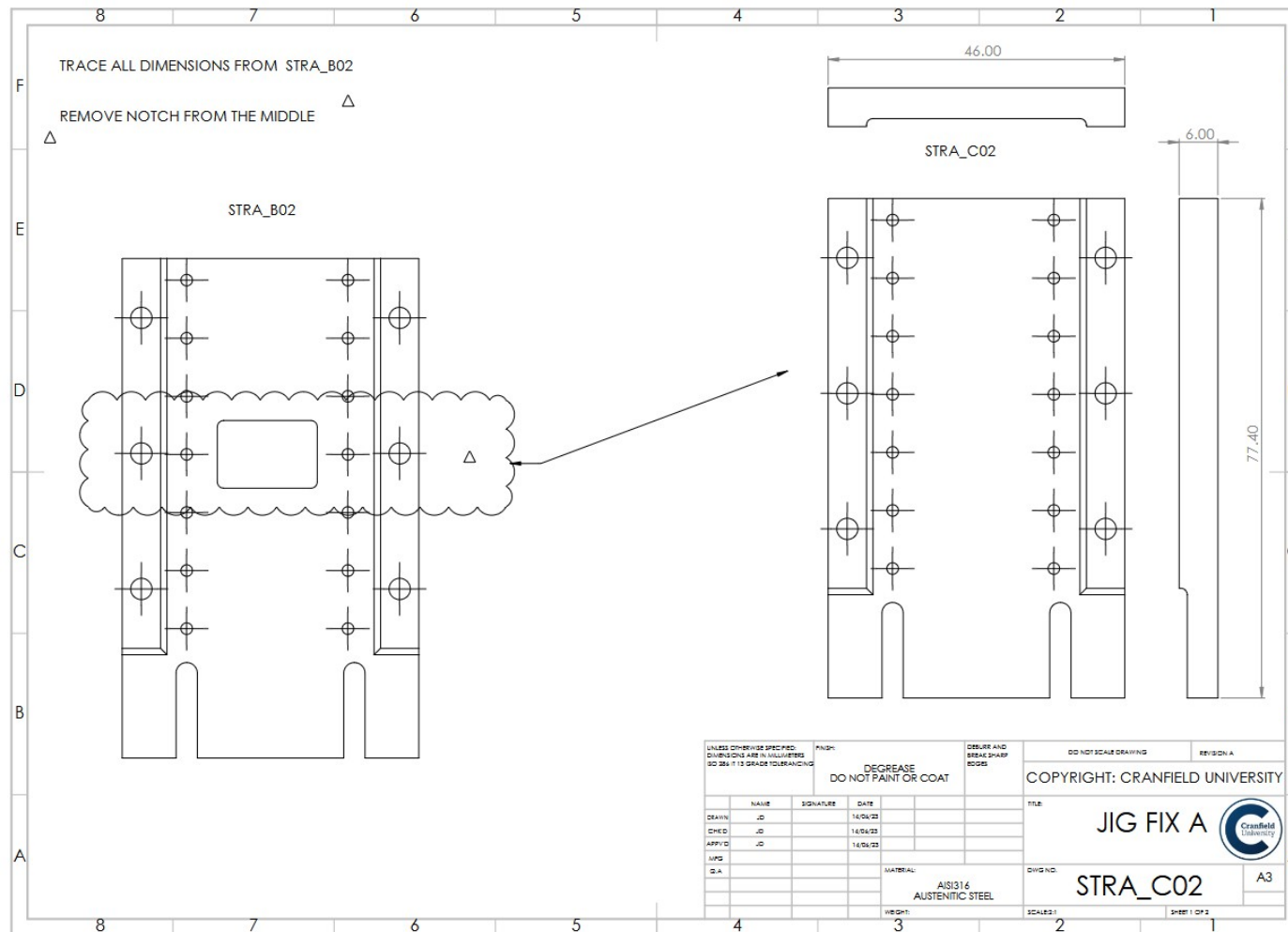


Figure I.6: Drawing of the part C02

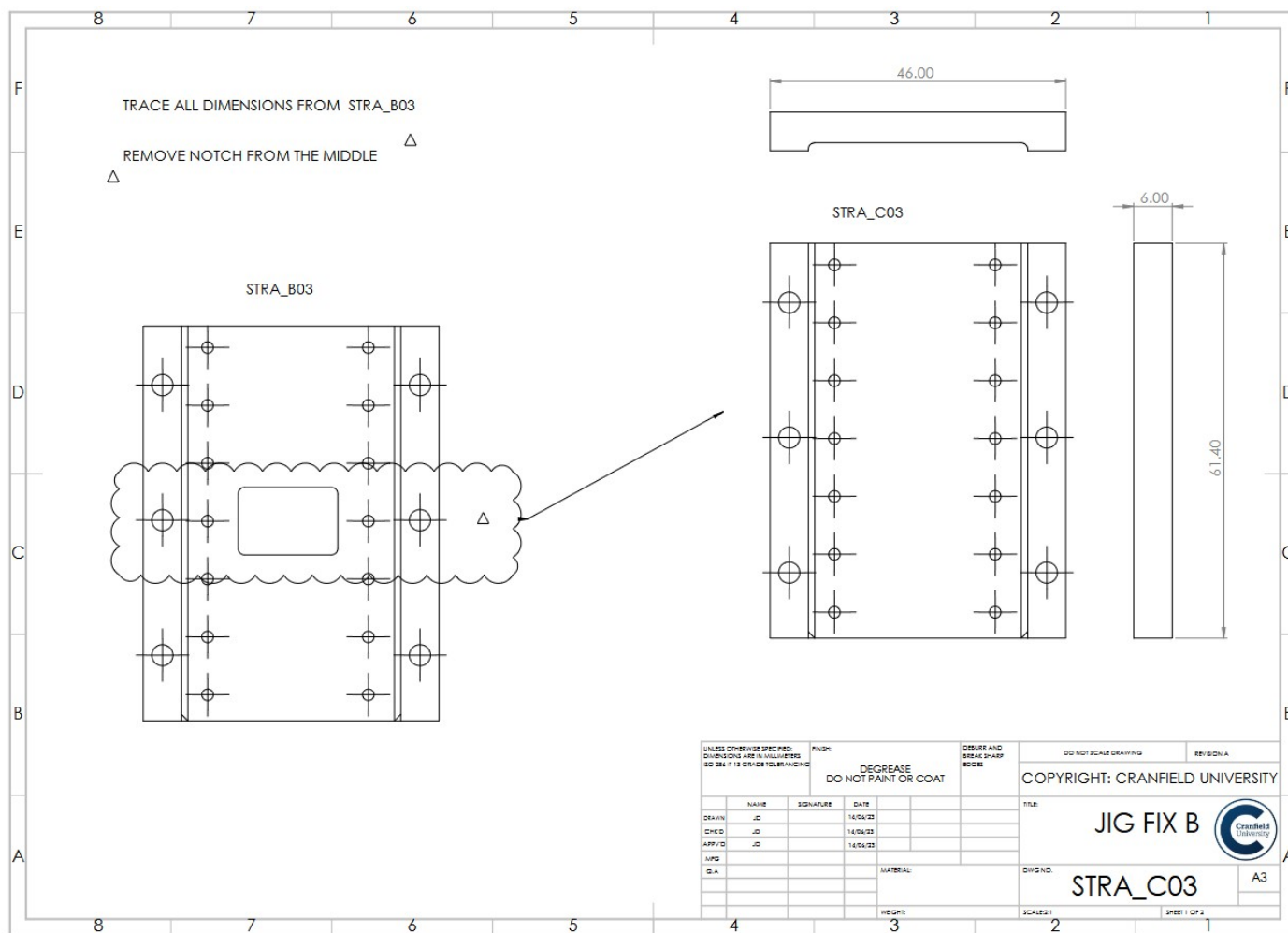


Figure I.7: Drawing of the part C03

产品质量证明书 INSPECTION CERTIFICATE

订货单位: 无锡宝昌金属制品有限公司 Customer: 无锡宝昌金属制品有限公司		产品名称: 不锈钢 Product: stainless steel		
收货单位: 无锡太钢销售有限公司 Purchaser:		交货状态: Condition:		
标准Specification EN 10204-3.1	牌号Grade SUS316L	合同号MITS No. 654779-70 客户订单Customer Order No. 0000663102	证书编号Certificate No. 6144911697899101 提单号Consignment No. 0803235636 车号Train Wagon No.	

