

CRANFIELD UNIVERSITY

ADEDAYO AJAYI

FUTURE GRID FOR A SUSTAINABLE GREEN AIRPORT:
MEETING THE NEW LOADS OF ELECTRIC TAXIING AND
ELECTRIC AIRCRAFT

SCHOOL OF WATER, ENERGY, AND ENVIRONMENT

Thesis Submitted for the Degree of

Doctor of Philosophy

PhD

Academic Year: 2019- 2023

Supervisor: Prof Patrick Chi-Kwong Luk

Associate Supervisor: Dr Liyun Lao

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Abstract

This thesis proposes a novel electric grid in the airside to meet zero-emission targets for ground movement operations in future airports, as mandated by Aeronautics Research performance target in Europe's (ACARE) FlightPath 2050. The grid delivers power from a renewable energy source through a flexible powerline using an autonomous electric taxiing robot (A-ETR) based on the concept of Energy As A Service (EAAS) for taxiing large aircraft and charging stations for ground vehicles. Four layers of optimisation are required to realise the viability of this new grid. **The first optimisation layer** involves creating an analytical model of the A-ETR using real-world data from Cranfield University's Airport based solar PV system and its Boeing 737 research aircraft and optimising its performance and efficiency using vehicle-level data-driven machine learning-based optimisation. As a result, the proposed grid achieves zero-emission taxiing and a 91% reduction in fuel compared to a standard baseline.

The second layer optimises energy management in the microgrid using machine learning-based forecasting models to predict PV output and optimise charging and discharging cycles of A-ETR batteries to match solar resources and electricity rates. The result shows that the support vector regression (SVR) model best predicted PV output and optimised BESS charge/discharge cycles to achieve zero-emission airport ground movement operations while reducing the microgrid operating costs. However, ground traffic and load profiles increase as the model expands to include commercial airports. Therefore, **the third optimisation layer** develops a machine learning-based data-driven energy prediction optimisation to ensure microgrid resilience under the increased load. The model employs the Facebook Prophet algorithm to enhance the precision of energy demand prediction for airport ground movement operations across three-time horizons. The results facilitate the generation of reliable forecasts for clean energy production and ground movement energy demand at the airport.

A fourth layer of optimisation has been developed to address the limitations of solar PV energy, which depend on the weather and cannot be dispatched, as well

as the increase in airport traffic. The layer uses wind power and data from a "green" airport to complement PV power output. This model uses the stochastic model predictive control-based cascade feedforward neural network (SMPC-CFFNN) to optimise power flow between the microgrid and RES sources and support V2G capabilities. The results demonstrate that a Zero-emission microgrid for ground movement at green airports can be achieved through optimal power flow management and time optimisation.

Reliability and resilience are crucial for a proposed microgrid ecosystem. We consider different network configurations to connect the existing airport grid. Two microgrid architectures, LVAC and LVDC, are compared based on their point of common connections (PCC) to evaluate the technical and economic implications on the airport's distribution network. We verify and validate the model's performance in terms of power quality, short circuit fault levels, system protection requirements, voltage profile, power losses, and equipment/system overloading to determine the optimal architecture. The results indicate that the A-ETR can provide ancillary services to the grid and enable novel emergency response systems. The comprehensive results from the multi-layered system-level optimisation approach adopted in this thesis not only validate the novelty of the proposed study but also serve to provide compelling evidence for its potential to provide viable solutions to the electrification challenges for future green airports by creating an ecosystem between airport ground operations and on-site renewable energy generating sources.

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List of Abbreviations

ACARE	Advisory Council of Aeronautics Research in Europe
AEA	All electric aircraft
AGPS	Airport ground propulsion system
ANN	Artificial neural network
APU	Auxiliary power unit
ASAI	Average service availability index
ASPV	Airport-based solar PV
A-ETR	Autonomous electric taxiing robot
Axel speed(max)	Maximum axel speed
BESS	Battery energy storage system
CO ₂	Carbon dioxide
CERTs	Consortium for electric reliability technology solution
CFCT	Critical fault clearing time
CFFNN	Cascaded feed-forward neural network
DSM	Demand side management
EAAS	Energy as a service
ECS	Environmental control system
EDA	Exploratory data analysis
EGSE	Electric ground service equipment
EGSV	Electric ground support vehicle
ENS	Energy not serve
E-taxiing	Electric taxiing
ETS	Electric taxiing system

EV	Electric vehicle
EVBs	Electric vehicle batteries
FCFS	First come first serve
GPU	Ground power unit
GSEV	Ground support electric vehicle
GSE	Ground support equipment
ICAO	International civil aviation organisation
LLA	London Luton Airport
LTO	Landing and take off
LVDC	Low voltage d.c
LVAC	Low voltage a.c
MAAS	Mobility as a service
MAE	Mean average error
MAPE	Mean absolute percentage error
MDAPE	Median absolute percentage error
MEA	More electric aircraft
MES.	Main engine start
MG	Microgrid
MILP	Mixed integer linear programming
MOAED	Multi-objective optimisation algorithm
MSE	Mean square error
MTOW	Maximum take-off weight
NSGA	Non-dominated sorting genetic algorithm
NOx	Nitrogen oxide

P-HEVs	Plug-in electric vehicles
PMW	Pulse width modulator
PSO	Particle swarm optimisation
RMSE	Root mean square error
SAIDI	System Average Interruption Duration Index
SAIFI	System average interruption frequency index
SMAPE	Symmetric mean absolute percentage error
SMPC	Stochastic model predictive controller
SOC	State of charge
SVR	Support vector regression
TCPD	Total cost per day
Torque axel (max)	Maximum axel torque
Torque motor(max)	Maximum motor torque
TOU	Time of use market price
TSA	Time series analysis
VRES	Variable renewable energy source.
VRPTW	Vehicle routing problem with time windows
V2G	Vehicle to grid

Nomenclature

ζ	Battery efficiency	(%)
ρ_l	Lower bound on the continuous workload variable	
Δt	Time stage interval length	(s)
ρ_u	Upper bound on the continuous workload variable	
E_T	Cumulative energy requirement	(kW)
f	Forecasted number of flights	
C_B	Battery degradation cost	(£/kWh)
$C_{BSS}^{Av}(k)$	available capacity at BSS at instant k	(kWh)
CGN	Price per kWh of the grid-supplied energy at stage M	(£/kWh)
C_{GT}	Price per kWh of the grid-supplied energy	(£/kWh)
C_{it}	Energy cost of the i^{th} EGSV	(£)
$C_{PV}(t)$	Cost of solar PV dispatched	(£)
C_R	Energy price per kWh from the renewable source	(£/kWh)
d_j	Stages of delay	
ds	Distance travelled on charging task	(km)
dT	Distance travelled on towing task	(km)
Dt	Power of discharging of BESS during t^{th} time interval	(kW)
d_{thre}	Threshold delay	(s)
EI_{eng}	Emission index of aircraft engine	(g/kg fuel)
ξ_i	Training error	
F_{drag}	Aerodynamic drag force	(N)
F_{dual}	Total fuel consumption of aircraft taxiing with double engine	(kg)

F_{engine}	Fuel consumption of an aircraft taxiing	(kg)
F_{etaxi}	Total fuel consumption of aircraft taxiing with autonomous electric taxiing	(kg)
F_{grade}	Grade resistance force	(N)
FLA	Linear acceleration force	(N)
F_{traction}	Traction force	(N)
$F_{\text{traction (max)}}$	Maximum traction force (N)	
i	EV index	
I_{trmax}	Maximum iteration	
j	Flight index	
MEV	Total number of EVs	
$N_{\text{UDP}}(t)$	Number of charging pile	
$P_{\text{air}}(t)$	General airside lighting load at time t	(kW)
$P_g(t)$	Power injected by the utility grid	(kW)
$P_i^{\text{dch}}(k)$	Sum of discharging power of vehicles	(kW)
$P_i^{\text{ch}}(k)$	Sum of charging power of vehicles	(kW)
$P_j^{\text{A}}(k)$	Charging load of class A electric vehicle	(kW)
$P_j^{\text{B}}(k)$	Charging load of class B electric vehicle	(kW)
$P_j^{\text{app}}(k)$	Electric load of all-electric applications in the airport	(kW)
$P_L(t)$	The load demand	(kW)
$P_{\text{re}}(k)$	Accumulative power of renewable resources	(kW)
$P_{\text{sr}}(k)$	Surplus power generation	(kW)
P_t	Total cost	(£)

$P_{t,n}$	Power of charging of the A-ETR battery of nth charging cycle during t^{th} time interval	(kW)
$P_{t\ bess}$	BESS charging power during t^{th} time interval	(kW)
$P_{traction}$	Traction power	(kW)
$P_{v_mg}(k)$	Bidirectional power flow from electric vehicles to microgrid	(kW)
$P_{pv}(k)$	PV power	(kW)
$P_w(k)$	Wind power	(kW)
t	Time stage index	
U_{it}	Control decision variable of the EGSV battery	
V_{it}	Discrete state of charging and working of the i^{th} EGSV	
v_s	Velocity during charging task	(km/h)
v_T	Velocity during towing task	(km/h)
X_{im}	SoC of the i^{th} EGSV	(%)
X_{max}	Upper bound of the SoC	(%)
X_{min}	Lower bound of the SoC	(%)
Z_c	Energy consumption during each stage	(kWh)
Z_{jt}	Number of the stages required for an EGSV to serve j^{th} flight that is waiting for service at stage t	
Z_w	Energy discharge at stage t	(kWh)

1. Introduction

1.1 Background

The aviation industry has developed globally and played an important role in developing a connection between countries. Despite the aviation industry having significant economic and socio-environmental impacts, it is constrained to achieve stringent performance targets to share its role in reducing the adverse environmental impacts along with meeting expectations of the increased number of passengers. According to Airbus's global market prediction for 2019–2039, air traffic is expected to increase by 4.3% annually over the next 20 years, which will result in a nearly twofold increase in flight numbers by 2040 [1]. Globally, other stakeholders predict a similar trend; that is, aviation will continue to grow in capacity until 2030-2040. Examples include the international air transport association (IATA) projected an average annual growth rate of 3.9% until 2036 [2], while the airport council international (ACI) and international civil aviation organisation (ICAO) predicted a 4.5% average annual growth rate up to 2040 [3].

The aforementioned predictions are positive signs for the aviation industry and, perhaps, for the world economy. However, the current global scenario requires economic growth that is well aligned with sustainable approaches. The aviation industry is certainly not excluded from adhering to the path of sustainable growth and therefore facing challenges in pursuing the path of sustainable growth [4].

A total of 30% of global CO₂ emissions are attributed to the transportation sector, out of which 8% are attributed to the aviation sector, as illustrated in Figure 1-1 for the distribution of CO₂ emissions from transportation by subsectors in 2020. Approximately 80% of these emissions are linked to international flights and 20% to domestic flights [5]. Therefore, the aviation industry needs to adopt greener practices in its operation.

Although the aviation sector's contribution makes up a small portion of the carbon dioxide emission by sectors, as shown in Figure 1-1, however, the impact is significant due to its high latitude. According to a recent study, aviation might use up to one-sixth of the temperature budget that is still needed to reduce global warming to 1.5 degrees

Celsius by 2050. Therefore, aviation emissions must be lowered annually to prevent future global warming [6]. This decarbonisation effort will start from the airport ground level, where a lot of new technology can be directly applied.

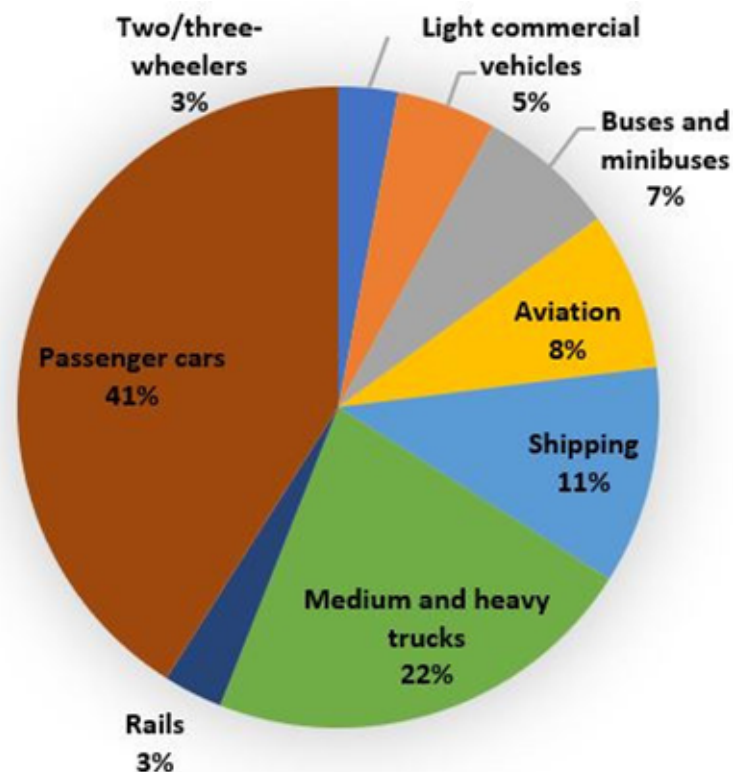


Figure 1-1 Distribution of carbon dioxide emissions produced by sectors worldwide in 2020, (%) [7]

Aviation regulatory bodies have proposed different approaches to reduce airport emissions without reducing the profit margin for both airborne and ground operations. Prominent among these approaches is the electrification of the airport operations, which is key to achieving the Advisory Council for Aviation Research and Innovation in Europe's (ACARE) Flightpath 2050's zero-emission objectives for green operations in the airport.

As a key stakeholder responsible for achieving the Flightpath 2050 objectives, the aviation industry is expected to reduce CO₂ emissions per passenger mile by 75%, nitrogen (NO_x) emissions by 90%, minimise noise and make airports emission-free by 2050 [3], [8], [9]. The ground movement operation of aircraft (Taxiing) is classified among the major contributors to greenhouse gas emissions, noise, and considerable

fuel losses at airports. This high emission rate is due to the aircraft's low efficiency-to-fuel consumption ratio during taxiing because jet engines are designed to run efficiently at cruising speed [10]. Since the last decade, airports have seen an increase in aircraft taxiing time due to air traffic growth, with taxiing in and out operations over 63 and 150 million minutes, respectively, by aircraft from their Apron in the United States in 2007 [11]. Further, it is estimated that single-aisle planes, which account for over 80% of regional flight traffic, consume 6 to 10% of their estimated fuel for regional flights during taxiing [12],[13]. In addition, big aircraft engines, such as the A380, emit as much as 5 kg of carbon per second during taxiing [14]. Taxiing can be carried out in one of the following ways: (i) Complete engine taxiing, (ii) Single engine taxiing, (iii) Operational towing and (iv) Electric taxiing. Each method has pros and cons concerning operational effectiveness,[11] [15] [16],[17],[18],[19],[20]. The electric taxiing system produces the least emission and is closer to achieving the zero-emission taxiing operation objective of FlightPath 2050 [21].

However, the airport's carbon footprint can be significantly reduced further if a renewable energy source is used to charge the electric taxiing system. The solar power system is considered the most suitable renewable energy source for the airport environment because of its modularity and availability of large land regions that can be used for solar systems [22], [23],[24]. Therefore, creating a link between the electric taxiing system and the onsite solar PV will further reduce operational costs and the carbon footprint of the airport towards achieving zero-emission ground transportation as required by the Flightpath 2050 policy. Wind energy is not considered because wind turbines near airports have the potential to create physical obstacles and interference with aircraft communication. In addition, the air navigation order (aviation law) also prohibits structures taller than 500 feet near airports [25]. These restricted zones are referred to as aeronautical easements [26]. Easements are needed when wind energy is extracted close to airports to prevent or reduce other negative impacts that could be hazardous to air navigation. Examples include (i) turbulence, which could affect take-off or landing procedures, and (ii) interference with the navigation system and the Air Traffic Control (ATC) [25].

This study aims to reduce emissions during aircraft ground movements and other ground movement operations at the airport using a novel microgrid infrastructure. Our

proposed microgrid will embody a novel autonomous electric taxiing system (A-ETS) to act as a mobile grid to connect aircraft ground movement operations to onsite solar PV. In addition, the A-ETS will perform plug-and-play roles to either serve as a load while charging or a generator delivering electric power to support ancillary and backup operations in the microgrid. This approach will deliver power close to the load without using a transmission infrastructure to send it over large distances. As a result, the power system's losses will be drastically reduced, negating the need for grid expansion to increase generation capacity.

1.1.1 Existing airport grid and their limitations.

According to research, the increased energy load due to the electrification of operations in the airport, among which are electric taxiing, charging stations for small electric aircraft, and ground support equipment, will likely strain the current power system [27]. In addition, the concerns spill over to the grid when many electric aircraft are being charged [28]. As a result, it is expected that several grid components, including distribution transformers, primary lines, substations, main circuit breakers, and protection, will need to be upgraded, resulting in considerable capital infrastructure investment. In addition, an all-electric aircraft with 30-minute flight turnaround times would require an increase in airport electric capacity of up to 2 MW, which would add a sizable increase in load to the grid [29].

However, most airport electrical systems have not traditionally been designed to enable such megawatt-level charging [30]. Therefore, providing that level of capacity from the grid will require an expensive expansion project. However, utilising onsite power generation and energy storage can lower the requirement for a grid upgrade [31]. As a result of recent advances in smart grid technology, powering clean energy systems from renewable resources and monitoring them with smart sensors and intelligent energy management systems has proved to be a more reliable and cost-effective energy system [32]. The airport's new electric grid system will represent a significant shift from the current infrastructure. It will promote distributed power generation with renewable power systems, as described in Table 1-1.

Additionally, it encourages the two-way exchange of information and power. The concept provides an appropriate framework for incorporating mobile storage systems

as new network players, boosts system robustness, and provides resilient operation. However, to securely transport mobile batteries for grid system support, some of the techniques used are secure containers, real-time tracking, safety protocols, and following regulations. Also, strong cybersecurity measures should be in place to prevent unauthorized access or tampering with the system's software or data [33]. It will further promote artificial intelligence and machine learning-based power management systems to improve the efficiency of operations [34].

Table 1-1 Airport existing grid VS future grid

Existing grid	Future grid
<ul style="list-style-type: none"> • Unidirectional electric power flow 	<ul style="list-style-type: none"> • Bi-directional electric power flow
<ul style="list-style-type: none"> • Centralised generation system 	<ul style="list-style-type: none"> • Distributed generation system
<ul style="list-style-type: none"> • Manual restoration after fault 	<ul style="list-style-type: none"> • Enable predictive maintenance and Self -healing
<ul style="list-style-type: none"> • Prone to failures and blackout 	<ul style="list-style-type: none"> • Adaptive and Islanding
<ul style="list-style-type: none"> • Few choices for Airport operators 	<ul style="list-style-type: none"> • Airport operators act as prosumers with more choices
<ul style="list-style-type: none"> • Did not support the integration of EVs 	<ul style="list-style-type: none"> • Enable incorporation of EVs and new energy storage alternatives.
<ul style="list-style-type: none"> • Centralised management system 	<ul style="list-style-type: none"> • Decentralised management

1.1.2 Grids for airport electrification

In the late 1880s, Nikola Tesla, George Westinghouse, and Thomas Edison competed to determine the best type of electricity system - alternating current (AC) or direct current (DC). But because AC (at the time) had so many advantages over DC, DC was eliminated from the contest, and AC won [32]. Subsequently, the AC became the main voltage of the electrical system up to the 20th century [35]. Airports are considered critical infrastructures whose operation depends on resilient and reliable energy and transportation infrastructure, and a lack of robust and reliable electricity would disrupt airport operations. This disruption would result in flight delays, protracted layovers, interruptions in the cargo industry's revenue-generating operations, and a reduced capacity for emergency support [36]. In addition, airport operations can be

severely disrupted when there is a power outage due to the control tower, navigation radio, and landing lights required to land an aircraft. Given the stated reasons, a microgrid can offer a cost-effective, dependable, resilient and uninterruptible electricity supply required in critical infrastructure such as the airport [37], [38]. The following incidents demonstrate the need for dependable and resilient airport electricity: For example, nearly 1,400 flights were cancelled due to the 11-hour outage at Hartsfield-Jackson Atlanta International Airport on December 17, 2017, affecting 30,000 passengers with severe financial repercussions. The outage was caused by a fire in an electrical utility service tunnel, which disrupted the primary and redundant feeders to the airport. In addition, there have been power outages at La Guardia Airport, John Wayne Airport, Los Angeles International Airport, Heathrow Airport and, most recently, Salt Lake City International Airport. These incidents demonstrate how crucial energy dependability and resiliency are for airports [36].

Luton Airport suffered a 20-second power outage on July 5, 2022, resulting in cancelled and delayed flights. The power outage was caused by a lightning strike, which also temporarily disabled navigational aids at the airport. According to reports, twelve flights were cancelled at the airport that day. Also affected are people waiting to pick up loved ones on the ground. Microgrids would have provided definite benefits in this circumstance [39], [40], [41].

Airports are critical infrastructures that support various interrelated energy and transportation end users, including passengers, businesses, airlines, cargo & logistic services, and in some instances, governments. Different authorities are in charge of various types of airports at different levels, i.e., international, continental, or local levels. Because each of these jurisdictions has specific planning and operational requirements, it is challenging from a regulatory perspective to standardise microgrid systems for the airport [36]. This thesis proposed a mobile microgrid system to address these challenges by creating a flexible grid system controlled by a machine learning-based energy management system to replace the existing rigid physical overhead lines.

1.2 Types of microgrid

Microgrids can be built to accommodate either direct current (DC) or alternating current (AC). Each solution has unique qualities, which suggest various benefits and drawbacks depending on the application requirements that should be considered. The ability to operate both connected to and disconnected from the mains grid is the main property of microgrids. Control, safety measures, and power loss comparisons between the two types of microgrids are provided in [35], [42]–[45]. However, choosing the right interconnection switch requires careful consideration of the microgrid technology and whether AC or DC is preferred.

1.2.1 AC microgrid

An AC microgrid is an isolated AC electric power system formed by a portion of the network made up of distributed generation (DG) units and load circuits. There are three primary types of AC microgrid distribution systems: single phase, three phases without neutral, and three phases with neutral [45]. The AC microgrids are connected to the utility at the point of common coupling, while the loads are provided by local sources (like RES-based DG units) and, if necessary, from the utility. If the amount of energy demanded by the load is less than the amount of energy produced by the DG units, excess energy can be exported to the utility. Figure 1-2 (b) illustrates an example of an AC microgrid system connected to the grid.

1.2.1.1 Advantages of AC microgrid

Some of the advantages of AC microgrids include (i) Easy voltage transformation; electrical transformers can be used to increase and decrease AC voltage easily. Conversely, DC voltage conversion is accomplished with DC-DC converters, which have a more complex implementation. (ii) The protection scheme for the AC microgrid is more mature than in the DC systems.

1.2.1.2 Disadvantage/ limitation of AC microgrid

The following are some drawbacks of AC microgrids: (i) Low conversion efficiency due to the presence of multiple converters, because it reduces the overall system efficiency and can result in increased energy costs. However, alternative system designs that minimise the use of converters or use more efficient converters can be implemented

to mitigate this limitation [46]. (ii) Complex control architecture brought on by reactive power management and frequency, voltage, and phase synchronisation. However, optimising the operation and control of the converters can also help to improve system efficiency. (iii) Larger cable size as a result of the skin effect [47].

1.2.2 DC microgrid

The ever-increasing demand, the dwindling of traditional energy sources, and the technological revolution in deploying renewable energy sources such as solar-PV have reignited interest in DC systems. In addition, the ability of these inverter-based renewable generators to produce multiple services, due to their ability to generate electricity from renewable sources and their ability to respond quickly to changes in the grid frequency and voltage, makes them an important component of the transition towards a more sustainable and reliable electricity system [48][35]. In most cases, DC-DC converters can replace some of these conversion stages when connected to a DC grid. Therefore, the DC grid is progressively gaining popularity and is expected to almost overtake the AC system [45]. There are three basic distribution types in DC microgrids: monopolar, bipolar, and homopolar. Additionally, some DC microgrids use numerous buses to increase reliability [49].

It appears that the microgrid concept and contemporary renewable energy solutions based on power electronics can bring back Thomas Edison's original conception of a DC-based power system, where energy sources and power electronics are combined in a DC grid system. As a result, it is possible to provide power at a sufficient voltage level and save a few conversion stages. Moreover, direct connections are possible with the energy storage system (ESS) through a DC-DC converter or directly to the main DC bus. Figure **1-2** (a) illustrates an example of a DC microgrid system connected to the grid.

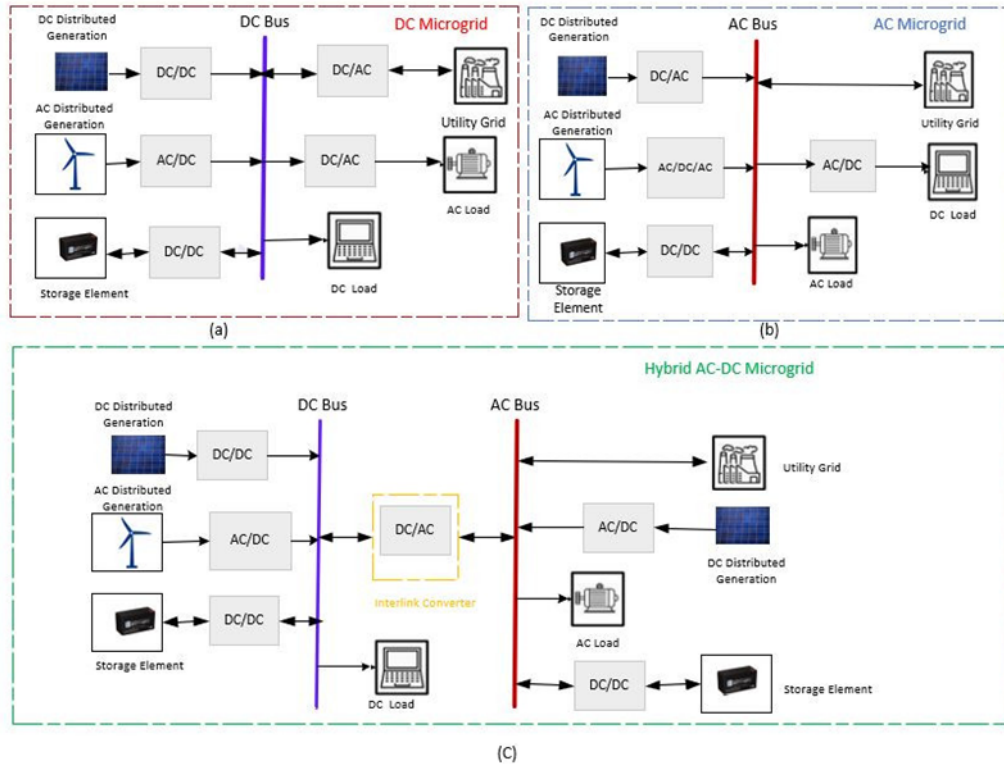


Figure 1-2 Microgrid classification based on distribution network configuration: (a) DC microgrid, (b) AC microgrid, and (c) hybrid AC/DC microgrid.

However, unstable DC voltage may compromise the security and stability of the DC grid. As a result, battery systems are frequently connected to the DC bus via DC-DC converters. Furthermore, a prominent argument against the use of DC in power systems is that because of the absence of natural zero crossing in the current in DC systems, short-circuit current interruption is more challenging to achieve than in an AC system. However, the correction factor of AC breaker ratings can be modified and used in low-voltage DC systems [32]. Due to this, it is intriguing to determine which AC system protection principles can be used and whether standard AC system protection is adequate.

1.2.2.1 Advantages of DC microgrid

In various applications, DC distribution systems can provide several benefits, including (i) the usage of fewer power converters and (ii) reduced cable size to reduce losses due to the absence of skin effect. (iii) Reactive power control and synchronisation are unnecessary for a DC system (iv) Improved power quality and stability [35]. Its planning, execution, and operation are, therefore, easier and less expensive. There is

also a comparison of AC (single-phase and three-phase) and DC (monopolar and bipolar) distribution lines based on conductor parameters [45]. The result shows that the DC bipolar transmission gives better performance. Additionally, the tests in [50] and [51] demonstrate that DC transmission lines are capable of transmitting more power under the same circumstances. Given the information above, it can be concluded that DC distribution has some advantages over AC distribution. However, there are some challenges to using a DC microgrid in practice.

1.2.2.2 Disadvantages of DC microgrid

Some of the disadvantages of the DC microgrid system include (i) a complex protection scheme due to the absence of zero crossing of the current in the DC grid system and (ii) DC systems have corrosion and grounding issues. In addition, due to the incorporation of new power electronic technology and the interface with the AC network, the DC microgrid system is more complicated than the conventional AC utility grid. Furthermore, because there is no zero crossing during short circuits, the fault current in DC is larger, and the dangerous arc persists. Therefore, a thorough evaluation is necessary for an effective grounding plan in the DC microgrid [32].

1.2.3 AC/DC Hybrid microgrid

One of the most intriguing methods for advancing the smart grid concept in the existing distribution network is the use of hybrid ac/dc microgrids. Figure 1-2 (c) depicts a typical hybrid microgrid structure. As can be seen from Figure 1-2 (c), interlink converters connect the AC and DC buses, which both have DGs and SEs. In contrast to the dc-coupled system, the AC/DC coupled hybrid microgrid also contains DGs and SEs on the AC bus, necessitating more voltage and current control coordination on the DC and AC subsystems. Because AC/DC loads may be linked at either an AC bus or a DC bus in the hybrid distribution grid, converters are needed to carry out this conversion operation [52] [53].

The AC/DC distribution system comprises various AC and DC components, such as buses, lines, power converters, and loads. In addition, there are also renewable technologies such as PV systems, geothermal, wind generators and hydropower. The incorporation of AC and DC components leads to non-linear input and output relationships compared to pure AC distribution systems. Additionally, power

electronics devices such as inverters and converters, commonly used in hybrid distribution systems, exhibit non-linear input and output relationships. Furthermore, integrating renewable energy sources such as solar and wind power can also contribute to non-linear behaviour in hybrid distribution systems. These sources are variable and intermittent, which can cause fluctuations in the system's voltage and frequency, leading to non-linear responses [54].

Therefore, modelling and creating energy management for AC/DC networks can be complex. Therefore, a number of AC or DC-powered devices are connected to the network directly using a minimum number of interfaces to reduce energy losses and associated conversion stages.

Hybrid microgrids are suitable for integrating increasing DC-based units, such as EVs, photovoltaic generation, fuel cells and ESS, while still connecting the AC-based loads to the AC grid. The hybrid microgrid is formed by including a power converter and communication network in the current distribution network to allow communication among devices. These additional components increase the cost of the main power converter, making the system more expensive than AC microgrids. Due to the use of interface power converters in the distribution network to generate the DC-link in hybrid microgrids, their reliability is lower than that of AC. Hybrid microgrid management is, therefore, more complicated than conventional microgrid management because devices connected to the AC and DC networks and the interconnections between them must be controlled [43].

The concept, however, faces many practical challenges, which can be categorised into (i) technical and (ii) economic challenges. The technical challenges include controlling the power flow among the distributed generators to achieve the desired voltage level. Further, hybrid microgrids consist of multiple power converters operating in grid-connected and island modes with complicating protection systems [55]. There is also synchronisation challenges in hybrid microgrid system due to voltage, frequency, and phase mismatch when connected to the grid, as its values should not exceed a prescribed value. It will also be necessary to filter the hybrid system to reduce harmonics due to unbalanced and non-linear loads connected to it [56] [57].

1.3 Microgrid supervisory control

Different control tasks are needed for AC and DC microgrids to ensure the system's proper operation. These tasks are often carried out through hierarchical control. For instance, providing electrical and/or thermal energy, engaging in the energy market, ensuring important loads receive a predetermined service level, initiating a black start after a breakdown, offering ancillary services, etc. The necessary operational and control procedures for a microgrid can vary greatly, even theoretically, from those of the traditional power systems, depending on the type and depth of distributed energy resource (DER) unit penetration [58].

The following three levels of control are discussed in order from outside to inner level control as follows:

1.3.1 Grid level.

A market operator (MO) and a distribution network operator (DNO) are found at this level. DNO can benefit from a number of control variables through active management approaches in microgrids that are not taken into account by their existing operating and planning method [59]. The MO control the microgrid's participation in the energy markets, and it can adhere to a variety of market policies, including meeting the microgrid's entire demand with locally produced energy or partaking in the open market by purchasing and selling active and reactive power to the grid [60],[61].

1.3.2 Management level.

A microgrid central controller (MGCC) carries out tasks of the management of the microgrid. Managing the frequency and voltage of the microgrid (AC microgrids), synchronising the microgrid with the grid (AC microgrids), load shedding, and optimising the microgrid's output are all part of the microgrid's control system [62].

1.3.3 Local level.

Each microgrid component has a single local controller (LC) (DGs, SEs or loads). The corresponding LC performs various responsibilities, such as internal control of DERs, and detection of islanding, depending on the type of element (DG, SS, or load) [45] [63]:

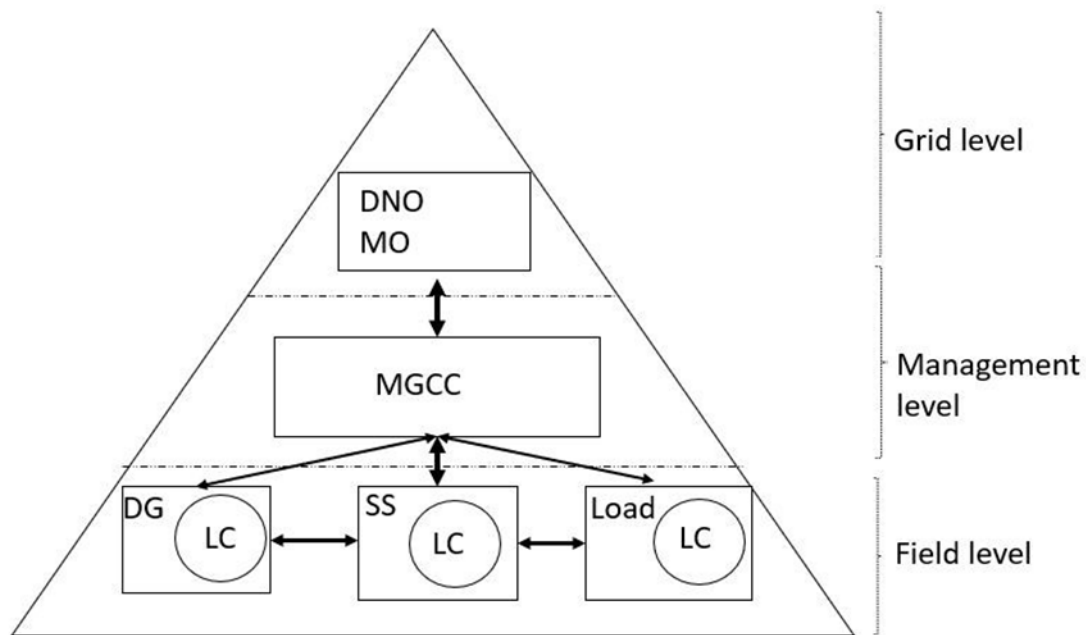


Figure 1-3 Centralised and decentralised microgrid control architecture

An MGCC resides on a central computer, and local controllers are located on power converters connected to each microgrid component, but DNO and MO functions are performed at the sub-grid level (DGs, SEs, or loads) [52].

1.4 Future grid

The future grids support the development of DERs, MGs, and other renewable resources throughout a digitally planned, designed, and operated lifespan. It is an automated energy delivery network that involves the transmission of both electricity and information. It will be able to monitor the power flow between the producer and consumer [64]. As a result, the power system is more adaptable, secure, reliable, efficient, and safe through automation and computer-based optimisation techniques [34]. The future grid system will be divided into numerous zones, called an island, thus keeping generation units and loads closer physically and electrically. Each island works hard to meet its local energy needs using primarily renewable energy sources. An island could be connected to another if electricity production exceeds demand at the point via a mobile energy storage system. The island idea increases system

robustness, offers resilient operation and a suitable framework for integrating EVs and mobile storage as new participants to the network [65].

The electricity grid is directly or indirectly used by a number of critical infrastructures, including those for communication, water, food, defence, transportation, and healthcare. Therefore, prolonged power outages in critical infrastructures, such as airports, can result in flight delays, extended layovers, interruptions of the operations that generate revenue for the cargo sector, and a decreased ability to provide emergency support [36]. It may also have an impact on the delivery of medical care both during and after the disaster, resulting in avoidable harm and fatalities in the medical field. The California rolling blackout in 2019 caused by wildfire and the Texas outage caused by a winter storm are recent examples of outages brought on by natural disasters [66]. Further, climate change is anticipated to result in more severe weather conditions and power outages.

In addition to weather-related occurrences, the grid has become increasingly linked and exposed to threats with increased potential for cyberattacks. This is due to the digitalisation of distribution, monitoring and control systems, and modern communication networks. An illustration of this type of attack is the coordinated attack that occurred in Ukraine in 2015 and resulted in a 6-hour blackout that affected close to 225,000 consumers [67],[68]. Furthermore, the attack's methodology is exploitable in different infrastructures worldwide. Therefore, enhancing the power grid's resilience can help lessen the impact of these occurrences [69]. Investments in grid resilience include operational strategies like installing microgrids or deploying distributed energy sources and system support strategies like underground cables laying and upgrading substation parts. Figure 1-4 (a) and (b) illustrate the general structure of the past and proposed future grid in the airport.

1.4.1 Mobile microgrid system

A microgrid can be created using mobile energy storage at a site or group of facilities with the right connecting infrastructure, minimising the amount of load lost during an outage. Incorporating mobile energy storage (MESS) enhances a microgrid-integrated power distribution system's operational effectiveness. Mobile energy storage can also be utilised to deliver electricity from a readily available energy source to an outage

location and support microgrids [70]–[72]. MESSs, also known as energy-on-wheel systems, are often container battery systems placed on vehicles or operated autonomously. They include physical interfaces that are standardised to enable plug-and-play operation. The energy used to power their conveyance might come from the batteries themselves, as well as from other sustainable sources. Some of the available and proposed mobile energy storage concepts include the MESS deployed by Power Edison to provide a utility-scale plug-and-play solution in the United States [73]. Three commercial MESS units with a capacity ranging from 660 kWh to 2MWh were released by Nomad transportable power system in 2021 and the proposed Tesla power wall virtual powered plant [74],[75].

Unlike portable diesel generators, which may experience interruptions in fuel supplies, MESS operation is not constrained by disaster or fuel availability. MESSs can be used to help achieve clean energy goals because they do not emit greenhouse gases or pollute the air when in use. MESSs can be moved to better support various applications according to the power system demand. The MESS will cost less due to lower manufacturing costs, advancements in battery technology, multi-use capability, and reduced installation and maintenance costs and avoid creating stranded assets compared to stationary storage technologies in power system applications [76]. MESSs can also provide energy in times of need, and their mobility allows them to be quickly deployed in areas where they are most required. The fundamental advantage of mobile energy storage versus stationary energy storage is flexibility. In order to assess the benefits of MESS, system cost and environmental emissions, as well as operational costs and energy losses, were analysed by authors in [77]. The simulation result demonstrates that optimum switch placements and MESS operation greatly enhance the operational performance of distribution systems. In order to establish several microgrids and shorten the duration of major load outages, [78] offer a two-stage restoration approach in which MESSs are pre-positioned before an incident and then assigned once the event occurs. To enable the integration of distributed RESs, load levelling, peak shaving, reactive power support, voltage management, and other localised ancillary services, MESSs are being investigated under typical operating situations [71],[76], [79]. Advantages of MESS in electric power systems include: (i) It can be a valuable relief service during times of emergency and

reduce procurement costs during normal operations. (ii) it could significantly facilitate renewable energy transition (iii) New business paradigms are introduced by mobile energy storage, i.e. Mobility as a service (MaaS) and Energy as service (EaaS) (iv) Energy could be harvested from stranded distributed sources by self-mobile (v) MESS could be used to create microgrids, reducing the effects of prolonged blackouts (vi) It could be used to participate in energy arbitrage at the wholesale level.

1.4.2 High-frequency AC microgrid system (HFAC)

The delivery of power at multiple kHz frequencies via electrical wires is the focus of high-frequency AC (HFAC) power distribution systems. Early research on HFAC systems has shown their many potential advantages, including their adaptability to meet loads at various voltage levels, their ease of electrical isolation using small high-frequency transformers and the possibility of significant component count and system integration savings. The high-frequency operation can also enhance the system's dynamic response and lessen or completely get rid of acoustic noise [80]. However, the adoption of HFAC has been extremely slow despite the numerous purported advantages [81]. HFAC power distribution has so far only been used in a small number of communications, computing, and information technology applications. However, in the future grid system, electrical power will be delivered at higher voltages, currents, and frequencies since our environmentally conscious economies are constantly seeking out more power at a higher efficiency due to the:

- **Integration of Renewable Energy:** Renewable energy sources such as wind and solar power are often located far from where the energy is consumed, and high voltage transmission lines can transport the energy more efficiently over long distances. This is important as the share of renewable energy in the electricity mix grows, allowing the grid to handle the variable power output from renewable sources more effectively.
- **Increasing Demand:** As electricity demand continues to rise globally, higher voltage and current levels can transmit more power over existing infrastructure, avoiding the need for new transmission lines and reducing investment costs.

- Technological Advancements: Advancements in power electronics and high-frequency power transmission allow for more efficient electrical grid use, transmitting more energy over shorter periods and at higher frequencies.

In addition, the flexibility to integrate a variety of smaller generation technologies, including wind, hydro, photovoltaic PV, fuel cells, batteries, ultra-capacitors, and flywheels, makes the microgrid a particularly viable choice for the implementation of HFAC. In addition, the microgrid idea greatly improves the controllability issues with distributed resources. Since most micro sources are power electronic-based, power electronic converters are crucial in maintaining microgrid operation as a single system.

The high-frequency AC power system uses an HFAC link as the power electronic interface to maximise microgrid efficiency. The grid components are connected by high-frequency buses. However, voltage distortions caused by source and converter nonlinearity, as well as load current harmonics due to non-linear loads, are present in the HFAC microgrid and constitute a significant challenge for power quality control [82]. The HFAC system addresses these voltage and current harmonics by employing an active filter known as the universal power quality conditioner (UPQC). In comparison, the universal active power line conditioner (UPLC) controls both active and reactive power flow in the microgrid [83].

The two controllers work on the principle of shunt and series filters according to the instantaneous power theory to calculate the compensating voltage and current in the microgrid [84]. As a result, electrical energy is delivered at frequencies higher than 60 Hz via HFAC power systems. Some of the advantages of the HFAC power system over the conventional 50/60 Hz supply are : (i) Electric equipment is lighter, smaller, and more affordable because fewer materials are used. The size of an electric machine can typically be reduced by 75% when the frequency is doubled. (ii) High-frequency mechanical vibration has the potential to reduce acoustic noise significantly. (iii) High-speed induction motors can directly drive turbines, high-pressure pumps, and compressors. (iv) HFAC systems can easily be filtered to reduce higher frequency harmonics. (v) Transformers and other passive circuit elements of high frequency are reduced in size. A more detailed analysis of the HFAC system's performance metrics

was provided in [81]. The system performance index is created using a weighting factor and a set of performance parameters.