序号 No.	材料号 Material No.	炉号 Heat No.	规格 Dimensions (mm)	数量 Quantity	重量 Weight(t)
1	FA706C5010W00	A2701999	Φ70*1000	1	30.196
尺寸及外观Acceptable Visual And Dimensions:合格OK 合计Total 1 30.196					



序号 No.	分析 Max. Min.	C%	Si%	Mn%	P%	S%	Cr%	Ni%	Mo%
1	H	0.02	0.44	1.14	0.029	0.002	16.10	12.05	2.44

序号 No.	位置	屈服强度	抗拉强度	伸长率	硬度
	方向	Y.S.	T.S.	EL	Hardness
	P.D.	Rp0.2 Mpa	Rm Mpa	A50 %	HRB
		常温	常温	常温	常温
	Max. Min.				
1	2	277	647	57	80.5

注释 Notes	M=Not cutting edge; H=冶炼分析Heat analysis; P=成品分析Product analysis; Y.S.=Yield Strength; 常温Room = Normal Temperature (Room Temperature); T.S.=Tensile Strength; EL=Elongation; A50.Lo=50mm; Z=纵向Transverse;
声明 Declare	本产品仅限国内销售不得出口, 经销商向用户出具本质量证明书复印件需加盖其公章。This product is for domestic sales in China only. Export is not allowed. This certificate, if provided by a re-seller in photocopy, is invalid unless with the re-seller's company stamp.
备注 Remarks	

声明: 本产品已按上述要求制造和检验, 结果符合要求, 特此证明。
We Hereby Certify That Material Described Herein Has Manufactured And Tested With
Satisfactory Results In Accordance With The Requirements Of The Above Material Specification.



中国 山西 太原市尖草坪街2号 邮编030003
Jiancaoping, Taiyuan, Shanxi, P.R. China. zip code 030003
服务热线 After-sale Service: 800-806-1998, 400-653-1998

SUN MINGSHAN
质量负责人 Quality Manager

日期Date: 2024/6/5 页码Page: 1/1

Figure I.8: AISI 316L Material Certificate from Xometry

APPENDIX I. JIGS PROCUREMENT: METALCUBE SP. Z O.O. AND XOMETRY

059261

sij acroni

10230278-21000018-277735

Izdajatelj Certifikata:
Originator of Inspection Document:
Aussteller der Bescheinigung:

SIJ ACRONI, d.o.o.
KRT-KAKOVOST
Cesta Borisa Kidriča 44
SI - 4270 Jesenice
Slovenia, EU

Tel.: +385 4 584 10 16
Fax: +385 4 584 10 71
E-Mail: gorazd.kosec@acroni.si
W: <http://www.acroni.si>

Page 1 / 4

Prezjemni certifikat 3.1 / Inspection Certificate 3.1 / Abnahmeprüfzeugnis 3.1 EN 10204:2004		 Tomasz Dzieński Waldemar Jarmula Agnieszka Jarmula Spółka jawna ul. Kochanowskiego 37, 33-100 Tarnów REGON 120698988 KRS 0000306076 NIP 0030557000	
Št. dokumenta / Document No. / Bescheinigungs Nr. 10230278-21000018-277735 z / dated / vom 29.04.2024		Proizvajalčeva št. naročila / Manufacturer's works order No. / Werksauftrag Nr. 21000018 z / dated / vom 25.03.2024	
Kupčeva št. naročila / Purchaser's order No. / Kundenbestell Nr. 93863		Kupčeva št. izdelka / Purchaser Article No. / Artikel Nr. des Kunden	
Št. Dobavnega lista / Packing list No. / Lieferschein Nr. 10230278 z / dated / vom 29.04.2024		Datum izdaje / Date of Issue / Ausgabedatum 29.04.2024	
Št. Računa / Account No. / Kontonummer 24201108525			
Izdelek / Product / Erzeugnis DEBELA PLOČEVINA / HOT ROLLED PLATE / WARMGEWALZTES GROBBLECH			
Zahteve / Requirements / Anforderungen		Oznaka jekla / Steel designation / Stahlbezeichnung	
ASME SA-240/SA-240M; BPVC.II.A-2023		S31600 316	
ASTM A240/A240M-23a		S31600 316	
ASME SA-240/SA-240M; BPVC.II.A-2023		S31603 316L	
ASTM A240/A240M-23		S31603 316L	
EN 10028-7:2016		1.4401 X5CrNiMo17-12-2	
EN 10088-2:2014		1.4401 X5CrNiMo17-12-2	
EN 10088-4:2009		1.4401 X5CrNiMo17-12-2	
EN 10028-7:2016		1.4404 X2CrNiMo17-12-2	
EN 10088-2:2014		1.4404 X2CrNiMo17-12-2	
EN 10088-4:2009		1.4404 X2CrNiMo17-12-2	
PED-2014/68/EU			
Customer Grade		HOT ROLLED STAINLESS STEEL W.NR.1.4404	
Specifikacija kupca / Customer specification No. / Kundenspezifikation			
Dodatne zahteve / Supplementary requirements / Zusätzliche anforderung			
Dobavno stanje / Product delivery condition / Lieferzustand des Erzeugnisses TOPILNO ŽARJENO, LUŽENO / SOLUTION ANNEALED, PICKLED / LÖSUNGSGEGLÜHT, GEBEIZT			
Stanje površine / Surface finish / Oberflächenbehandlung ASME Finish: No. 1 - on both sides ASTM Finish: No. 1 - on both sides Brez popravila z varjenjem / No weld repair / Keine Schweißreparatur EN Surface: 1D - on both sides EN10163:B3			