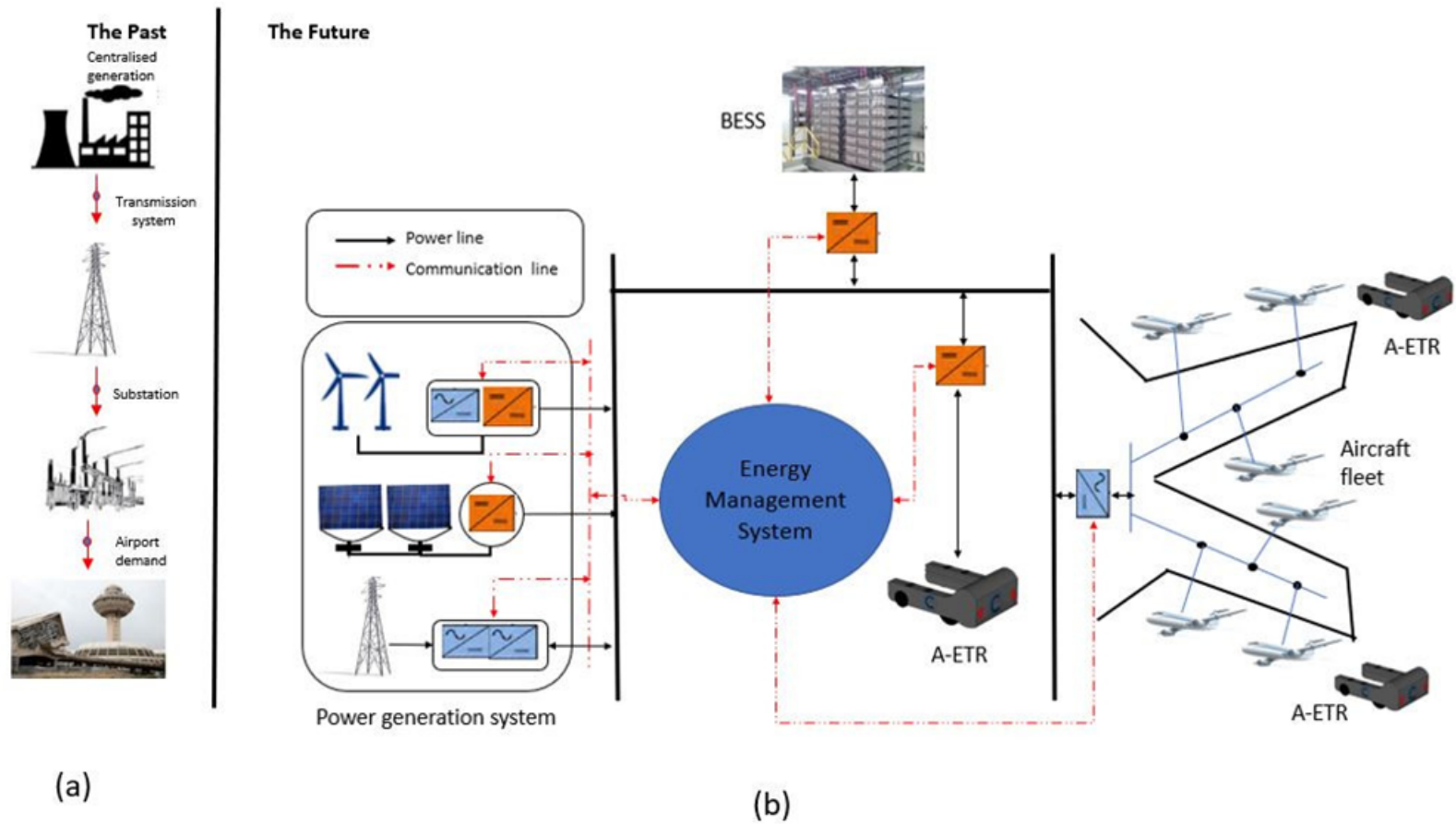


Figure 1-4 The general structure of the conventional power system and the smart grid system for airport electrification

1.5 Research gap

Ground operation emissions contribute a large proportion of the airport's carbon footprint, and there is an urgent need to achieve zero-emission operation in the airport, according to FlightPath 2050. However, existing measures on ground movement emission reduction in airports have not achieved the zero-emission target because they cannot link ground movement operations with onsite renewable energy-generating sources in the airport. Most of the research on airport-based solar-powered systems (ASPV) mainly focuses on meeting the airport load demands or the suitability of solar power installation in airports [85],[86],[22],[87]. Also, most research studies on electric taxiing systems focus on vehicle-level technology, emphasising mitigating aircraft-level emission impact and fuel savings [21],[88]. In addition, the existing work on autonomous electric taxiing systems has an average speed between 2 to 6 knots, which is far less than the average of 20 knots required for an off-board taxiing system. To date, there is no research study on grid systems that meet the zero-emission electric-taxiing in the context of airport grids.

In this research work, a holistic solution for electric taxiing of aircraft to overcome some of the shortcomings of meeting the requirement of emission-free ground movement in future airports is discussed. It concerns the development of a novel microgrid ecosystem infrastructure using an innovative grid-taxiing interface using an autonomous electric taxiing robot (A-ETR) between aircraft ground transport, onsite solar farm, and the airport grid. This novel grid system based on a concept of autonomous mobile storage to advance zero-emission ground movement operation in the airport has not been reported in the literature. This research is the first attempt in the literature to link these two infrastructures in the airport towards achieving the zero-emission target of FlightPath 2050. Figure **1-5** illustrates the basic concept of the proposed novel microgrid ecosystem for zero-emission electric taxiing in the airport.

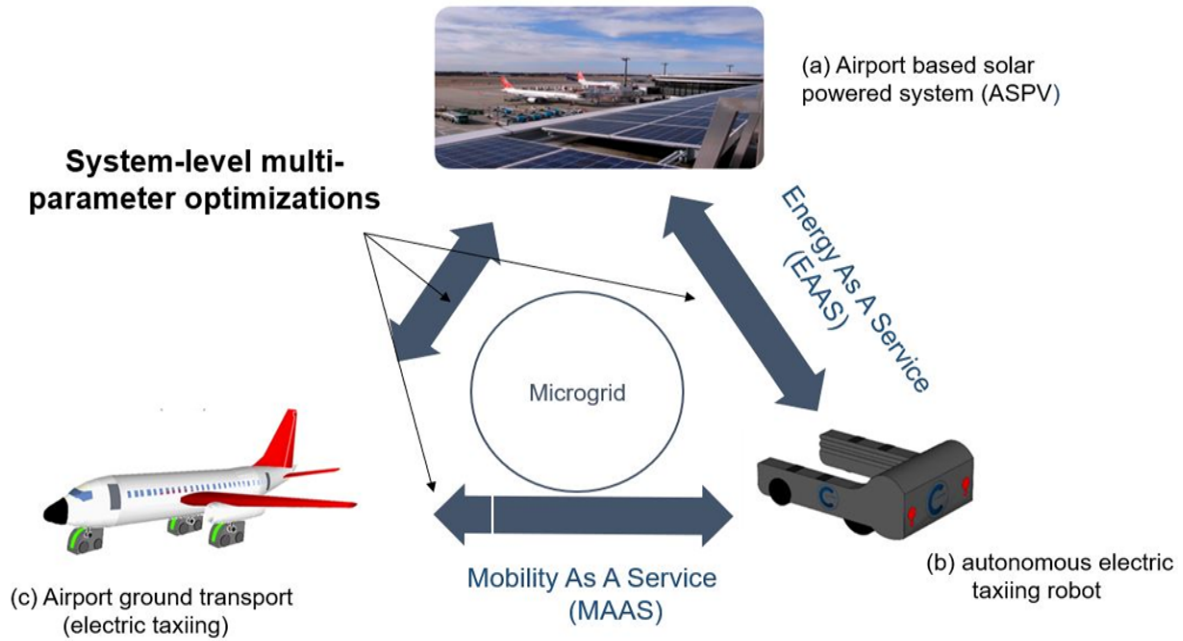


Figure 1-5: Novel microgrid ecosystem infrastructure

1.6 Aim and Objectives

This thesis aims to develop a novel grid system to meet the demand for zero-emission ground operation in the airport by integrating a mobile interface between ASPV and aircraft ground movement. Machine learning-based system-level optimisation has been used in the energy management of the microgrid to achieve zero-emission taxiing and ground movement operations in the airport. The main contribution from the proposed methodology focuses on the coordination of locally available energy sources, mobile energy storage in A-ETRs, and airport flight data to achieve a novel microgrid ecosystem that will support emission-free ground operation in the airport. To achieve this major goal, a set of objectives and hypotheses have been established:

- Explore the storage system in the mobile interface to provide a framework for developing innovative scheduling and charging algorithms based on the proposed Cranfield's A-ETR. The hypothesis is that taxiing is the main source of emissions and noise for airport ground movement, and electric taxiing will be the first phase of aviation electrification at the airport level.

- Develop a microgrid ecosystem that links the A-ETR to a grid-connected ASPV to meet zero-emission ground transportation needs in future airports. The hypothesis is that the grid (not carbon-free till 2030) cannot provide a zero-emission solution now, and the cost of grid infrastructure upgrade is high [89]. Currently, conventional energy sources like coal, fossil fuels, etc., provide most airports with all their electricity needs.
- Develop an intelligent energy system using flight information to forecast and optimise energy demand in green airport electrification. The stochastic behaviour of renewable power generation and airport flight schedules is integrated to develop power management solutions for the microgrid.
- Model and simulate the whole ecosystem using scenario studies such as typical taxiing load profiles in high-fidelity Dig SILENT power factory software. Here the main objective is to investigate the optimal microgrid architecture required to meet the expected electric taxiing load and integration of the A-ETR to improve the resiliency of future green airport electrification.

1.7 Contributions

In achieving the research objectives, the investigation has made the following contributions to the literature.

- A model for generating aircraft traction load profiles and determining the kinematic parameters of an A-ETR, which acts as a charging and discharging interface for a solar-powered microgrid, is developed. The developed model matches practical operating conditions with 95% accuracy.
- The dynamic loading demand and varying A-ETR charge/discharge duty cycle have been modelled as a mobile interface to the ASPV battery-based microgrid power management strategy. Here the A-ETR introduced the concept of mobility as a service (MaaS) into the microgrid. The simulation results under three weather conditions show that the proposed architecture can meet the daily taxiing load demand in the airport.

- The performance of different machine learning algorithms in forecasting the PV output power has been compared, and the best-performing algorithm is deployed to optimise the battery energy storage size required to meet the taxiing load demand in the microgrid. The developed model matches the airport's flight schedule within a 3.4% error with the available solar resources and electricity tariffs to minimise the microgrid's operation cost. The model performance has been validated based on taxiing load profiles derived from real-world data obtained from Cranfield Airport.
- A novel data-driven machine learning-based energy prediction model using Facebook Prophet to develop univariate and multivariate time series models to forecast the net energy demand of ground operation in the airport using historical flight data and ASPV has been developed.
- A novel model predictive control-based cascade feedforward neural network (SMPC-CFFNN) has been developed to integrate the multivariable constraint and stochastic behaviour of renewable power generation and flight information to optimise energy management in the microgrid to achieve zero emission operation.
- Finally, two different types of microgrid architecture have been analysed for future EV grids in a green airport to meet the ground movement operation demand. And the integration of the A-ETR to support the microgrid for resiliency improvement was investigated. Here the A-ETR bring about the concept of energy as a service (EAAS) as an additional contribution to the microgrid. The microgrid operation is evaluated by key performance indices within a high-fidelity model.

Hence, this thesis contributes to zero-emission ground movement operation as a holistic system approach by interfacing these two technologies, namely A-ETR and ASPV, via a microgrid ecosystem in the airport, employing multidisciplinary optimisation approaches to achieve emission-free ground operation.

1.8 Thesis structure

This thesis is organised into eight chapters, followed by references. The outline of these chapters is explained below and described in Figure 1-6:

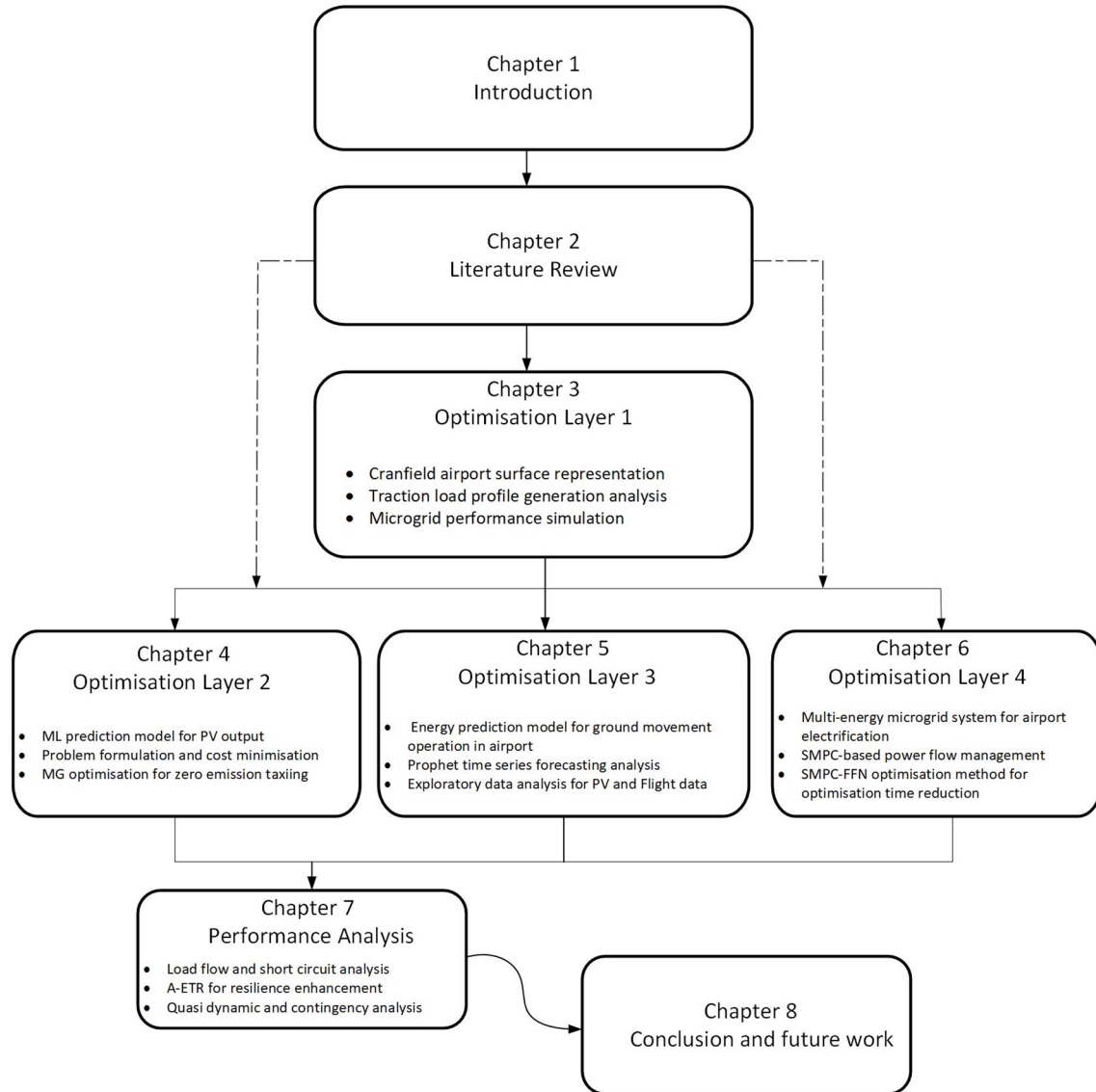


Figure 1-6: Outline of the thesis structure

Chapter one introduces and provides the background of the electric taxiing concept, airport electric grid system and their limitations to meet the new electrified loads in the airport and the proposed future grid incorporating a mobile storage interface concept in microgrid operation to meet ground movement

operation emission challenges in the airport. It also set out the aim, objectives, motivation, and contribution of this research.

Chapter two provides literature reviews of the microgrid concept in airports, electric taxiing systems, airport-based solar power systems, and green airport concepts. The research trend focuses on the framework structure of the green airport concept through electrification and renewable power generation. The challenges to green airports are also explored.

Chapter three Introduces and describes the first optimisation stage, i.e., (hardware/ planning optimisation). This optimisation stage involves an analytical model for determining the kinematic parameters of the proposed A-ETR for taxiing aircraft. The opportunistic charge and discharge of the A-ETR are modelled in relation to the airport flight data and onsite solar-powered green energy source. Based on real-world data from Cranfield University's Airport and its Boeing 737 research aircraft, a vehicle-level data-driven machine-learning-based optimisation is undertaken.

Chapter four introduces and discusses operational optimisation for the microgrid. This optimisation stage includes developing several machine-learning-based models and comparing their performances in terms of forecasting PV output power. These models are used to optimise the A-ETRS batteries' charging and discharging cycles to match solar resources and electricity rates and estimate the optimal battery size required to support the proposed microgrid for energy and ground traffic at the airport level. The ground movement operation load of London Luton Airport is employed in additional simulation scenarios in the model to extend its coverage to include commercial airport operations. The impact of the joint optimisation on the operating cost of the microgrid is discussed.

Chapter five presents an enhancement of the microgrid operational optimisation. Here a novel energy prediction model (EPM) for ground movement operation in the airport has been developed using historical flight data and real-world data from the on-site ASPV to manage energy in the microgrid. Historical flight data and PV output are used to develop multivariate and univariate time series models

to forecast ground movement operation energy demand in the microgrid over different time horizons using the Facebook prophet algorithm. These models aim to provide important information for airport managers in making energy-efficient plans and provide predictions with adequate accuracy for realistic ground movement energy demand and clean energy production at airports. The impact of the EPM on the optimal operation of the microgrid is in the improved resiliency and continuity of supply in the microgrid due to future net energy forecasts. As a further extension of the concept and broader analysis, the next chapter explores integrating additional energy sources in the airport, such as vertical wind turbines and vehicle-to-grid concepts, to complement solar PV production. However, wind energy generation is hitherto not feasible around the airport due to structural integrity.

Chapter six presents a further enhancement of the airport operation optimisation by incorporating additional RES, including wind and exploiting the data repositories of a 'green' airport environment to complement the shortcoming of solar PV. Here, a novel stochastic model predictive control architecture is developed, adapting a cascaded feedforward neural network (SMPC-CFFNN) to optimise energy management in the ecosystem. Here the potential of incorporating the batteries of the A-ETR and the electric ground support vehicles (EGSVs) as a vehicle-to-grid (V2G) capability to support power flow in the airport is explored. The iterative convergence to the optimal solution in the model predictive control algorithm is replaced with an intelligent artificial neural network model to minimise the optimisation time and incorporate the uncertainties associated with renewable sources and the behaviour of the A-ETR and EGSVs in the microgrid. A high-fidelity model is developed in the next chapter to investigate the best architecture for integrating the proposed microgrid into the existing airport electrical network and the feasibility of the proposed A-ETR to promote resilient operation at the airport.

Chapter seven presents the performance analysis of the proposed microgrid in terms of reliability and resiliency in the high-fidelity DigSILENT power factory model. This investigation studied the possible network configurations to link the

existing airport grid. Here two alternative microgrid architectures based on their point of common connections (PCC) are compared, one with a low voltage AC (LVAC) architecture and the other with a high-rating centralised converter connection with low voltage DC (LVDC) architecture, in terms of technical and economic implications of the new loads on the existing distribution network in the airport. Then, the concept of the A-ETR as EAAS is incorporated to test the reliability and resilience of the proposed ecosystem by performing contingency and reliability index analysis on the model. Contingency and reliability index analyses are performed in terms of system average interruption frequency Index (SAIFI), system average interruption duration Index (SAIDI), average service availability index (ASAI) and grid stability on the microgrid to analyse A-ETR capacity for grid resiliency support. Finally, the microgrid operation is evaluated by key performance indices within the high-fidelity model.

Chapter eight concludes the thesis, summarises the research's main contributions, and makes suggestions for future work related to this thesis's subject.

2 . Literature Review

2.1 Introduction

This thesis study includes a critical review of the research and advancements in the fields of the green airport, electric taxiing, microgrid concept in the airport, machine learning-based optimisation for energy management in the microgrid, and mobile storage for grid resilience. While the review of the green airport and its findings are covered in this chapter, the reviews of electric taxiing and airport-based solar PV will be covered in chapter 3, which also contains the existing related works. Chapters 4, 5, 6, and 7 will provide the review and works related to time series forecasting for ground movement energy prediction, machine learning-based energy management in the microgrid, and mobile energy storage for grid resilience.

The continuous development in the air transportation industry and increased air traffic flow have stressed most airport operational capabilities to their limit. Subsequently, the existing airport infrastructure needs to be enhanced along with the capacity, which helps to improve its operational efficiency [90]. Furthermore, the recent increase in passenger air traffic demand has led to a continuous yearly increase in airline fleets. As a result, the aviation industry market is likely to foresee unparalleled growth in the coming years, resulting in a consequential effect on the environment and economy. Different approaches have been proposed among the airlines and regulatory bodies to minimise these effects and control emissions in the sector [8], [91]. Zero-emission ground operation is one of the initiatives which has been considered in this context. According to ACARE, all ground movements in the airport are required to be emission-free by the year 2050 [8].

Optimisation of ground operation in the airport has been one of the popular subjects among researchers over the last few years [92]–[95]. The methods associated with airport ground operation can be broadly classified into operational and technological techniques [96]. Among various well-known

operational methods, the most prevalent is single-engine taxiing (SET) [13],[27]. The operational techniques are relatively more successful than other techniques because they are easy to implement and focus on improving airport operations. However, the operational solutions still depend on using an engine for ground mobility and are not recommended when deicing operations are needed or on slippery and sloppy surfaces [11]. The nose wheel steering and braking capabilities may also be compromised under such scenarios [20]. In addition, taxiing with fewer engines also requires more thrust per engine, particularly when breaking away or turning 180 degrees.

Therefore, it is essential to minimise the number of jet blasts and foreign object damage (FOD) during ground movement [11]. An analysis of the effect of SET on fuel consumption and pollutant emissions has been conducted for London Heathrow Airport [18]. The presented model has reduced fuel consumption and emissions at ground level by reducing the initiation time of SETs. The result indicates that reduced fuel load, when coupled with lower aircraft weight, tends to reduce fuel consumption throughout the flight. On the other hand, [11] evaluated the opportunities related to surface emission reduction through optimisation and the potential benefits and implementation barriers for adopting the different approaches at the airport. The study concludes that airports can reduce emissions and fuel burn without compromising operational efficiency by combining these strategies. Other operational strategies include ground traffic optimisation, such as improved queue management and active routing systems, to shorten taxiing times [93], [98].

Whilst the technological-based solutions utilise technologies that promote smarter and greener taxiing operations, such as dispatch towing and electric taxiing systems (ETS) [11], [97], [99]. The ETS has attracted more attention due to the potential for zero-emissions taxiing compared to other factors, such as lower noise levels [20]. [88] evaluate the economic impacts of adopting an ETS and identifies the threats and potential impact of introducing this system to aircraft operation. The study concludes that introducing the ETS elevates savings and is quite attractive to most air operators amidst these problems and areas of concern.

[100] examined the potential speed limitations and delays that may arise from implementing electric taxiing, using Amsterdam Schiphol Airport as a case study. The findings indicate that an average speed of 10 m/s (equivalent to 20 knots) would not result in significant delays for other aircraft.

While aircraft manufacturers recognise the relative advantage of the aforementioned approach, they also raise some concerns and ultimately leave this to the operators [101]. Furthermore, airport operations also generate a large amount of noise and air pollution, which adversely affect the environment and surrounding communities and are deemed inevitable burdens as far as aviation activities are concerned [102]. As a result of these challenges, green electric taxiing concepts have been proposed to reduce air and noise pollution and costs associated with aircraft ground movement operation.

2.2 Solar-powered electric taxiing system (ETS)

This section discusses the concept of ETS by presenting its practical implications, advantages, and limitations. In addition, an overview of the currently available ETS is provided. Finally, different types of ETS are compared, and their main characteristics are outlined. The process of electric taxiing involves attaching an electric motor to either the nose or main landing gears of the aircraft during ground movement. This motor is powered by the auxiliary power unit (APU) and allows the aircraft to take off and land without starting the main engines [88].

Researchers have examined a trade-off for the initial design of landing gears with electro engines for a new taxiing concept [20]. Although integrating ETS into the aircraft increases carriage weight resulting in a higher fuel requirement, it reduces the use of fuel and emissions associated with taxiing.

[102] identify three basic functions that the ETS must be capable of performing, such as pushback and taxiing the aircraft from a standstill along the taxiway with a suitable acceleration. [20] introduced the concept of ETS and described various technologies along with environmental and economic benefits and challenges associated with the technology implementation. [98] analysed four taxiing

scenarios, in which single-engine and twin-engine taxiing are considered as the first two scenarios, while off-board and on-board taxiing systems are considered in the third and fourth scenarios. A comparative analysis of the emissions from all four scenarios shows a trade-off in fuel consumption and emissions among these modern technologies. Off-board taxiing offers better fuel burn efficiency, while onboard taxiing provides better emission reductions. Both techniques allow pushback and taxi operations to be performed even when the aircraft's engines are off, thus reducing fuel consumption, pollution, and foreign object damage (FOD). During conventional taxiing, it is a common practice to set the thrust level of engines to idle, which is generally too high for taxiing or executing certain (turning) manoeuvres. Due to these limitations, the pilot requires a lot of braking, which leads to the wearing down of brakes resulting in higher prices for maintaining them than the ETS procedure, which uses comparatively less expensive carbon brakes less excessively [20].

The ETS is classified into two categories, onboard ETS, such as a wheel tug on the nose landing gear (NLG), or an electric green taxiing system integrated into the main landing gear (MLG) [103]. The NLG configurations benefit from a larger amount of available space than MLG due to the brake mechanism of the latter. On the other hand, when traction efforts are reduced by snow, ice, or rain, using ETS at the NLG might not be as effective. However, the MLG's high tractive forces make it an attractive location to install motors, despite the challenging space constraints [21]. In addition, the shorter working period of jet engines results in less noise pollution and lower engine maintenance expenses [88]. A generic system architecture for both external and onboard ETS is shown in Figure

2-1

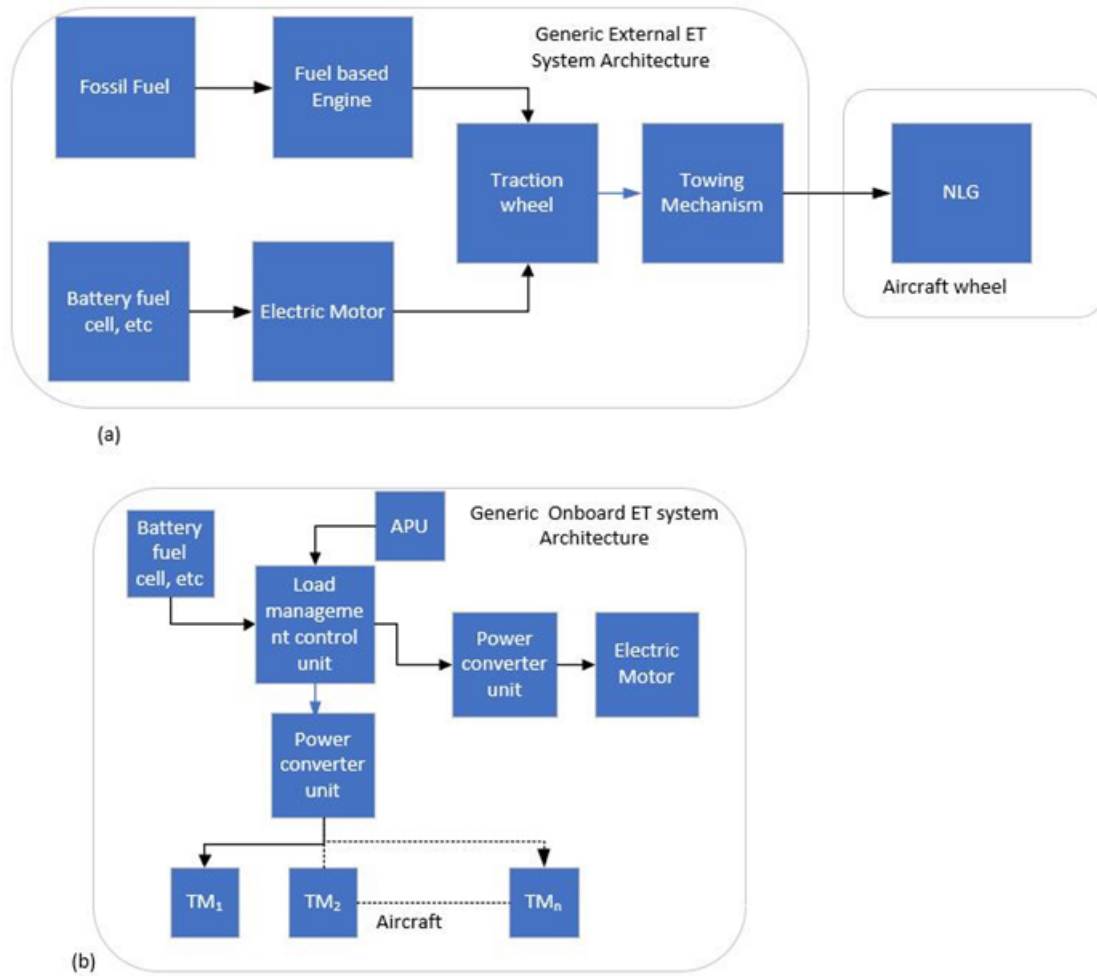


Figure 2-1: A generic system architecture for both (a) external and (b) on-board ETS [20]

Table 2-1 presents the comparison between off-board and on-board electric taxiing system

Table 2-1 Comparison of ETS

Parameters	Off-Board electric taxiing system	On-Board electric taxiing system
Weight	<ul style="list-style-type: none"> Do not add extra weight to aircraft 	<ul style="list-style-type: none"> Add additional weight to the aircraft
Architecture	<ul style="list-style-type: none"> Require little or no modification to aircraft architecture 	<ul style="list-style-type: none"> Modification to aircraft architecture is necessary to accommodate the system

Parameters	Off-Board electric taxiing system	On-Board electric taxiing system
Airport congestion	<ul style="list-style-type: none"> • Congestion at the airport surface level will increase due to space occupied by ETS in-between flight 	<ul style="list-style-type: none"> • Minimise airport surface congestion due to the absence of external ETS movements
Delay	<ul style="list-style-type: none"> • Causes delay in taxiing movement due to time lapse when attaching ETS 	<ul style="list-style-type: none"> • No delay in taxiing movement as aircraft drive autonomously
Push-back	<ul style="list-style-type: none"> • Longer push-back time 	<ul style="list-style-type: none"> • Lower push-back time
Certification complexity	<ul style="list-style-type: none"> • The certification process is considerably easier 	<ul style="list-style-type: none"> • Certification and legislation required considerable efforts

In the literature, the ETS load has been identified as the major load demand for the future green airport due to the proposition of electrification of the ground movement operation in Flightpath 2050's objectives [55]. However, the rapidly increasing ground movement loads would be able to meet the FlightPath 2050 zero-emission objective if their charging is from a green energy source. On the other hand, if the conventional utility grid is used to charge the new electric load, then the carbon footprint will be transferred from the airport to the power generation sector, which is still not a complete zero-emission ground movement operation in the airport. Therefore, it is desirable to consider a sustainable and cost-effective way of meeting this load demand by employing an on-site ASPV-based microgrid in the airport.

2.2.1 Airport-based solar power system

The second stream of literature surveys concerns airport-based solar power systems. Many airports worldwide have become conscious of the benefits of using renewable energy resources for the environment and have increased the effort to introduce solar photovoltaic systems to the available free spaces within the airfield [105]–[108]. Typical examples are the 1MW solar plant in Cranfield and Cardiff Airport.

Airports are uniquely positioned to become a major force in the green energy transition because they occupy vast portions of land. A study by the University of Colorado Denver reports that 20% of public airports in the US have installed solar power systems over the past decade [109]. The number will likely grow as cities and states adopt clean energy targets and move closer to achieving net-zero status. With massive solar panel installations, airports are poised to become an important player in pushing for a carbon-neutral environment by federal and state governments. In addition, solar energy advocates would like to see the expansion of solar-powered airport services in the coming years, such as the possibility of going to solar-powered airports through zero-emission public transportation, travelling through solar-powered airports, and boarding from solar-powered airports [110].

Therefore, a major objective of airports is to develop methods to reduce their energy use and make them more reliant on renewable sources. [111] analysed the return on investment (ROI) of a PV system and various ways to mitigate carbon dioxide (CO₂) emissions at the Kalimarau Airport in Indonesia. The results conclude that the electricity price determines the ROI on a PV installation, and some considerations must be accounted for prior to installing a PV system in an airport. [86] comprehensively discussed the danger and effect of installing a PV system on aviation safety. The risk identification and classification have been clarified based on the European Aviation Safety Agency (EASA) risk assessment matrices. The study emphasised that solar PV is a significant opportunity at airports that operate within the aerodrome boundaries.

[112] stated that solar PV systems would be the most cost-effective way for Incheon International Airport (South Korea) to attain energy self-sufficiency. [113] studied building-integrated PV at airports. [114] address the safety concerns associated with implementing large-scale PV systems in airport locations, while authors in [115] examined Istanbul International Airport's energy consumption and carbon dioxide emissions.

The sustainability ranking of Rome and Leonardo da Vinci International Airports in Italy has been investigated in [116],[117],[118]. A 12 MW solar PV power plant at Cochin International Airport in India has been analysed for its economic and environmental performance [105]. [119] conducted a feasibility study for an international airport in Bhopal, India. The greenhouse gas (GHG) reduction potential of solar PV power installations at ten Indian airports has been estimated in [23]. [120] studied the energy management of sustainable airports and the certified emission reduction savings from solar PV plants.

[107] discussed the occurrence of glare from solar panels installed at airports and its possible solutions. The exergy and energy performance of the 12 MWp solar PV power plant at Cochin International Airport has been analysed in [121]. [122] discussed plans for building an integrated PV system using community solar power in Switzerland.

The use of integrated PV systems for airport terminal design was discussed in [123]. [124] evaluated the performance of rooftop solar systems in Lucknow, India. [125] discussed building-integrated PV systems in terms of their costs, benefits, risks, barriers, and improvements. [126] evaluated the solar PV cells in West Bengal, India, in terms of their earned carbon credits and carbon footprints. Finally, [87] discussed the expected problems associated with installing a PV system in an airport and its possible solutions. The results indicate the suitability of Egyptian Airports for installing a photovoltaic generating plant for electricity generation.

2.2.2 Suitability of solar PV in airport

In developing large-scale PV systems, finding suitable locations that are flat, secured and close to power lines is a major concern [114]. In addition, as the global population grows at 1.15% annually [2], densely populated areas are experiencing an increase in economic value for productive land and waterways. It is, therefore, imperative to utilise all uncultivated arable lands before energy production affects food production. A major source of solar PV deployment opportunities in the vicinity of airports is the large surface areas that are

unsuitable for food production and largely overlooked for PV deployment [127]. Generally, a large percentage of airport land is unused due to existing design standards and located near large population centres with higher electricity needs [127]. Therefore, among other factors, large solar farm projects are affected by the cost of acquiring, maintaining, and securing suitable land. However, despite being among the lowest (GHG) producing energy sources and other economic and environmental benefits, the installation of large PV-Solar systems in airports locations raises some safety concerns, such as (i) radar interference, (ii) panels reflectivity, (iii) physical penetration of airspace, (iv) site selection, and (v) grid connections [128], [129].

The solar plants have no moving parts, requiring little or no maintenance cost (in most cases). In addition, installing a solar plant has a much lower environmental impact than building an airport or a power plant since no major machines or foundations are needed. A typical example of ground-mounted PV at Cranfield Airport is shown in Figure 2-2.



Figure 2-2 1MW solar farm installed in Cranfield Airport

The development of airport-based solar projects is more complicated than implementing typical solar PV plants (land-based or roof-mounted). Therefore,

airport solar systems must be installed in a way that does not pose a risk to aircraft or disrupt airport and aeronautical activities [24].

2.2.3 An overview of solar systems design for airports

2.2.3.1 Types of airports and surface selection

Due to the limited land availability per unit of size for airports located in cities compared to airports located in rural areas, solar PV can be installed on rooftops of buildings. Then ground-based systems can be developed to play a supporting role [127]. In contrast, the land area per unit load of an airport located in a remote location, on the other hand, is relatively large. Therefore, ground-mounted PV systems (GMPV) would be preferable in such cases, with building-integrated PV (BIPV) and roof-mounted systems playing a minor or supporting role.

Secondly, airport PV systems are designed according to the annual and seasonal weather conditions at the airport. Although the airport location already ensures that the weather is favourable for landing and taking off, the weather still affects the efficiency of PV systems. Therefore both the adverse and positive effects of weather must be considered when installing ASPV in the airport [130],[127],[131].

A third consideration is the amount of energy the airport consumes in island modes. This refers to situations where the airport operates independently of the main power grid, such as during a power outage or other emergency. Understanding the airport's energy consumption in these scenarios can help ensure enough energy storage capacity is available to keep essential airport operations running smoothly.

Since energy consumption can fluctuate greatly depending on the airport's traffic, the unpredictability of the airport demand should be considered when contemplating airport PV systems, as the variability can be large. Therefore, PV systems for airports should be modelled carefully to account for the variability of the airport's load [127]. Table 2-2 presents a comparison of land-based and airport-based solar PV systems.

Table 2-2 Comparison of land-based and airport-based solar PV systems

PV Systems	ASPV	GMPV
Constraints	<ul style="list-style-type: none"> In addition to general constraints, airport-specific factors are considered; PV arrays can penetrate airspace due to glare, radar interference, and radar penetration. 	<ul style="list-style-type: none"> Site selection is influenced by climatic conditions, soil composition, and solar resources.
Module Orientation	<ul style="list-style-type: none"> PV modules are oriented to mitigate the glare hazard in the location. 	<ul style="list-style-type: none"> The orientation of PV modules in the northern hemisphere or vice versa depends on the latitude of their location.
Technology	<ul style="list-style-type: none"> Occasionally, low-reflectivity PV module technologies are preferred. 	<ul style="list-style-type: none"> PV technology based on crystalline silicon is mostly used.
Certification	<ul style="list-style-type: none"> Project implementation requires approval from a variety of regulators and certification. 	<ul style="list-style-type: none"> Fewer numbers of approval are required.
Structure	<ul style="list-style-type: none"> PV structures are recommended not to exceed 3 m above ground level. 	<ul style="list-style-type: none"> PV structures are fixed without height limitation.
Environmental Impact	<ul style="list-style-type: none"> There is less green cover in airport regions, thereby minimising the effects on wildlife and vegetation. 	<ul style="list-style-type: none"> The environmental and wildlife impact is more significant when placed in vegetated areas.

2.2.4 Swot analysis of ASPV systems

A Swot analysis measures a project's competitive position using its strengths, weaknesses, opportunities, and threats [132],[133]. Swot analysis is typically displayed as a square in which each of the four sections constitutes one quadrant. The swot analysis quadrant for solar PV development in the airport is shown in Figure 2-3 and described in Table 2-3



Figure 2-3 Swot analysis quadrant for solar PV development in airport

This diagram gives a quick summary of the project's viability. SWOT analysis provides insight into the viability of a project and aids in formulating strategies to prepare for potential risks [134]. The SWOT analysis of installing a solar PV power plant at an airport is briefly discussed in this section.

Table 2-3 Swot analysis for ASPV systems.

Strength	<ul style="list-style-type: none"> • Solar PV systems can be easily tailored to any location on the airport property. • Solar panels' flat shape makes them easy to mount to various surfaces, including poles, parking lots etc. • The amount of electricity generated and the system's effectiveness varies according to the location. • Solar PV's modest height profile eliminates physical obstructions and safety risks to safe navigational operation.
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Opportunities	<ul style="list-style-type: none"> • A solar PV system can be installed on unused land, buildings, or parking lots. • The airport can save money on its energy bill by utilising solar energy, which has a steady cost of power (no operational fuel costs, low maintenance costs) and is less expensive than fossil fuels. • Airports with renewable energy projects benefit from increased reliability during grid outages and power failures. • By lowering carbon emissions, the project aids the local government in addressing climate change.
Weakness	<ul style="list-style-type: none"> • A backup source must be employed to compensate for the shortfall since solar PV can only produce electricity during the day. • Compared to other renewable energy technologies (RETs), such as hydro, wind, and so on, solar panels often produce barely 15% of their installed capacity [135]. • The amount of electricity generated, and the system's effectiveness varies according to the location • Given the low conversion efficiency of solar PV modules, solar power plants require a large area for installation
Threats	<ul style="list-style-type: none"> • Because solar panels have a smooth and shining surface, glare can occur, especially when the sun is

	<p>low in the sky, obstructing pilot and air traffic control officials' view.</p> <ul style="list-style-type: none"> • If improperly sited, solar PV installations can physically intrude into safe navigational airspace and interfere with navigational aids (NAVAIDS). • Solar PV projects can occasionally cause environmental issues such as ecosystem disruption, water quality degradation, toxic chemicals, etc. • If suitable handling and disposal procedures are not followed, traces of chemical substances found in PV modules could escape into the environment [136].
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Unlike airport and power plant construction, the environmental impact of solar plant installation is minimal because massive machinery and foundations are not required. Moreover, because of their high density of power use and distance from power generation centres, airport land is desirable for local power generation. Therefore, it is recommended that five acres are designated for 1MW of crystalline silicon-based solar PV facilities [135]. A list of some airport projects around the world is presented in Table 2-4.

Table 2-4 A list of some airport solar projects around the world.

	Airport	Country	Year	Capacity (MW)	Fraction of load supply (%)	Reference
1	Melbourne Airport	Australia	2021	12	15-20	[108]
2	Cochin International Airport	India	2015	12	100	[105]
3	Kuala Lumpur Int Airport	Malaysia	2015	19		[24]

	Airport	Country	Year	Capacity (MW)	Fraction of load supply (%)	Reference
4	Chattanooga Metropolitan Airport	USA	2013-2019	2.164	100	[37]
5	Cranfield Airport	United Kingdom	2018	1	30	[137]
6	Minneapolis-ST Paul Int Airport	USA	2015	3	20	[138]
8	Kansai International Airport	Japan	2012	12	9.5	[139]
9	Cardiff Airport	United Kingdom	2021	1		[140]

2.3 Microgrids and their application for airports

Public infrastructure operators have historically relied on the local utility grid to power their facilities, where electricity was generated at large power plants and transmitted to all utility customers. However, due to rapid advances in distributed energy generation, storage technology and declining costs, on-site power generation and storage have recently become an affordable and valuable alternative. In addition, with the emphasis on more electric aircraft (MEA) and zero-emission ground operation, there is a need for more motivation and driving forces to expand existing airports or build new ones. However, given the enormous energy requirements and the round-the-clock operation of most airports which make them energy-intensive, making airports typically spend 10% to 15% of their operating budget on energy [24], the environmental and sustainable development issues from the expansion will become even more significant and complex [37].

Furthermore, the roles played by the airport in the country's transportation network are disrupted whenever faults occur. For example, power outages cause flight delays, extended layovers, loss of income for airport concessions, and the

vulnerable area's inability to quickly receive emergency aid by aircraft [141]. Therefore, a possible solution to reduce the risk and acute negative effect of power outages and GHG emissions is for airports to be self-sufficient in generating and managing their power.

The building codes consider airports as critical infrastructures with an emergency power system to ensure continuity of supply to critical life-safety systems and flight operations in the event of sudden power loss. Conventional airports around the globe depend on the power supply from the local utility for continuous electricity while having an additional backup generator (typically diesel-powered) that can keep critical operations running during power outages [40]. However, this generator is usually delayed a few seconds before it kicks in and emits greenhouse gas, which disrupts critical operations and leads to poor air quality around the airport. Consequently, the aviation industry has shifted attention towards microgrid technology as a dependable and instantaneous supplementary power source to ensure reliability and continuity of operation in airports in the case of any eventuality [40].

Microgrids are local electrical systems built to generate their power while operating parallel with the utility (grid-connected) or separated from the utility (island mode), providing load balancing to achieve stable operation. An ideal microgrid typically incorporates a variety of local generators and storage systems, including cogeneration engines, wind power, fuel cells, and solar photovoltaics [142]. In addition, microgrids offer other benefits, such as mitigating supply and power quality problems from the local utility supply by deploying on-site energy storage [143].

Several authors have defined microgrids in different ways. [144] defined the microgrid as "a system approach which views generation and associated loads as subsystems". [145] referred to a microgrid as a platform for integrating demand-side (micro-generators) and supply-side (storage) resources in a local distribution grid. [146] described a microgrid as a low-voltage network that connects its loads with a few small modular generating systems for both electricity

and heat. The Consortium for electric reliability technology solutions (CERTS) has viewed microgrids as an aggregate of micro sources and loads that work as a single unit to provide power and heat [147]. A typical airport microgrid is shown in Figure 2-4

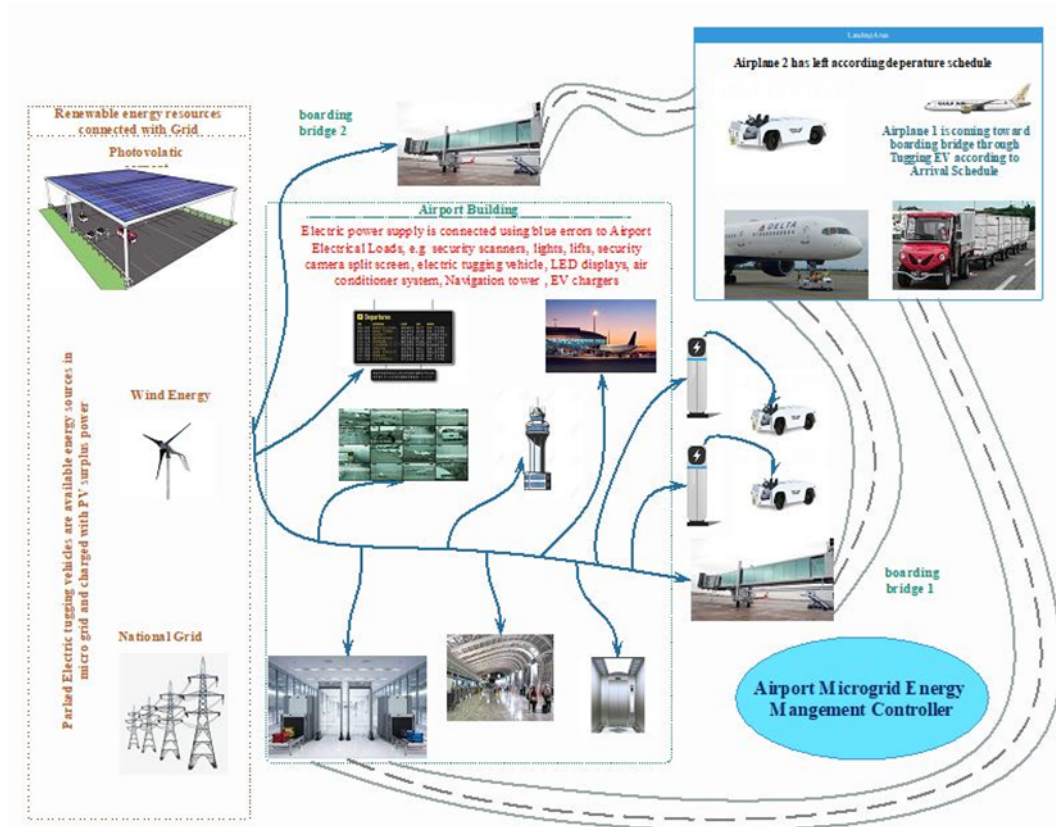


Figure 2-4 Typical microgrid layout for airport

The US Department of Energy defined a microgrid as a network of loads and distributed energy resources that operate on the grid as a single, controllable entity [148]. University campuses, military bases, townships, and even island micronations have begun pilot microgrid projects as a source of energy. US international Airports in San Diego, Denver, New York, New Jersey, the Indianapolis International Airport, John Wayne Airport and Kula Lumpur Airport in Malaysia have recently set up microgrid systems [143].