Figure I.9: AISI 316L Material Certificate from MetalCube

Appendix J

Lumped Thermal Network: MATLAB/Simulink implementation

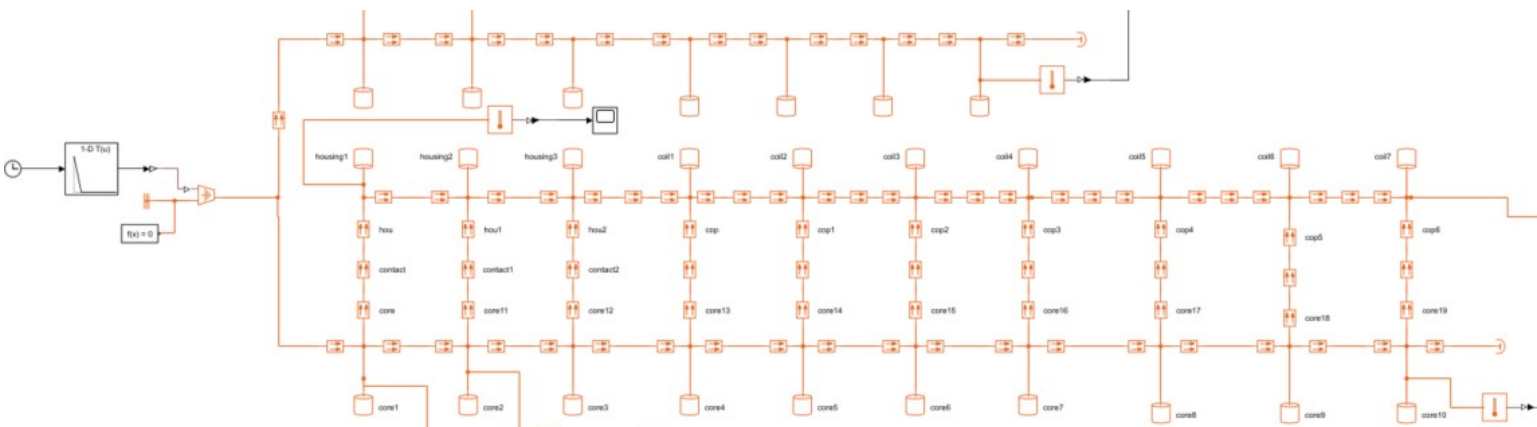


Figure J.1: *Lumped Thermal Network: MATLAB/Simulink implementation*

Appendix K

Cranfield University Ethical Approval Evidence

APPENDIX K. CRANFIELD UNIVERSITY ETHICAL APPROVAL EVIDENCE



16 June 2021

Dear Mr Deja ,

Reference: CURES/13892/2021

Title: Energy Recovery for Commercial Aircraft During Landing Phase

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your CURES application, reference CURES/13892/2021 has been reviewed. You may now proceed with the research activities you have sought approval for.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team