Although each stakeholder implements a microgrid for different purposes, the primary objectives are to (i) protect critical infrastructures from loss of power

during grid outages, (ii) reduce vulnerability to cyber and terrorist attacks, (iii) increase operational resiliency by sustaining critical operation during prolong utility outages, and (v) reduces environmental impact.

Airports resemble small cities that serve as the connecting point for the local, national and global transportation systems and facilitate business establishment and transportation [149]. Airports may not represent a high percentage of the total energy consumption in a country as the number in each country is lower than the number of hotels, schools, hospitals etc. However, they represent specific points of large energy consumption that could sometimes exceed that of a medium-sized city [143]. Therefore, optimising and reducing this energy consumption is a key objective for airport management for economic and environmental impact [99].

2.4 Green Airport concept

The concept of a green airport can be classified under the green transport plan (GTP) and green architecture plan (GAP), using a range of renewable energy and energy-efficient technologies [150]. The term "green airport" refers to a number of creative initiatives that improve the overall environmental performance of airport operations, intermodal transportation of people and goods between airports, and airport infrastructure. These Initiatives include electrification and the use of renewable energy sources. An airport with a green concept reduces GHG emissions and improves energy efficiency and surface accessibility by integrating new concepts in public transportation.

Therefore, implementing a green airport will catalyse energy independence and economic growth simultaneously. Furthermore, based on the FlightPath 2050 recommendation, by 2050, all ground movement operations at the airports in the European Union must be electrified [8]. Various airports and airlines have set their own ambitious targets for electrifying ground vehicles. For example, Amsterdam's Schiphol Airport has set a goal of having 100% of its ground handling equipment be electric by 2030 [151]. Similarly, Norwegian airport

operator Avinor has set a goal of electrifying all of its airports' ground handling equipment by 2025 [152].

Therefore, the direction of future research in the airport has shifted from the land side to the airside due to the ongoing efforts to decarbonise the aviation sector through electrification [108], [153]–[158]. Table 2-5 presents the trend in the research area in the aviation industry.

Table 2-5 Past VS Future research areas in the airport

Past research areas	Current/future research areas
<ul style="list-style-type: none"> Runway design and construction to accommodate larger aircraft 	<ul style="list-style-type: none"> Development of electric aircraft and electric ground support equipment to improve efficiency
<ul style="list-style-type: none"> Improvement of air traffic control systems to enhance safety and efficiency 	<ul style="list-style-type: none"> Use of renewable energy sources to power airport operation
<ul style="list-style-type: none"> Development of more efficient and reliable airport terminal buildings 	<ul style="list-style-type: none"> Development of urban air mobility solutions, such as electric vertical takeoff and landing (eVTOL) aircraft
<ul style="list-style-type: none"> Improvement of baggage handling system to reduce waiting times for passengers 	<ul style="list-style-type: none"> Reduction of environmental impact through the use of sustainable fuels
<ul style="list-style-type: none"> Development of new materials and technologies to improve aircraft safety and performance 	<ul style="list-style-type: none"> Use of artificial intelligence and machine learning to optimise air traffic management.

Given the complexity and unpredictability of real-world decision-making situations, evaluating, and choosing a green airport strategy is crucial. Therefore, only adopting multifaceted anti-pollution strategies and continued research can lessen its detrimental environmental effects. The measures must address the effects of emissions at various levels and environments, such as (i) The effects of hazardous pollutants from aircraft taxiing, taking off and landing in and around

airports, as well as ground-based airport traffic due to ground support equipment and vehicle traffic at the local level. (ii) Regional level pollution from aircraft approaching and departing airports or flying low; and (iii) Pollution from pollutants emitted at high altitudes, which is the most harmful on a global scale in terms of accelerating climate change [159]. The selected solutions to achieve green airports fall into the following categories:

2.4.1 Green transport plan (GTP)

The GTP focuses on reducing emissions during aircraft ground movement and other ground operations in the airport. In addition to supporting Flightpath-2050's four-hour door-to-door transport in Europe, it saves fossil fuels and reduces emissions [150], [160].

2.4.2 Green Architecture Plan (GAP)

A seamless and environmentally friendly service can only be achieved through the right infrastructure. It is, therefore important to address the buildings, the landscapes, and the road and rail networks around airports in the context of green air transportation initiatives [161] [162] [163]. Examples of green terminals include the Oslo green airport terminal, Norway [164]. Other airports that have implemented various degrees of green architectural plans in various sectors include Austin Bergstrom Airport, Boston Logan Airport, Indianapolis Airport, Hyderabad International Airport, Indira Gandhi International Airport and Gatwick Airport.

2.4.3 Green Airport challenges

2.4.3.1 Green Airport electrification

More sophisticated energy systems are also necessary for the increasing electrification of airport operations through integrating EGSEs, ETS, and other vehicles. In order to operate a zero-emission green airport, a local microgrid is a possible alternative. However, such an electrification method presents the technical difficulty of incorporating new energy supplies, such as solar energy, to decarbonise the current system [165]. Cranfield has a world-class aerospace

research reputation and unique infrastructure for aerospace research. However, electrification in aerospace, aviation and airports is a global trend and an emerging area.

2.4.3.2 Green airport renewable energy storage

Since power consumption is frequently the most significant contributor to airport carbon emissions, the availability of renewable energy on the electricity grid is crucial for decarbonising airport operations. Approaches that consider hydrogen would also need significant amounts of renewable electricity to produce. If the fuel is made onsite or nearby, this electricity would need to be generated and transported to the airport. This idea is thoroughly discussed by [31].

2.4.3.3 Glare assessment

Solar PV installations often face questions regarding reflections. According to a study published by [128] in 2021, solar PV systems may cause glare for an airport, posing a risk to its operations. Furthermore, airports are also characterised by solar reflections, often caused by glass facades, parking lots, or even art installations. As a result, glare assessment plays a crucial role in the design stage of an airport's solar PV system [166].

2.4.3.4 Wildlife impact

Large photovoltaic arrays placed close to air operations areas to offset energy needs would undoubtedly be advantageous to airports from both an environmental and financial standpoint, while the usage of solar installations needs to be carefully investigated before being widely adopted. Photovoltaic arrays might attract birds that are hazardous to aviation since they offer shade and perches, both of which are prohibited at grassland airports. PV array panels can also reflect polarised light, luring insects and their predators [87]. Reflected polarised light may also cause some bird species to mistake glass panels for open water, resulting in fatalities if they collide with them or become stranded on the surface.

2.4.3.5 Energy management

The airport infrastructure consumes a large amount of electricity. Air conditioning, ventilation, and heating are responsible for the majority of energy consumption in the airport [167]. Renewable energy can save airports a substantial amount of cost, as well as reduce carbon footprints [108]. The airport's energy requirements can be met by installing microgrid technologies and renewable energy sources such as wind, biomass, hydropower, solar photovoltaics, and geothermal heat pumps. However, the stochastic and intermittent nature of most renewable energy sources poses an energy management challenge to green airports [168].

2.4.3.6 Ecosystem challenges

Large areas of land must be developed to construct an airport's primary infrastructure, which includes runways, taxiways, aprons, terminal buildings, and ancillary infrastructures like roads and trains [169]. However, this change can impair the performance of nearby ecosystems and result in a decline in biodiversity. Therefore, the economic, social, and environmental implications of airports must be balanced to enable effective planning and management in the transportation sector [170].

2.4.3.7 Inclement Weather

Concern about the implications of climate change and how it may affect infrastructure is spreading across the globe. If not addressed, climate change effects, including temperature, weather, wind, and storm patterns, are projected to pose a major risk to green airport operations. For example, around 70% of yearly flight delays are thought to be caused by bad weather, and upcoming weather changes can make things even more difficult [171].

2.5 Conclusion

This chapter surveys the literature about emerging technologies in green airports; electric taxiing, airport-based photovoltaic power systems and electric grid infrastructure for the green airport. The future of airport operations is the green airport concept. In both the landside and airside of the airport, some major operational areas have been identified for the introduction of green transformation, such as terminal building lighting and ground movement operation. Airport pollution reduction, noise reduction, operational efficiency, onsite green power generation, and resource optimisation are key elements in implementing green airport services. The ETS, ASPV, EGSVs, A-ETR, onsite green hydrogen production, and other elements of green transformations have been identified as application tools of the green airport concept. Based on the concepts introduced in chapter one, a review of the literature in chapter two shows no documented studies linking ground movement operations with onsite renewable energy sources. Consequently, in chapter three, we conceptualise new hardware A-ETR to link the airport's renewable energy and new electric taxiing loads into a microgrid ecosystem.

3 .Towards a Green Airport using Novel Electric Taxiing

3.1 Chapter Summary

This chapter envisions a green airport inspired by the performance goals set by ACARE Flightpath 2050 on future aircraft ground movements. The proposed green airport vision embraces a novel A-ETR concept as a mobile charge and discharge interface to an on-site solar-powered microgrid. It exploits the dynamic loading demands and charging opportunities arising from the varying duty cycles of the A-ETR to maximise airport operators' economic and environmental benefits. Cranfield University's Airport and its Boeing 737 research aircraft are used to generate realistic data for typical electric taxiing scenarios, which are deployed in this chapter to validate the concept. The airport's 1MW solar farm output is modelled as a green energy source to a battery-connected microgrid for opportunistic charge and discharge of the A-ETR. The simulation results from three weather scenarios show that the airport will benefit from using the novel A-ETR to achieve FlightPath-2050's zero-emission target of aircraft ground movements. The results show that the grid using the optimised A-ETR not only can achieve zero-emission taxiing but also result in fuel reduction of 91% when compared against a standard baseline according to the international civil aviation organisation (ICAO) aircraft engine emissions databank.

3.2 Introduction

All European airports are expected to achieve zero-emission aircraft ground movements by 2050, as mandated by FlightPath 2050, an initiative by ACARE [8]. This policy is against the backdrop of an aviation industry that is very demanding on fossil fuels and is responsible for nearly 3.6% of the world economy's gross domestic product [172]. Moreover, as a strong contributor to global economic and social development, the aviation industry has been predicted to experience a rapid annual increase in global passenger air traffic until at least 2050-2060 [1],[2].

Airbus claims that ground operations and taxiing for European flights can account for up to 30% of the whole journey time and 5% to 10% of mission fuel [173], which represents consumption of 5 million tonnes of fuel per annum with an estimated cost of £5.63 billion and producing 13 million tonnes of CO₂ [13], [174]. Therefore, it is necessary to focus on ground movement optimisation and taxiing mechanisms to reduce emissions at the airport [175]. The ICAO defines taxiing as 'the phase of flight where an aircraft moves under its power on an airfield surface, except for take-off and landing' [20]. However, the efficiency-to-fuel consumption ratio of aircraft is very low during taxiing at the airport because jet engines are designed to run efficiently at cruising speed [176].

The ground movement emission reduction efforts in the airport can broadly be classified into operational and technological-based solutions [96]. Optimisation of ground procedures, such as SET, is the most prevalent operational method and has been relatively successful because it is easy to implement [98], [11]. When using a single engine for taxiing, there is a chance that the fuel load will be reduced, lowering the aircraft's weight and, ultimately, reducing fuel consumption for the entire trip [18]. However, the operational solutions still depend on using an engine for ground mobility and are not recommended on uphill slopes, slippery surfaces or during deicing operations [11]. There is also a risk of losing braking capability and nose wheel steering. In addition, when taxiing is performed with fewer engines, more thrust is needed per engine to manoeuvre, especially on a

breakaway and 180-degree turns. It is, therefore, essential to avoid excessive jet blasts and foreign object damage (FOD) [11]. Other operational strategies that aim to cut down on taxiing times include active routing and enhanced queue management [93] [98]. The advanced queue management system may significantly reduce fuel consumption and emissions through improved coordination on the surface, information sharing and collaborative planning. However, doing this at airports will be challenging as it requires the optimal scenario with uninterrupted taxi-out time. Additionally, there has to be more cooperation between surface traffic [177].

On the other hand, technology-based solutions involve the use of technologies such as dispatch towing and ETS [97], [20]. During departure tow-outs, the engines are not started until five minutes prior to take-off (that is, for warm-up), during which time the tugs produce the power required to tow the aircraft. Aircraft emissions decrease as a result, while tug emissions have been added [11]. The ETS has attracted more attention due to the potential for zero-emissions taxiing and lower noise levels [20]. ETS is based on using electric motors to propel aircraft around airports without having to start the main engines [88]. The ETS is classified into two categories: the first is an onboard ETS, such as the wheel tug installed in the nose landing gear (NLG), or an electric green taxiing system (EGTS) installed in the main landing gear (MLG). The NLG configurations benefit from a larger amount of available space than MLG due to the brake mechanism of the latter. On the other hand, the use of ETS at the NLG would not be effective during severe weather conditions such as snow, ice, and rain when traction efforts reduce. However, due to the high tractive forces possible at the MLG, it is an attractive location to install motors, despite the challenging space constraints [21].

The electricity is supplied through the APU, so there is no need to activate the engines in both cases. In addition, these systems allow the pilot to push back autonomously, thereby saving pushback time by avoiding any type of tug connection and disconnection; hence, it is safe for ground operators. However, installing onboard ETS adds additional weight to the aircraft, making it unsuitable

for long-range flight and requiring reconfiguration of the aircraft architecture, which would present substantial challenges in terms of certification and legislation [21]. The second type of ETS is the off-board taxiing system, such as Taxibot, a semi-robotic, towbar-less, diesel-electric tractor [14] - [18]. The main advantage lies in the fuel consumption, i.e., the fuel consumption of a Taxibot is much lower than the fuel consumption of a wide-body jet during taxiing. In addition, Taxibot eliminates bottlenecks in gate areas. Other significant advantages of Taxibot are the prevention of FOD and lower environmental impact due to reduced sound levels [14].

However, since the Taxibot is diesel-operated, it is not a completely carbon-neutral solution, emitting pollution according to the engine type. In addition, this solution creates congestion at the airport due to space occupied between two aircraft at the holding point, increasing the risk of an accident while waiting for the arrival of the aircraft on the taxiway [14]. Some electric systems are currently used for pushing back bigger aircraft, such as the B737, but they are not fast enough to handle a proper taxi-in or taxi-out without delays because their average speed is between 2 knots and 6 knots, in other words, 3.7-11.1 km/h, which is far less than 20 knots needed for optimal taxiing [20].

[102] has identified three basic functions that the ETS must be able to perform, that is push-back, movement of the aircraft from a standstill with sufficient acceleration, and driving the aircraft along the taxiway. [20] introduced the concept of ETS, described various technologies and detailed the environmental and economic benefits and challenges faced during the implementation of the technology. [98] compared four taxiing scenarios. Single-engine and twin-engine taxiing are considered in the first two scenarios, while the third and fourth scenarios involve off-board and onboard taxiing systems. A comparative analysis of the emissions from the four scenarios shows that there are trade-offs in terms of fuel consumption and emissions among these modern technologies. The onboard taxiing system shows a better performance in terms of emission reduction, while the off-board taxiing system provides better performance in terms of fuel burn. Both techniques allow pushback and taxi operations even

when the aircraft's engines are off, thus reducing fuel consumption, pollution, and FOD.

[18] developed a model to evaluate the impact of SET on fuel consumption and pollutant emission using London Heathrow Airport as a case study. The model has further reduced ground-level emission and fuel consumption by reducing the time set for SET initiation. The result indicates that there is a potential for reducing fuel load, which consequently lowers aircraft weight leading to a decrease in fuel consumption across the flight. [11] evaluate the opportunities for surface emission reduction through optimisation and assess the potential benefits and implementation barriers in adopting the different approaches at the airport. The paper concludes that combining these measures in an intelligent manner will allow the airport to reduce fuel and emission without compromising operational efficiency. [88] evaluates the economic impacts of the adoption of an ETS, by identifying the threats and potential impact of introducing this system to aircraft operation. The paper concludes that the introduction of the ETS will create savings and is attractive to most air operators amidst these problems and areas of concern. [100] studied the speed limitation and delays resulting from ETS. The authors used Amsterdam Schiphol Airport as a case study. The study showed that an average speed of 10 m/s (20 knots) should not cause significant delays to other aircraft. [98] investigate fuel savings and emission reductions for different electric taxi systems. The study found that onboard systems have the highest carbon monoxide (CO) reduction, while external systems have maximum fuel savings but higher NO_x emissions. As described above, the concepts of ETS in eliminating emissions in airports have their advantages and disadvantages, but they are undeniably advantageous in comparison with conventional taxiing systems.

However, currently, there are deficiencies and challenges to achieving zero-emission ground movement operations through ETS in airports [181],[14] because there is no connection between the reduction of emission efforts through ETS and on-site renewable energy sources in the airport. Therefore, this study explores the use of a mobile interface, i.e. A-ETR, to link ground movement

operations and ASPV [114], [119], [182]. This study is among the initial studies that provide the first phase of a greener airport. Conducted using a novel A-ETR as a mobile interface to an ASPV.

3.3 Methodology

3.3.1 System modelling

Cranfield Airport has a 1MW solar farm on-site and owns a Boeing 737, one of the most popular medium-range commercial airliners, which is very suitable for off-board ETS because of its weight and configuration of leading gear, as shown in Figure 3-1. The airfield is a research platform for the development of aviation technologies. It is supported by world-leading facilities such as the recently opened Digital Aviation Research Technology Centre (DARTeC) [183]. DARTeC aligns with Cranfield University's three research themes: Transport Systems, Aerospace, and Manufacturing and Materials. It aims to address aviation challenges, such as integrating drones into civilian airspace, enhancing airport efficiency through tech, establishing safe airspace, and improving aircraft reliability via self-aware tech. The capacity of the PV solar farm is 1 MW, the capacity of the A-ETR is 50kWh, while the maximum capacity of the grid line is 5 MW. The following assumptions are used in this study.

Table 3-1 Assumption and simplifications

S/N	Assumption and simplifications	Value	Reference
1	Maximum state of charge for A-ETR and BESS	100%	[184]
2	Minimum state of charge for A-ETR and BESS	25%	[184]
3	Thrust level of taxiing aircraft	7%	[185][94][20] [186] [187] [188],[189]
4	Maximum speed on straight and turning section	23knot,10knots	[185][21]
5	All flights taxi under the international standard atmosphere		[97]

S/N	Assumption and simplifications	Value	Reference
6	Rolling resistance coefficient	0.015	[190], [186], [191]–[194]
7	Charging and discharging efficiency	0.9	[195] [196]
8	BESS finance interest	6%	[124]
9	Cost of BESS per 100 kWh	£60000	[197]
10	Maximum charging power of BESS	50%	[198][99]
11	Taxiing time	4.5 minutes	
12	A-ETR in operation and on standby to meet the demand	4	
13	Microgrid BESS capacity	400kWh	
14	Maximal charging power of the BESS system	1000kW	
15	maximal charging power of A-ETR	50kW	

This SOC range is implemented to extend the battery's lifespan by minimising the frequency and depth of discharge cycles, which can cause the battery's chemistry to degrade over time. Additionally, it is essential to maintain a certain level of charge in the battery to ensure that it can serve as a reliable backup power source during emergencies or outages.

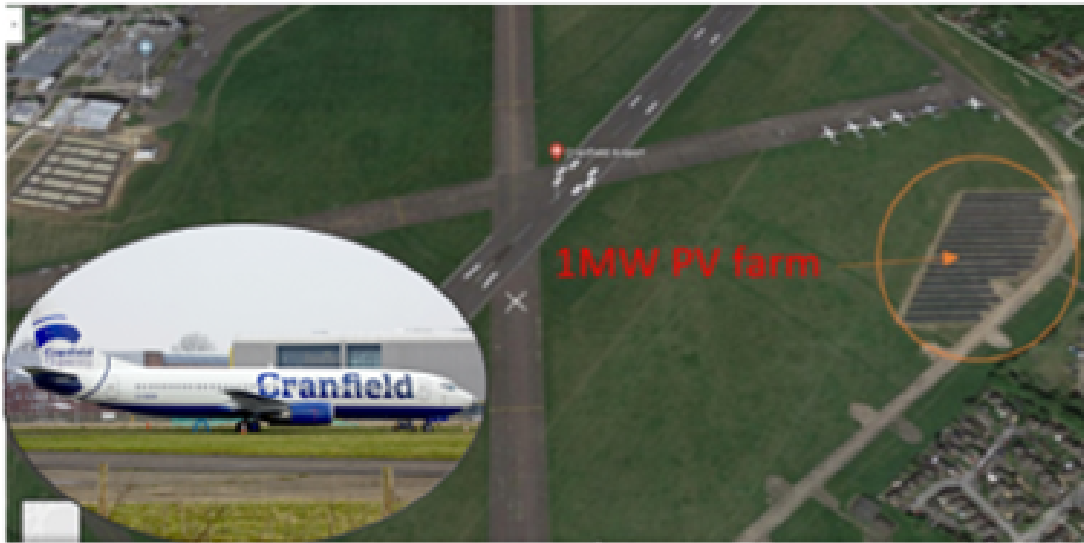


Figure 3-1: Cranfield Airport with its 1MW solar farm and its Boeing 737 aircraft (inset)

3.3.2 Cranfield Airport surface representation

The airport is shown in Figure 3-2, with the taxi route of outgoing aircraft highlighted from the gate to the runway. The taxi route segment property is given in Table 3-2. The initial speed V_0 at the beginning of segment one is 0 knots. To navigate along this segment, a variety of speed profiles are available. The aircraft exits segment one with a speed $V_4 = 10$ knots which is the initial speed V_0 for segment two. Since segment two is straight, the aircraft taxi at constant speed V straight set to 15 knots. For the last segment, i.e., three, as it is a turning segment with stopping, the aircraft decelerates to 0m/s. Some aircraft may cross an active runway during taxiing operation and might need to stop before crossing, although this is not related to our case study. In such a case, V_4 of that segment would be set to 0, which will introduce additional constraints that will ensure the aircraft continues taxiing only when it is safe.

The comfort of the passengers in an aeroplane on taxiing is related to the lateral and longitudinal accelerations, which remain entirely dependent on how the pilot controls the aircraft on the ground [199]. Airports around the world sometimes publish maximum and minimum taxi speeds for aircraft. Most airports and regulatory authorities, such as FAA, CAA, GCAA, ICAO, etc., expect airlines and

aeroplane pilots to exercise sound judgement and best-operating practices when taxiing. Seldom do Air Traffic Controllers (ATCs) ask or even instruct pilots to increase their taxi speed. However, it is always the pilot's prerogative (to accept or decline directives from the ATC) to follow what he deems to be the safest course of action in his judgement.



Figure 3-2: The Cranfield Airport taxiway path: Source (Google Earth)

Table 3-2 Airport segment properties

SEGMENT PROPERTIES					
SEGMENT NUMBER	segment type	V ₀ (kN)	V ₄ (kN)	Length (m)	Taxiing time
	starting	0	0	0	0
1	Turning	7	7	36.07	10.0164395
2	straight	15	15	78.55	20.1957931
3	straight	15	15	48.22	26.4446592
4	straight	15	15	30.58	30.4075444
5	straight	15	15	27.55	33.9777696
6	straight	15	15	42.57	39.494448

7	straight	15	15	110.31	53.7896039
8	straight	15	15	32.31	57.9766811
9	straight	15	15	58.77	65.5927296
10	turning	7	7	69.07	84.7730866
11	turning	7	7	112.37	115.977614
12	turning	7	7	45.27	128.548843
13	turning	7	7	46.58	141.483851
14	turning	7	7	26.53	148.851085
15	turning	7	7	28.65	156.807032
16	straight	15	15	51.55	163.487435
17	straight	15	15	24.79	166.69999
18	straight	15	15	151.38	186.317438
19	straight	15	15	309.64	226.443919
20	turning	7	7	49.96	240.317534
21	turning	7	7	44.38	252.641615
22	turning	7	7	36.54	262.788571
23	stopping	7	0	24.59	262.788571
				1486.23	

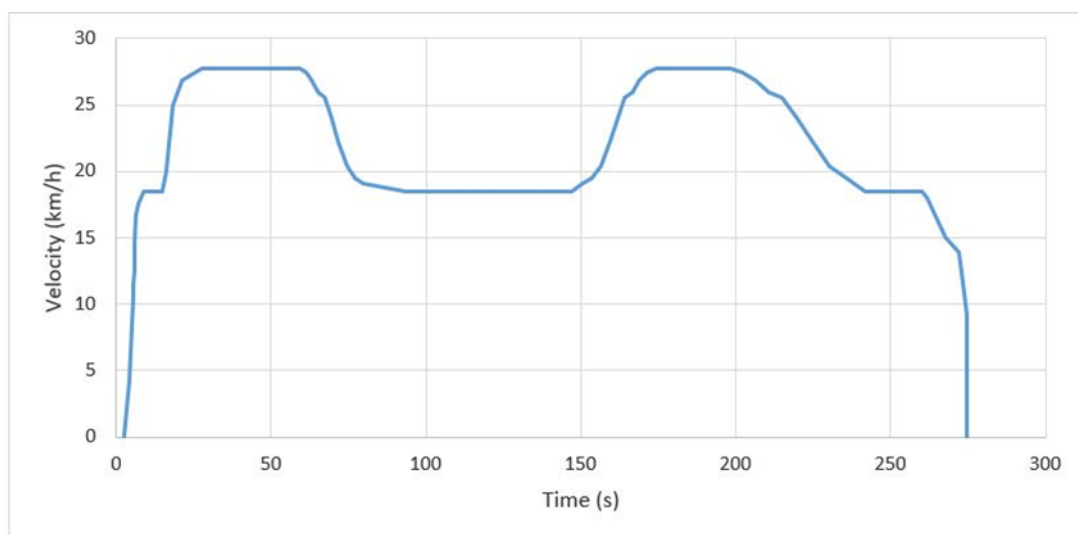


Figure 3-3: Velocity-time profile for Cranfield Airport

3.4 Traction load profile generation analysis

The taxi route of the airport is divided into different segments (starting, straight line, turning and stopping), and for each segment, there is a nominal speed profile[200]. After an initial velocity of $V = 0$ knots at the starting segment, a variety of speed profiles are generated to navigate along with the segments at a maximum limit of $V = 10$ knots during turning and between 15 and 23 knots in straight lines for the datum aircraft according to the ICAO.

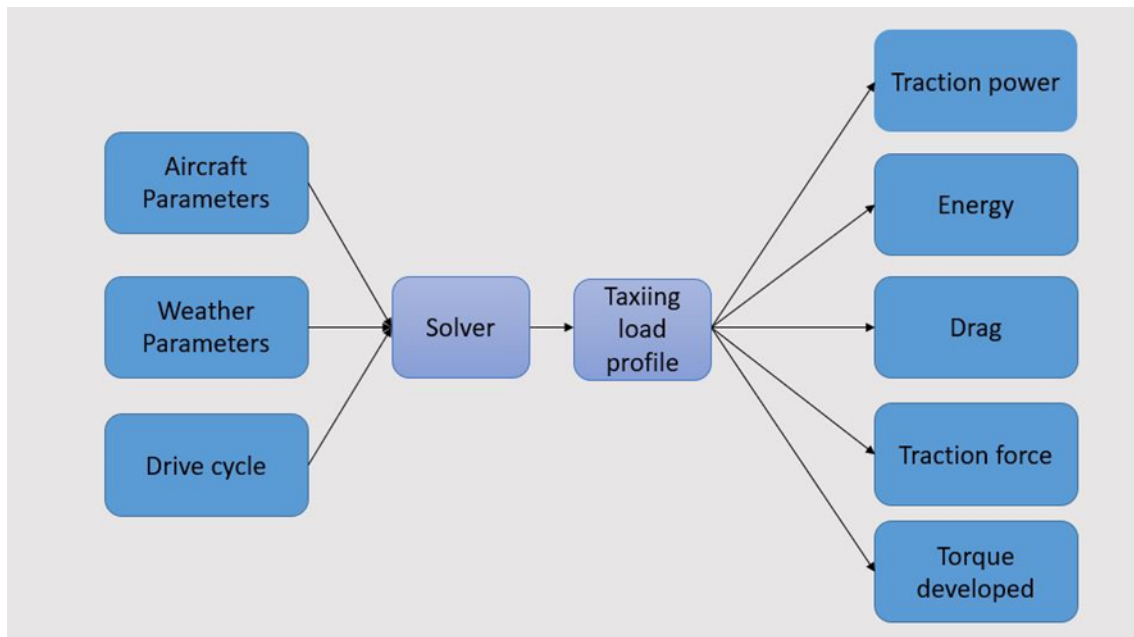


Figure 3-4: Architecture of aircraft traction load profile analysis

The drive cycle speed profile is one of the inputs of the traction load profile model (shown in Figure 3-4) that is required to generate the kinematic parameters of the A-ETR, i.e. (i) maximum power (kW), (ii) maximum torque (Nm), (iii) maximum speed (Rpm) and (iv) maximum tractive force.

3.4.1 Aircraft dynamic model

The behaviour of an aircraft during electric-taxiing can be represented by a two-dimensional longitudinal dynamic model [201]. During taxiing, the traction force exerted by the electric traction units, F_{tract} , must overcome the total resistive

forces opposing the ground movement of the aircraft, such as road load, rolling resistance, aerodynamic drag, and taxiway gradient. The force acting on a taxiing aircraft is shown in Figure 3-5. According to the Base of Aircraft Data (BADA), the dynamic equations describing the longitudinal motion of an aircraft.

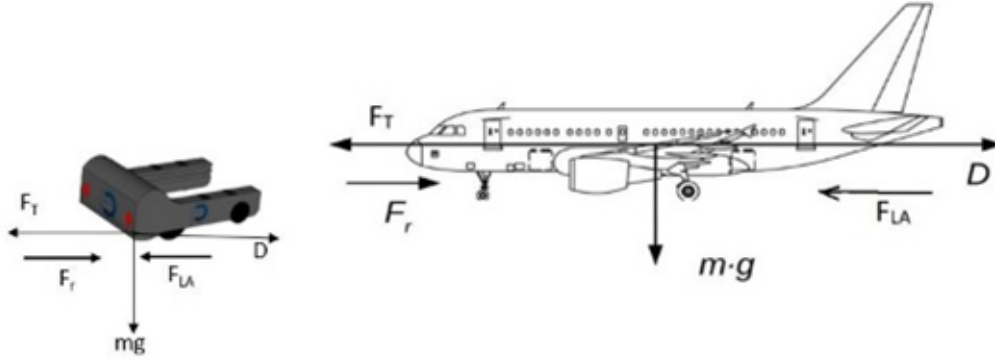


Figure 3-5: Forces acting on E-ATR and aircraft during taxiing.

used in this study are derived from the total energy model (TEM) [93]. The model considers the forces acting on the aircraft and the A-ETR during ground movement operation, such as traction force (F_T), linear acceleration force (F_{LA}), rolling resistance force of the tire (F_r), aerodynamic drag force (D), and grade resistance force (F_{grade}) are based on the interaction between the aircraft mass, wheel and tarmac as expressed below [93]:

$$F_{traction} = F_{LA} + F_{grade} + F_r + D \quad (3-1)$$

3.4.2 Traction power

The gross traction power to the wheel depends on the traction force F_T (N) and the instantaneous taxi velocity V (m/s):

$$P_{traction} = (F_{LA} + F_r + D + F_{grade}) \times V. \quad (3-2)$$

The dynamic equations (3-1) - (3-7) form part of the input parameters to the traction profile generation model to determine the parameter specification of the A-ETR.

3.4.3 Aerodynamic drag force

The aerodynamic drag is a resistance force acting on the aircraft and the A-ETR during motion. Its magnitude depends on the current taxiing velocity (V), the air density ρ (1.2 kg/m³ at 20°C), the aircraft drag coefficient C_D and A-ETR drag coefficient C_X , headwind speed (Hd), the frontal area of the aircraft (A_F), and drag area (S) for the A-ETR as represented in (3-3) [202].

$$F_{drag} = \begin{cases} \frac{1}{2} \cdot \rho \cdot (V + Hd)^2 (S \cdot C_X + A_F \cdot C_D) & \text{when towing} \\ \frac{1}{2} \cdot \rho \cdot V^2 \cdot (S \cdot C_X) & \text{otherwise} \end{cases} \quad (3-3)$$

The aircraft experiences maximum drags when the maximum taxi velocity is substituted for V in (3-3).

3.4.4 Rolling resistance force (F_r)

The rolling resistance F_r is proportional to the weight (mg) due to the masses of the A-ETR m_t , and aeroplane m_{air} , the rolling resistance coefficient (μ), $g = (9.81 \text{ m.s}^2)$, and m_{air} (maximum take-off weight (that is 71.5 tonnes) of the aircraft according to its weight category (3-4) [203]. The effective rolling resistance depends on the tire conditions, which means the operator's attitude toward tire maintenance (tire pressure, tire wear, etc.) can have a consequential impact on energy consumption. The rolling resistance coefficient (μ) ranges from 0.01 to 0.015 for aircraft tyres [190]. In this study, μ is set as 0.015 for the concrete surface, and the frictional force considered is the rolling resistance between tires and the ground. This value is widely accepted in the aviation industry as a conservative estimate based on validated research studies [186], [191]–[194].

The impact of the rolling resistance is higher for heavier aircraft because the relationship between the masses ($m_t + m_{air}$) and the required power to overcome the friction is linear. The total length of the taxiway is 1.5 km, with an average taxiing time of 4.5 minutes. The rolling resistance F_r can be expressed as in (3-4) [202].

$$F_r = \begin{cases} (m_t + m_{air}).g.\mu.\cos\alpha & \text{if towing} \\ m_t.g.\mu.\cos\alpha & \text{otherwise} \end{cases} \quad (3-4)$$

$$F_{LA} = \begin{cases} (m_t + m_{air}).a & \text{if towing} \\ m_t.a & \text{otherwise} \end{cases} \quad (3-5)$$

3.4.5 Grade resistance

The grade resistance (F_{grade}) is another resistance force that affects the available net traction force to the road (F_T). This resistance appears when moving the aircraft uphill, i.e., an inclined plane separating the airport's apron from the taxiway or its equivalent. If the inclined plane grade in degree gradient is known as the angle of climb (α) and can be derived as:

$$\alpha = \arctan\left(\frac{gr}{100}\right) \quad (3-6)$$

The maximum allowable inclined plane grade (gr_m) in airports is standardised, i.e. the slope of taxiways must be $\alpha \leq 3\%$ [186], thus, it can be neglected and depends on the type of aircraft that is supposed to taxi along the taxiway. Generally, the grade resistance depends on the weight of the aircraft (m_{air}) and the angle of climb α and can be estimated as follows [202].:

$$F_{grade} = \begin{cases} (m_t + m_{air}).g.\mu.\sin\alpha & \text{if towing} \\ m_t.g.\mu.\sin\alpha & \text{otherwise} \end{cases} \quad (3-7)$$

The slope is a critical parameter because the required taxiing power depends on the variation of potential energy [186],. The electric energy demand of the A-ETR in a region with a high hill requires more energy than in a flat region. Because the extra power needed to climb a slope is proportional to the mass of the aircraft. In this study, the grade is set to zero, which means no grade resistance in the dynamic model of the electric-taxiing system.

Time(s)	Velocity (ms-1)	Velocity (km/h)	Acceleration(ms-2)	Head wind (ms-1)	Tractive force (N)	Tractive Power (kW)	Axel Torque (Nm)	Axel speed (RPM)	Lumped transmission efficiency [0,1]	Motor Torque (Nm)	Motor Speed (RPM)	Motor Power (kW)	distance (m)	Battery power (kW)	Battery energy required (kWh)
0	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	0	184.2633	0
9.276	12.8611	46.29996	0.8319	0	80514.20	1035.50	30595.40	323	1.00	2549.6	3878	1035.50	36.07	966.1714	2.489502
17.006	12.8611	46.29996	0	0	15626.04	200.97	5937.89	323	1.00	494.8	3878	200.97	55.7	187.5135	0.402633
27.055	5.1444	18.51984	-0.76791	0	-44541.58	-229.14	-16925.80	129	1.00	-1410.5	1551	-229.14	75.335	-534.498	-1.49199
38.65	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	114.62	184.2633	0.593481
44.834	10.8033	38.89188	0.915087	0	86907.92	938.89	33025.01	271	1.00	2752.1	3258	938.89	162.84	1042.896	1.791464
54.11	5.1444	18.51984	-0.61006	0	-32229.35	-165.80	-12247.15	129	1.00	-1020.6	1551	-165.80	193.42	-386.751	-0.99653
77.3	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	220.97	184.2633	1.186963
78.84	6.1733	22.22388	0.668117	0	67491.01	416.64	25646.58	155	1.00	2137.2	1862	416.64	220.97	809.8931	0.346454
81.165	5.1444	18.51984	-0.44254	0	-19162.75	-98.58	-7281.84	129	1.00	-606.8	1551	-98.58	263.54	-229.952	-0.14851
92.76	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	263.54	184.2633	0.593481
103.582	12.3466	44.44776	0.665515	0	67510.90	833.53	25654.14	310	1.00	2137.8	3723	833.53	263.54	810.1319	2.435346
112.085	5.1444	18.51984	-0.84702	0	-50712.27	-260.88	-19270.66	129	1.00	-1605.9	1551	-260.88	263.54	-608.546	-1.43735
119.815	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	373.85	184.2633	0.395654
124.453	9.26	33.336	0.887365	0	84685.24	784.19	32180.39	233	1.00	2681.7	2792	784.19	373.85	1016.224	1.309235
131.41	5.1444	18.51984	-0.59158	0	-30787.80	-158.38	-11699.37	129	1.00	-974.9	1551	-158.38	373.85	-369.453	-0.71397
146.87	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	406.16	184.2633	0.791309
154.6	11.8322	42.59592	0.865175	0	83060.13	982.78	31562.85	297	1.00	2630.2	3568	982.78	407.16	996.7226	2.140185
162.33	5.1444	18.51984	-0.86517	0	-52128.43	-268.17	-19808.80	129	1.00	-1650.7	1551	-268.17	420.16	-625.54	-1.34317
181.655	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	464.93	184.2633	0.989136
193.25	9.26	33.336	0.354946	0	43156.55	399.63	16399.49	233	1.00	1366.6	2792	399.63	464.93	517.8796	1.668004
200.98	5.1444	18.51984	-0.53242	0	-26173.50	-134.65	-9945.93	129	1.00	-828.8	1551	-134.65	474.93	-314.081	-0.6744
220.305	5.1444	18.51984	0	0	15355.19	78.99	5834.97	129	1.00	486.2	1551	78.99	484.93	184.2633	0.989136
228.4	10.8033	38.89188	0.699061	0	70057.88	756.86	26621.99	271	1.00	2218.5	3258	756.86	494.93	840.6956	1.890397
235.5	10.8033	38.89188	0	0	15531.11	167.79	5901.82	271	1.00	491.8	3258	167.79	494.93	186.3744	0.367572
245.655	13.3755	48.1518	0.253294	0	35409.27	473.62	13455.52	336	1.00	1121.3	4033	473.62	504.93	424.9123	1.198607
255.47	13.3755	48.1518	0	0	15652.34	209.36	5947.89	336	1.00	495.7	4033	209.36	514.93	187.8292	0.512095
262.788	0	0	-1.82775	0	-142564.77	0.00	-54174.61	0	1.00	-4514.6	0	0.00	524.93	-1710.78	-3.47763
													6516.09		11.8071

Figure 3-6: Electrodynamic traction load profile generation program in Microsoft excel

3.4.6 Energy consumption model

The battery pack has a specific usable energy capacity that determines the range of the A-ETR for specific energy consumption. While the power required depends on the drive cycle, the battery pack must deliver the required energy to fulfil the taxiing operation. The mechanical power P (defined in (3-2), required to move the A-ETR and tow the aeroplane at the speed V , is enumerated considering the forces acting on it in (3-1) - (3-7), the aerodynamic drag (D), the rolling friction F_r , linear acceleration force F_{LA} , and slope resistance F_{grade}

The total energy consumption during acceleration/deceleration time is given as [204]:

$$\Delta E^{bat} = \begin{cases} \frac{\Delta t}{\eta_d \times \eta_{out} \times \eta_m \times 3600} \times P_{traction} & \text{if } P_{traction} \geq 0 \\ \frac{\Delta t \times \eta_c \times \eta_m \times e_{rec}}{3600} \times P_{traction} & \text{if } P_{traction} < 0 \end{cases} \quad (3-8)$$

where η_c , η_d , η_{out} , η_{in} , η_m and e_{rec} in (3-8) are the energy storage charging and discharging efficiency, power electronics discharging and charging efficiency, electric motor efficiency and the fraction of the recovered braking energy. The average energy demand for one taxiing operation in the airport is around 12kWh, as shown in Figure 3-6. it is assumed that sensors and nose wheel locking/lifting will be required an additional 3kWh. Moreover, the A-ETR should be capable of doing one taxi-in and taxi-out between recharging so that the capacity of one A-ETR is sized to be 50kWh.

3.5 Autonomous electric taxiing robot (A-ETR)

The A-ETR proposed in this study is battery-powered with modular electric motors and a maximum speed limited to 40 km/h. They are directed to move to an assigned waiting area illustrated in Figure 3-7 around the gate at the beginning of the taxiing operation.

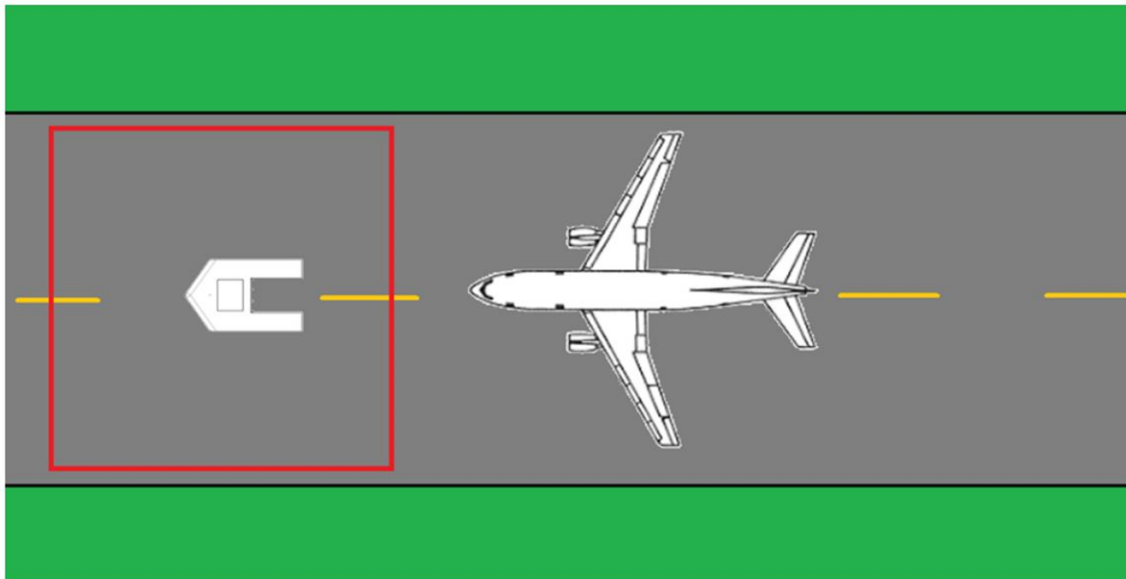


Figure 3-7: Waiting area for the taxi-in on the runway.

As shown in Figure **3-8**, the A-ETR is equipped with a four-laser ranger to locate the aircraft's nose wheel for alignment. It uses the right and left laser range finders to detect obstacles around the nose wheel to prepare for interlocking with the aircraft. The A-ETR will be aligned with the aircraft's nose wheel and can begin the locking and lifting procedure after the four laser rangefinders have determined that there are no impediments within range. The standby space previously described is required because the A-ETR must be reasonably close to the nosewheel at the beginning of the operation for it to function.

The patent-pending interlocking mechanisms (not shown) allow the pilots to take complete control of the taxi in and out.

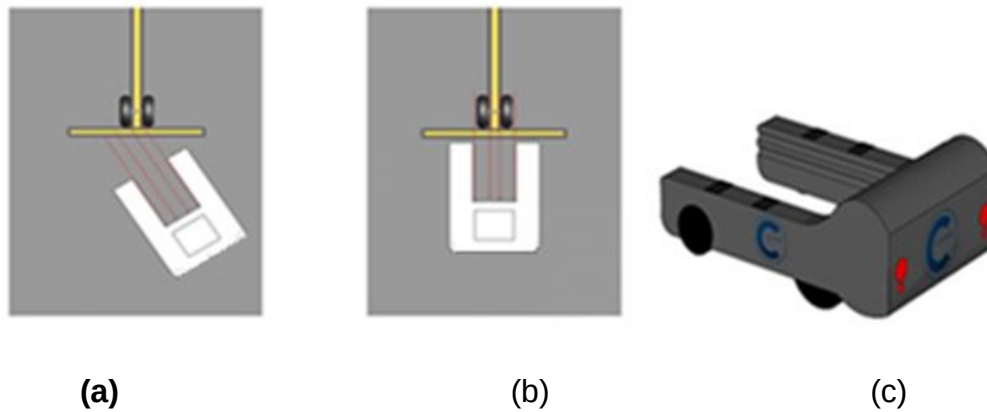


Figure 3-8: Electric-taxiing nose wheel alignment procedure

: (a) obstacle detected by laser finder (b) alignment with nose wheel (c) Cranfield's A-ETR (details not included)

3.6 Calculation model for fuel consumption and pollutant emission

This section develops the model that provides a taxiing emission baseline based on the taxiing behaviour, which distinguishes between unimpeded taxiing, where the taxiway is not crossed by other taxiways or runways and impeded taxiing, where the taxiway is crossed by other taxiways or runways, fuel consumption and emission of conventional taxiing systems. This baseline information offers insight into potential emission saving with the proposed A-ETR. The thrust levels during taxiing operations are crucial for determining the emissions and fuel consumption associated with taxiing. The taxiing time of an aircraft is classified under four different phases: (i) break-away and acceleration, (ii) taxiing at a constant speed, (iii) holding, and (iv) turning.

The evaluation of aircraft fuel burn is essential in estimating the effect of air traffic operations on the environment. The fuel consumption of an aircraft is calculated using the engine performance model under ideal conditions.

However, it is challenging to acquire the performance of the Boeing 737 aircraft. Consequently, researchers searched for information on aircraft performance, which led to the creation of engine emission databases that can offer fuel flow

and emission indices as functions of engine thrust [205]. There are currently two widely used databases that are included in these data lists, aircraft engine emissions by ICAO [186] and BADA by Eurocontrol experimental centre [206]. The latter data set is mainly used to calculate fuel consumption during flight stages of aircrafts rather than during aircraft taxiing.

Data on engine performance and emissions from full-engine tests conducted at sea level are contained in the former data list. This database provides fuel flow and emissions for most jet and turbofan engines under 7%, 30%, 85% and 100% of their rated output power [186]. In the present study, an ICAO database has been used to calculate aircraft taxi fuel consumption because it provides standardised and reliable data on the fuel burn rates of different aircraft types based on a range of factors such as engine type, aircraft weight, and ambient conditions. This allows for accurate and consistent estimates of fuel usage across different aircraft and operational scenarios. Secondly, the ICAO database is regularly updated and maintained to reflect changes in aircraft technology and performance, as well as evolving industry standards and regulations. This ensures that the fuel consumption data is up-to-date and reflects the latest developments in the aviation industry [189] [88] [188].

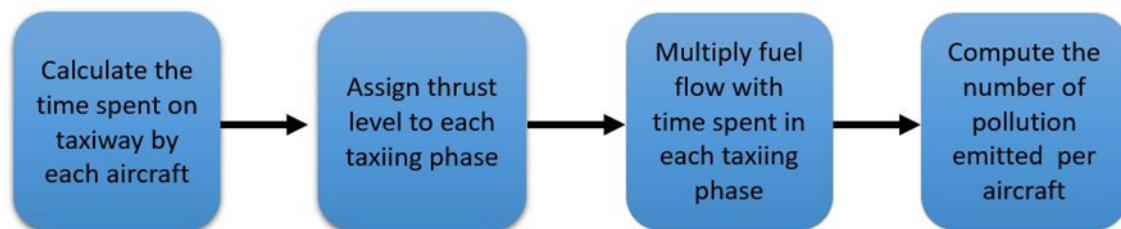


Figure 3-9 Steps for estimating fuel consumption and pollution emitted

The ICAO database method has been used in studying aircraft emissions at Turkish airports in 2006 [207]. The study concluded that taxiing is responsible for approximately 72% of the airport's landing and take-off (LTO) emissions. The climbing, take-off and approach phases cause around 15%, 7% and 6%, respectively, of the LTO emission around Turkish airports. Different taxiing modes are studied with different engine thrusts and interpolation of the ICAO fuel indices

between 7% and 30% thrust [205]. In addition, a novel approach for estimating fuel burn during ground movement operations has been presented in [208]. In the study, the fuel flow rate values have been calculated for the four phases of ground movement: breakaway, idle, constant speed, and stopping. Based on the results, the fuel burn rate is overestimated by 17% relative to the ICAO values. However, the methodology has not been fully validated due to the lack of actual fuel burn data. In addition, the results were influenced by the traffic condition at the airport at the time data was collected.

In another study [17], taxiing fuel consumption is estimated using data from flight data recorders (FDR) based on taxi time and acceleration events. As compared to ICAO fuel consumption indices or other dynamics-based approaches, the model provides realistic fuel consumption estimates. However, FDR read-out and analysis often produce poor data quality and are detrimental to air safety [209]. [210] compare the run times, fuel flow rates, fuel burn and quantity of emissions produced during the LTO cycle for different aircraft and aircraft combinations using FDRs and the ICAO databank. The steps used in estimating the consumption and emissions during the taxiing mission are shown in Figure 3-9 and expressed in (3-4)– (3-10). Based on the ICAO aircraft engine emissions databank [187], the aircraft's fuel flow and emissions indices for B737 are analysed under the 7% power setting level for taxiing fuel consumption and pollutant emissions.

3.6.1 Full-engine taxiing

During taxiing, the aircraft's main engines are on and running at a uniform speed. Therefore, the fuel consumption of any aircraft (*i*) taxiing under full engine can be expressed in terms of the engine fuel flows under different taxiing states [13]:

$$F_{eng} = \sum_{x=1}^4 (t_{xi} \times f_{xi(eng)} \times N_i) \quad (3-4)$$

Where F_{eng} is the total fuel consumption of aircraft (i) during surface taxiing in (kg), t_{xi} is the taxiing time of aircraft spent in engine state (x) in seconds, f_{xi} is the single-engine fuel flow of aircraft (i) in (kg/s), and N_i is the number of engines.

The magnitude of pollutant emission k with emission index corresponding to fuel flow is as follows:

$$E_{ik} = \sum_{x=1}^4 (t_{xi} \times f_{xi(eng)} \times EI_{ik(eng)} \times N_i) \quad (3-5)$$

where $EI_{ik(eng)}$ is the emission index of pollutant k in the single-engine aircraft i under the taxiing state x .

3.6.2 Single-engine taxiing

An aircraft entering a runway under SET must preheat the main engine because only after preheating can the main engine power the aeroplane to take off. The engine spool-up time (ESUT) is generally 2 to 5mins [29] and hence is set to 4mins (240 s) in this study. The fuel consumption (F_i^S) of any aircraft under SET can be determined as:

$$F_{ik}^S = \sum_{x=1}^4 \left(t_{xi}^S \times f_{xi(t)} \times \frac{N_i}{2} \right) + \left(240 \times \frac{N_i}{2} \times f' \right) \quad (3-6)$$

where t_{xi}^S is the SET time of the aircraft(i) at state x , $\frac{N_i}{2}$ indicates that only half of the aircraft's engines are operating to produce thrust while taxiing. f_{xi} is the single-engine fuel flow of aircraft i (kg/s) at state x . f' is the fuel flow in idling mode when preheating or cooling the engine. The emissions of pollutant k ($E_{ik(t)}$) under single-engine taxiing can be expressed as [98]:

$$F_{ik}^S = \sum_{x=1}^4 \left(t_{xi}^S \times f_{xi(t)} \times \frac{N_i}{2} \times EI_{ixk} \right) + \left(240 \times \frac{N_i}{2} \times f' \right) EI_{ik} \quad (3-7)$$

EI_{ixk} is the engine emission index for aircraft i emitting pollutant k at state x and APU under the taxiing state x , and EI_{ik} is the emission index of the engine in idle state, and N_i is the number of engines in the aircraft i .

3.6.3 Autonomous electric taxiing robot (A-ETR)

The A-ETR is battery-powered with modular electric motors with a top speed limited to 40 km/h. The APU is set to environmental control mode (ECM) to supply the cabin's necessary comfort during taxiing. When taking off, the main engine must be started and cooled after landing; as with SET, the fuel consumption F_{A-ETR} of any aircraft i under A-ETR can be expressed as:

$$F_{AFR} = \sum_{x=1}^4 (t_{et} \times f_{ix}^{APU}) + (240 \times N_I \times f') \quad (3-8)$$

where (t_{et}) is the A-ETR time of the aircraft, (f_{ix}^{APU}) is the fuel flow of the APU in ECM mode. The emissions (E_{A-ETR}) of pollutant k can be expressed as

$$E_{A-ETR} = \sum_{x=1}^4 (t_{et} \times f_{ix}^{APU} \times EI_{ik}^{APU}) + (240 \times N_I \times f' \times EI_{ik}) \quad (3-9)$$

where EI_{ik}^{APU} is the emission index of pollutant k under A-ETR, and EI_{ik} is the emission index of pollutant k when engines are idling under the following condition:

$$t_{ATR-out} \geq ESUT \text{ and } t_{AT-in} \geq ECDT \quad (3-10)$$

Otherwise, the ground taxiing fuel for the aircraft with A-ETR is similar to the baseline aircraft and, therefore, calculated in (3-10) using ESUT and ECDT parameters.

3.7 PV-based microgrid

Cranfield Airport has a 1MW PV solar farm, which is currently grid-connected. Therefore, this study proposes to explore the energy required for the A-ETR assuming that the energy is supplied by the ASPV located at the airport. The ASPV and the A-ETR create an infrastructure for zero-emission electric taxiing, as shown in Figure 3-10. However, accurate irradiance and solar power forecasting are important for solar power integration to mitigate the negative impact on the grid [211]. The power output of the PV plant can be calculated by (3-11) [212]:

$$P_{pv-out} = P^{STC} \times \frac{I}{I_{ref}} \times [1 + k_t \{(T_{amb} + (0.025 \times I)) - T_{ref}\}] \quad (3-11)$$

Where P_{pv-out} is the output power of PV, P^{STC} is the rated power under standard conditions; (I) is the solar radiation in (w/m^2), I_{ref} is 1000 w/m^2 , T_{ref} is 25°C , K_t is the power temperature coefficient ($-3.7 \times 10^{-3} (1/^\circ\text{C})$) and T_{amb} is the ambient temperature. The PV efficiency is assumed to be 0.84, and the current state of charge equation of the battery is as described in (3-12) [198].

$$c(t) = c(t + 1) - \Delta t \frac{D_{BESS t}}{\eta_{disch}} + \Delta t \cdot P_{BESS t} \eta_{charg} \quad (3-12)$$

Where $D_{BESS t}$ is the BESS discharge power during time t , and $P_{BESS t}$ is the BESS charging power during time t . The parameter $c(t)$ is the energy stored in the BESS at time t , and Δt is the interval duration. The parameters η_{charg} and η_{disch} are the charging and discharging efficiency coefficients, respectively.

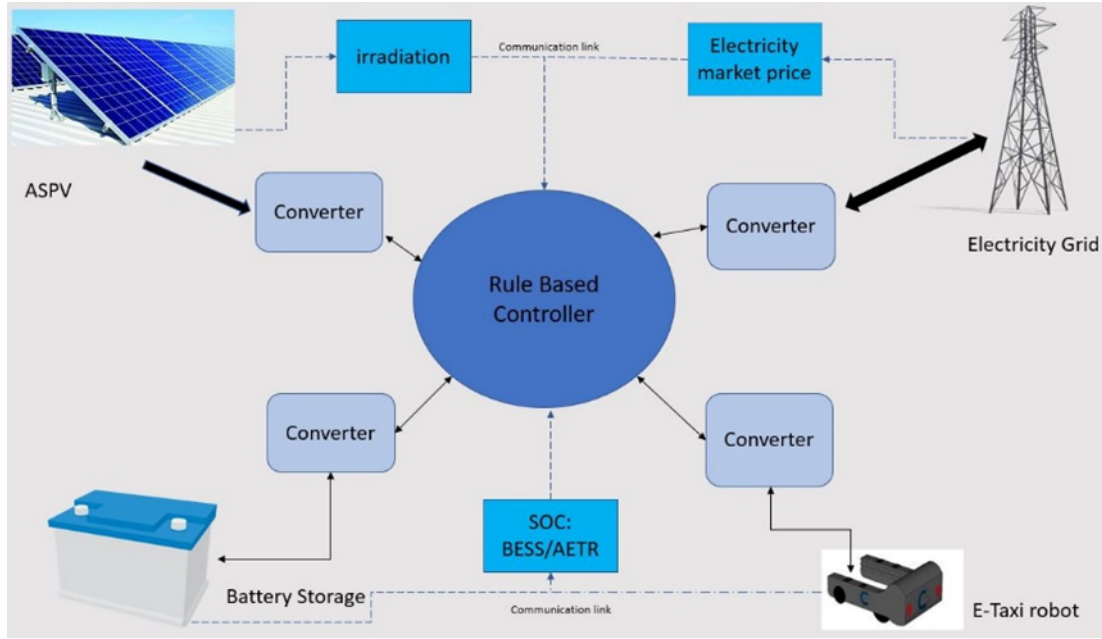


Figure 3-10: The proposed microgrid ecosystem energy management

3.8 Energy management strategy

The energy management strategy (EMS) has a significant impact on the operational behaviour of the microgrid. The EMS is employed to monitor, control and optimise the performance of the microgrid [213]. As PV output is intermittent, this strategy aims to optimise power flow between the grid, load, and BESS, thus minimising grid power purchase costs and meeting load demands continuously [214]. Furthermore, a rule-based EMS [215] is used to avoid the need for renewable and load forecasting for optimal operation in the microgrid, as shown in the flowchart in Figure 3-11. The advantage of using a rule-based energy management system in a microgrid is that it eliminates the need for complex load and generation forecasting models. Such models are often challenging to create and maintain for small-scale systems. Instead, a rule-based system relies on pre-defined rules that are based on the knowledge and experience of the system designers and operators. Consequently, we have chosen this energy management system as the first stage of our multi-layer optimization approach in this research.

The optimal scheduling in this study is summarised in the following scenarios.

- Scenario 1: The energy generated by the PV system can fulfil the load demand, and any extra energy is used to charge the BESS.
- Scenario 2: This scenario is similar to scenario (1), except that the BESS is fully charged, and the additional power generated is fed into the grid.
- Scenario 3: The PV output is insufficient for the system load demand. The algorithm decides whether to import power from the grid or discharge the battery according to the required load.
- Scenario 4: The PV output is insufficient to meet the required load, and the state of charge is low. In this case, the grid supplies the remaining power and charges the BESS.

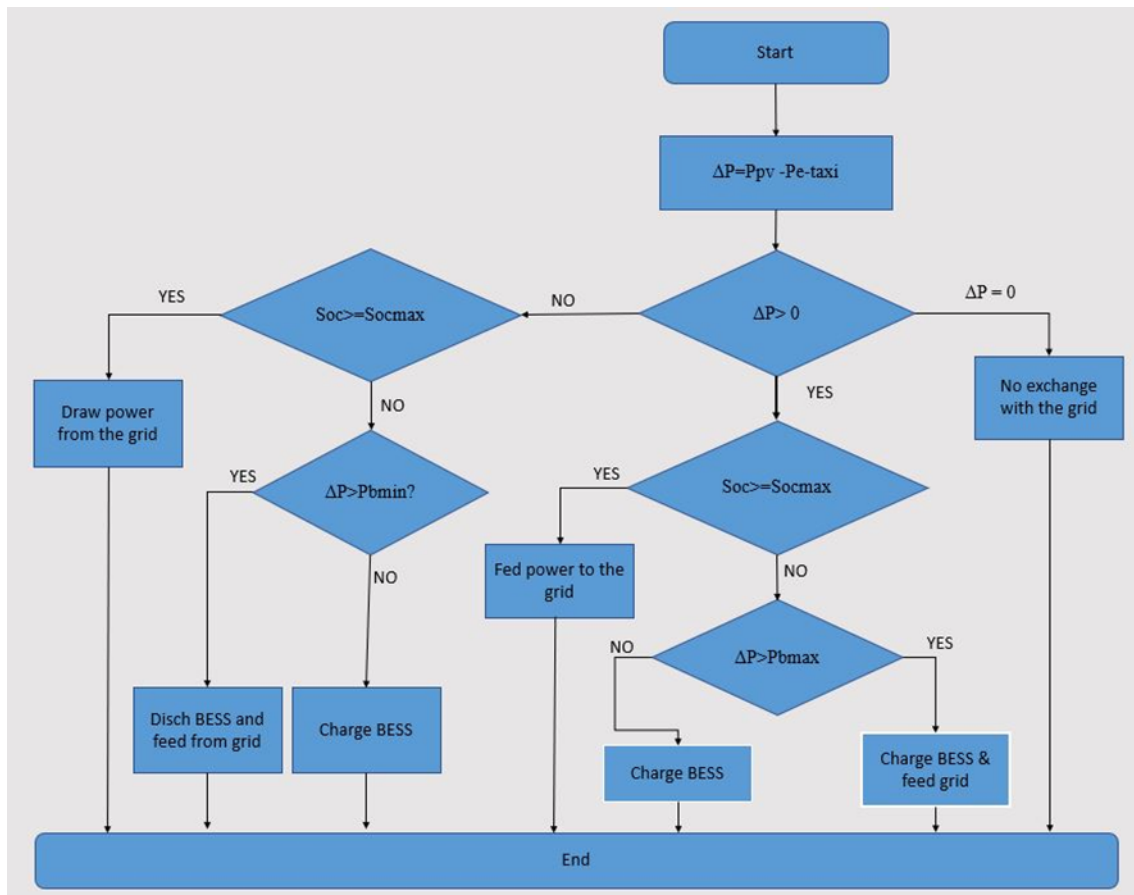


Figure 3-11 The flowchart of the power management strategy

3.9 The A-ETR charging schedule.

The scheduling of the A-ETR is based on the airport's flight schedule, and the A-ETR is reconnected to the charger after every two taxi manoeuvres. The operating time of the airport is between 07:00 and 19:00 for a typical day in the simulations. The other variables and constraints considered are:

- S_{BESS_t} = SoC (State of Charge) of the BESS system at the beginning of t^{th} time interval.
- $S_{t,n}$ = SoC of an A-ETR battery of n^{th} charging cycle at the beginning of t^{th} time interval
- $P_{t,n}$ = Power of charging of the A-ETR battery of n^{th} charging cycle during t^{th} time interval
- $p_{cheg}(t)$ = charging price
- $P_{dichg}(t)$ = discharging price.

Further constraints are subject to:

- $S_{BESS}^{min} \leq S_{BESS_t} \leq S_{BESS}^{max}$
- $S_{taxi}^{min} \leq S_{t,n} \leq S_{taxi}^{max}$
- $0 \leq P_{BESS_t} \leq P_{BESS}^{max}$
- $0 \leq P_{t,n} \leq P_{taxi}^{max}$
- $0 \leq D_{BESS_t} \leq D_{BESS}^{max}$
- $P_{BESS_t} + D_{BESS_t} \leq P_{BESS}^{max}$

And the following objective function:

$$Min (F) = p_{charg}(t) \sum_{t=1}^T P_{BESS_t} - P_{disch}(t) \sum_{t=1}^T D_{BESS_t} \quad (3-13)$$

The battery system SOC_{BESS_t} at the end of the interval depends on the previous $SOC_{BESS_{t-1}}$, charging from the external grid, consumption of all A-ETR, and charging from the solar power plant is expressed as:

$$S_{BESS_t} = S_{BESS_{t-1}} + \eta_{charg} * P_{pV} + \eta_{charg} * P_{BESS_t}(t) - \frac{D_{BESS_t}(t)}{\eta_{disch}} - \sum_{n=1}^N P_{(t,n)} \quad (3-14)$$

The two A-ETRs in operation undertake 12 charging cycles per day. One A-ETR is switched for another when the charge has been reduced to 25% or after two taxi operations. A 90% efficiency rating is assumed for battery storage systems because it represents a realistic estimate of the energy losses that occur during charging and discharging [195][196].

However, the effectiveness of rule-based energy management in a microgrid depends on the accuracy of the rules and the system's ability to adapt to changing conditions. If the rules are too rigid or do not account for unforeseen events, the system may not optimize energy usage or respond adequately to changes in energy demand or supply. Therefore, while rule-based energy management is a useful tool for microgrids, it may need to be supplemented with other approaches, such as load and generation forecasting, for more effective energy management, as we consider in the next optimization layers of this thesis.

Table 3-3 Economic parameter input

Parameter		Value	Units	Reference
Installation cost	PV	1 million	£/MWp	[216]
	Charger	10000	£/each	
Purchase installation cost	BESS	450	£/kWh	[217]
Maintenance cost	BESS	1500	£/annum	
Life expectancy	BESS	10	Year	[218]

Parameter		Value	Units	Reference
Electricity price	0:00-7:00 h	0.049	£/kWh	[219]
	7:00-17:00,21:00-23:00	0.119		

3.10 Scenario study and discussion

3.10.1 Kinematic parameter requirement

The A-ETR's kinematic parameter requirements (i.e., traction power, motor torque, axel torque, speed, and traction force) for taxiing the datum aircraft Boeing 737 are calculated based on the parameters stated in section 3.4. The simulation results of the A-ETR maximum traction power obtained from the aircraft traction load profile model is 1.036MW (1,416 HP), compared to the capacity of the Taxibot at 1.119MW (1500 HP) [14]. The result represents 95% accuracy. In addition, a maximum torque of 2.75 kNm, a maximum rotational speed of 336 rpm and a battery capacity of 50 kWh have been obtained from the kinematic parameters simulation result shown in Figure **3-12**.

The weight of the load applied on the nose wheel is the most important for the design. The minimum static load on the nose wheel can be considered to be around 8% of the aircraft's weight, while the maximum load is about 15% of the aircraft's weight [220]. Based on this, a maximum load of 10.7 tonnes has been considered in the model of the parameter requirement of the A-ETR. Since the torque is required to pull part of the aircraft weight, a high rpm may not be necessary.

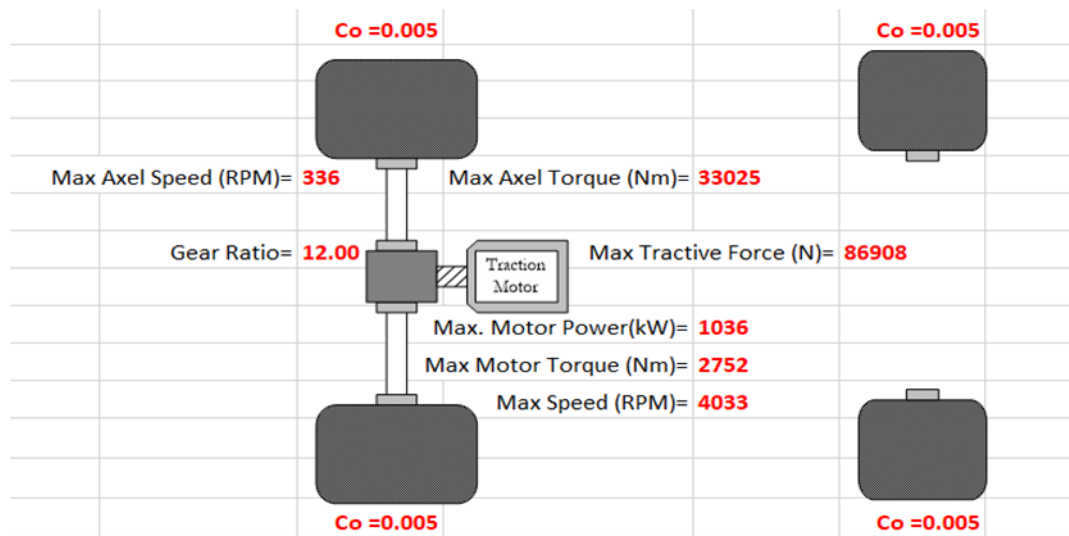


Figure 3-12 Kinematic parameter specifications for taxiing load profile of the datum aircraft in Microsoft excel

3.10.2 Meteorological effect on taxiing power and energy demand

The wind has little effect on the motion of a vehicle travelling on the ground because it moves in the direction in which it is steered or headed. However, an aircraft rarely travels in an exact direction because of the wind. A crosswind blowing from the side can cause the aircraft to deviate from its path, so more energy is needed to adjust the direction of the aircraft to keep its trajectory. There are pre-defined wind limits for each aircraft on a given runway, whether it is wet or dry, and a pilot must consider the wind during all phases of operation, including ground movement.

As headwinds increase, the aircraft lifts during take-off, ground speed is reduced, and runway distance is shortened before take-off. Landing into the headwind has similar advantages: (i) shorter runway distance and (ii) lower landing ground speed. A tailwind in flight makes the aircraft move faster and consumes less fuel and emissions since less power is needed to steer the aircraft. In contrast, headwinds require more fuel and result in longer taxi times, resulting in higher emissions.

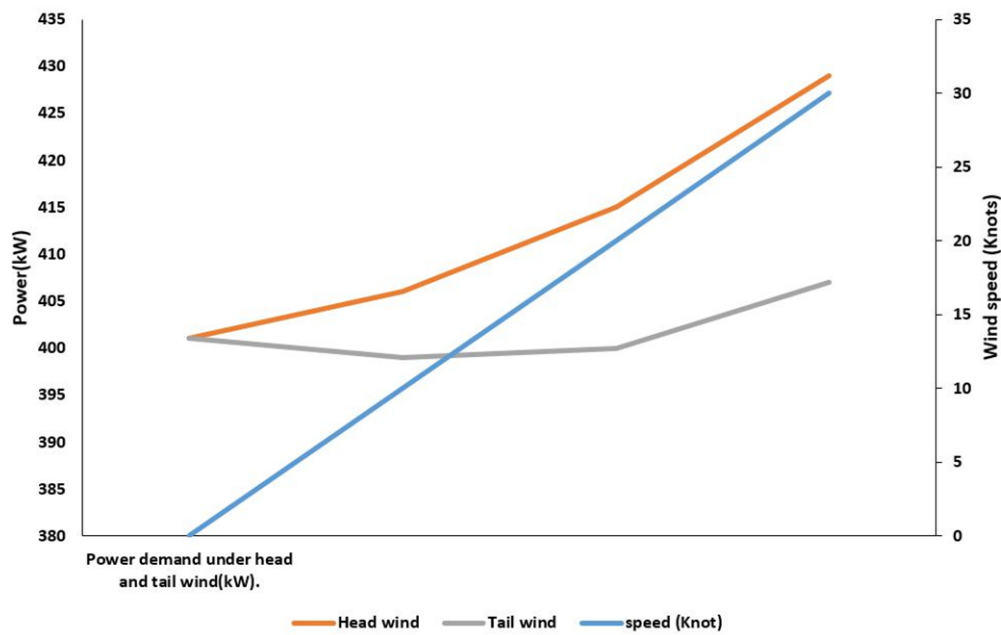


Figure 3-13: Wind speed/direction vs power demand

The nature of the taxiway and the runway surface, i.e., dry, snowy, or icy, affect the friction coefficient. Water on the runway causes dynamic hydroplaning, reducing friction between the tires and the ground and reducing braking efficiency due to the layer of water that separates the tires from the ground. This reduced friction will affect the aircraft's ground stability and taxiing control depending on the longitudinal and transverse resistance forces. The values of the forces on dry surfaces are high, resulting in a higher taxiing speed than on wet surfaces [221]. As illustrated in Figure 3-13, the simulation results show a strong correlation between the taxiing power of aircraft and energy demand and the wind speed and direction in the airport from the output of the electrodynamic traction load profile generation program in Microsoft excel.

While moving on the ground at the same speed, an aircraft experiences different energy and power profiles under the influence of tailwinds and headwinds. The aircraft needs more power when taxiing into a headwind than a tailwind at the same speed. A 100% increase in wind speed results in a 3.00 - 3.75% increase in power demand for aircraft taxiing into a headwind and a 0.87 - 2.16% increase in power demand for aircraft taxiing with a tailwind. The results also demonstrate

higher fuel consumption and emissions while taxiing under the influence of a headwind than a tailwind.

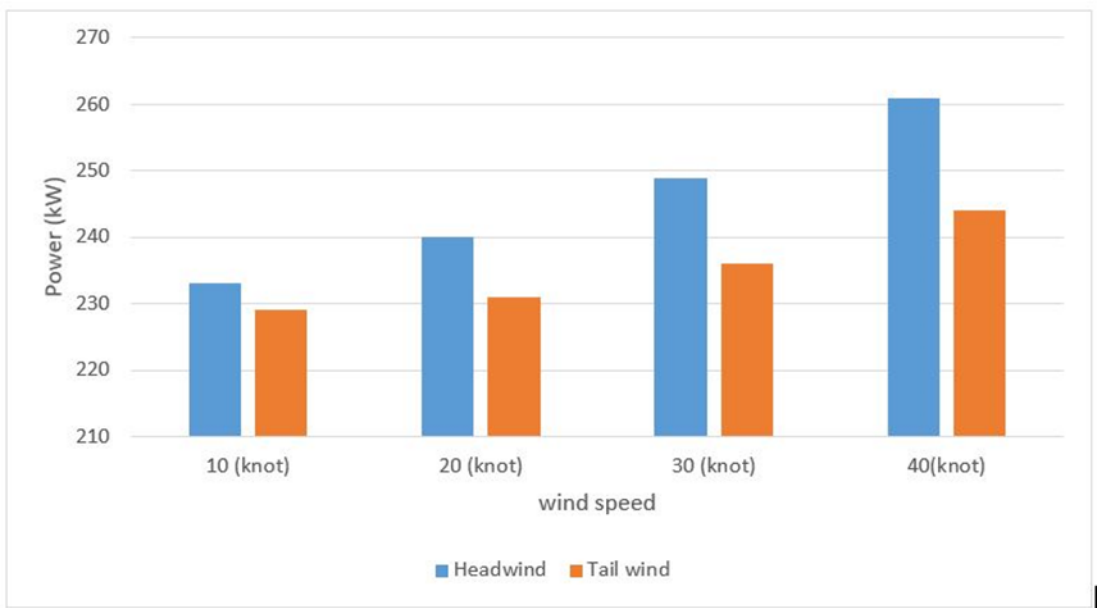


Figure 3-14: Comparison of taxiing power demand under different headwind and tailwind

The maximum taxiing load demand of the datum aircraft B737 under headwind and tailwind increases with an increase in wind speed, as shown in Figure 3-14 and decreases with an increase in crosswind angle, as shown in Figure 3-15

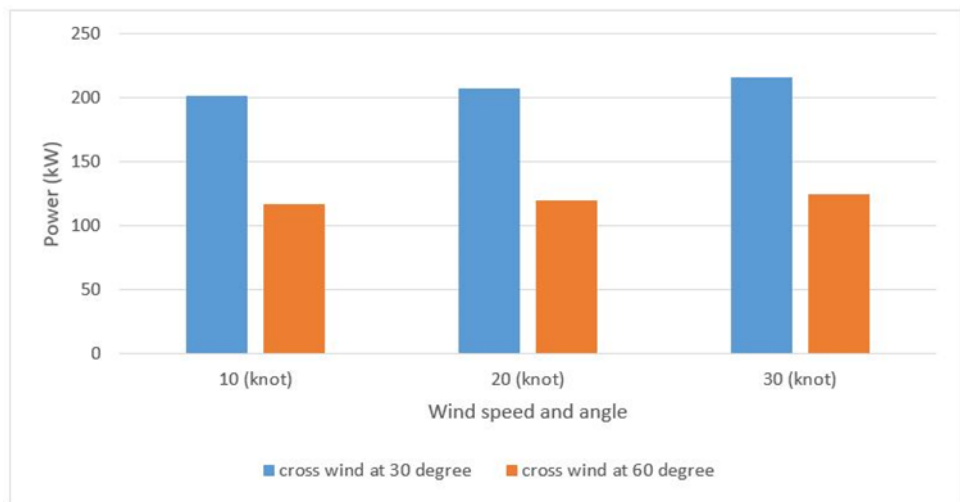


Figure 3-15: Comparisons of taxiing power demand under different crosswind

3.11 Results for maximum taxiing power demand for different categories of aircraft.

Three categories of aircrafts: narrow body (A320), wide body (A333) and ultra-wide body (B747), are simulated under unimpeded aircraft ground movement at permissible taxiing speed.

Table 3-4 Taxiing power demand at different headwind speeds

Headwind(knots)	Power demand (kW)		
	A320	A333	B747
0	229	675	1313
10	233	679	1317
20	240	685	1323
30	249	692	1333

Table 3-4 and Figure 3-16 show that the taxiing load demand of an aircraft is proportional to the categories of the aircraft. The power demand is higher for the ultra-wide body B747 compared to the wide-body A333 and narrow-body A320

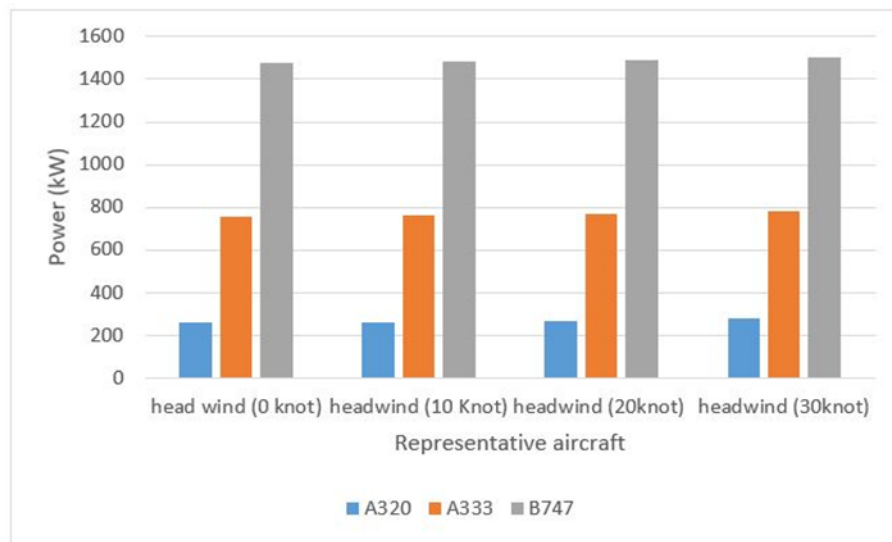


Figure 3-16: Comparison of taxiing power under different headwind speed

3.12 Microgrid performance simulation

There are approximately 15 flights on a typical day at Cranfield Airport [37], thus requiring about 750 kWh for all the taxiing operations, assuming the flight schedule is based on the datum aircraft B737. The charging time of the A-ETR is 45 minutes. Lithium-ion (Li-ion) batteries are considered in this study due to their popularity for different automotive and aerospace applications, having high energy and power density and being lightweight, with no memory effect, very low self-discharge and high efficiency [222]. The airport's daily operation time is from 07:00 to 19:00 (12 hours), allowing six charging manoeuvres per day per A-ETR in this study. Two additional backup A-ETRs are considered for standby in the event of A-ETR failure.

3.12.1 A summer's day

Simulation results of the proposed microgrid model on a typical summer day for the A-ETR operation charging load demand are shown in Figure 3-17. The results include PV output power (kW), load power (kW), A-ETR's battery SOC (%), microgrid ESS battery SoC (%), and power exchange with the grid (kW). A solar power plant with a capacity of 1 MW is considered. The proposed microgrid can meet the taxiing load demand of the airport for a typical day for two A-ETRs. A-ETR 1, with an initial SoC of 100%, performs two taxiing operations, T_1 and T_2 , at 07:45 and 08:15, respectively. After that, its SoC reduces to 37.5%, close to the minimum value of 25%. At this point, A-ETR 2, with an initial SoC of 100%, performs the next taxiing operations T_3 and T_4 , at 8:45 and 9:15, respectively. When A-ETR 2 operates, A-ETR1 is fully charged ($SoC_{max}=100\%$) in approximately 45 minutes. The taxiing operation uses the two A-ETRs to swap after every two manoeuvres or when their charges drop to $SoC_{min} = 36.5\%$. The simulation result shows that both robots have a final state of charge (SOC) of 100%. However, the robot's stopping location is determined by the traffic conditions on a particular day. If the SOC of a robot is above 36.5%, it will retain this level of charge for the next taxiing operation. This constraint is included in the model to prevent excessive charging, which can reduce the lifespan of the

robot's battery. Therefore, the model aims to extend the battery life of the robots by limiting unnecessary charging.

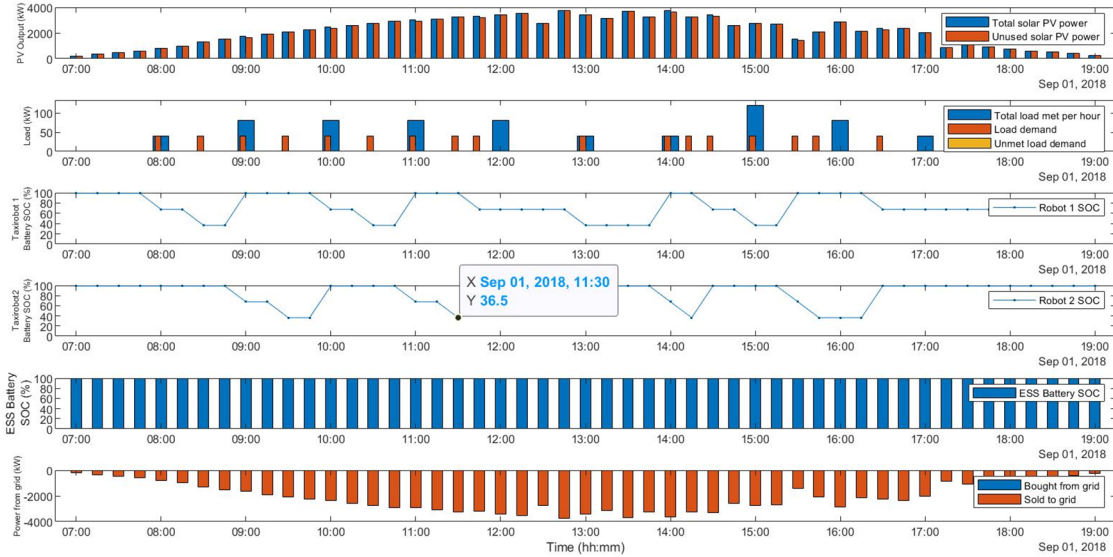


Figure 3-17: Microgrid simulation results in Matlab on a typical summer's day: (i) PV output power (kW), (ii) Taxing load power (kW), (iii) A-ETRs battery SOC (%), (iv) Microgrid ESS battery SOC (%), (v) Power exchange with the grid (kW)

Figure 3-17 (iv) indicates the SoC of the BESS in the microgrid, whose duty is to charge the A-ETRs when the PV output is insufficient. Because the solar farm's capacity is far more than the load demand in this case study and has stronger solar radiation on an average summer day, the SoC of the BESS is nearly 100% throughout the majority of the day and is available to supply the load. The A-ETR consumes 32.25% of the battery capacity (16.13 kWh) per taxiing operation as shown in Figure 3-17 and recharges after two taxiing manoeuvres, after which its charge drops to $SoC_{min}=36.5\%$. Though the specified battery SoC_{min} is 25%, the A-ETR returns to charging up at SoC_{min} of 36.5% to compensate for any delay in traffic and ensure that the battery has sufficient residual power to travel back to the charger. As shown in Figure 3-17, excess power generated from the PV is sold to the grid once the BESS reaches SOC_{max} (100%). The A-ETR batteries are fully charged overnight to have enough charge to support the taxiing load in the earlier part of the morning between 07:00 and 08:00.

3.12.2 A winter's day

The simulation results of the proposed microgrid model on a typical winter day are presented in this section. Figure 3-18 shows the results for PV output power (kW), load power (kW), A-ETR SoC (%), BESS SoC (%) and exchange of power with the grid (kW). In this scenario, the A-ETRs continuously support the taxiing load from 07:45 to 08:45 at 09:00 and 15:30, the taxiing load demand exceeds the PV+BESS, and the BESS_{SoC} has dropped close to the minimum threshold of $SoC_{min} = 25\%$. Therefore, grid power complements the total PV and BESS generation supply to meet the load demand. The trend continues in all other cases where the BESS SoC is around the minimum level and the PV output is less than the load.

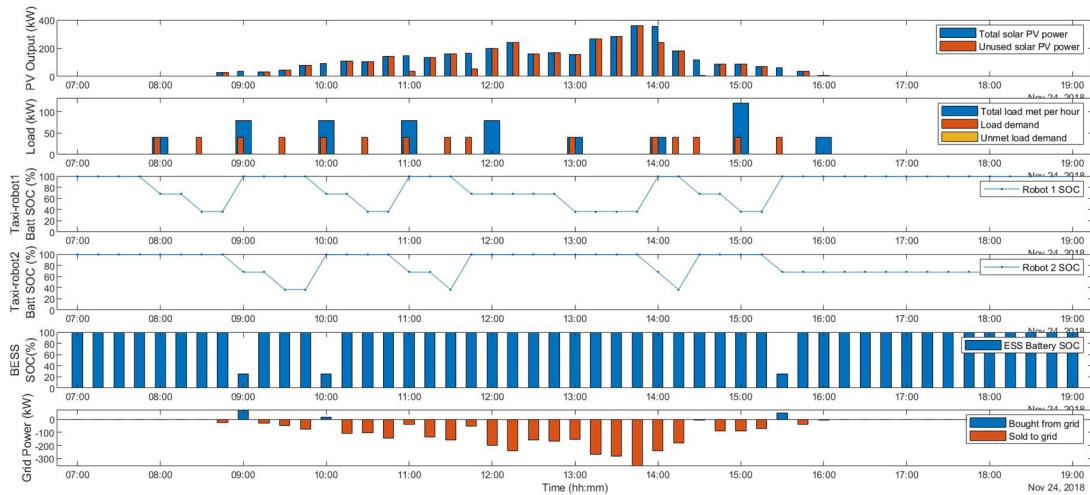


Figure 3-18: Microgrid simulation results in Matlab on a typical winter's day: (i) PV output power (kW), (ii) Taxiing load power (kW), (iii) A-ETRs battery SOC (%), (iv) Microgrid ESS battery SOC (%), (v) Power exchange with the grid (kW)

3.12.3 A cloudy day

This section presents the simulation results on a typical cloudy day, as shown in Figure 3-19. The BESS discharges close to the minimum threshold of $SoC_{min} = 25\%$ between 08:00 and 09:45 while supporting the A-ETRs taxiing loads continuously. At 08:00 and 09:00, the taxiing load demand exceeds the total

supply (PV+BESS), while the BESS SOC has already dropped close to SOC_{min} . Therefore, the grid power complements the total supply of PV+BESS to meet the load demand.

The exchange of power with the grid ranges from (09:45 - 14:45) due to low power output on the typical cloudy day resulting from low solar radiation, compared to the previous scenarios: summer (07:00-19:00) and winter (08:45-16:00). The microgrid has successfully met the A-ETR taxiing load in the airport, as shown in the simulations for all three scenarios.

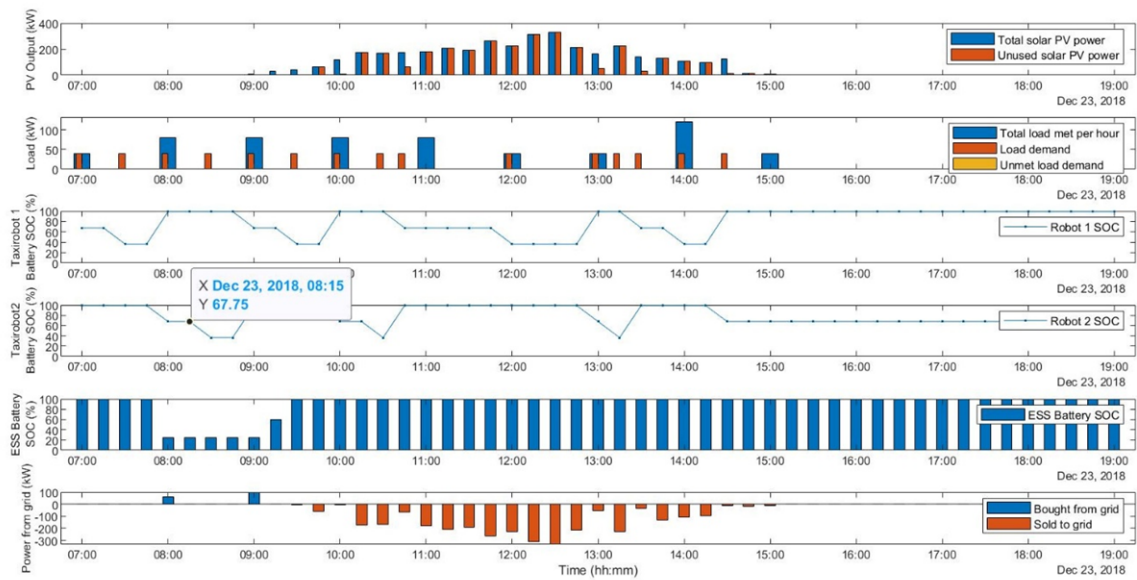


Figure 3-19: Microgrid simulation results in a typical cloudy day: (i) PV output power (kW), (ii) Taxiing load power (kW), (iii) E-ATRs battery SOC (%), (iv) Microgrid ESS battery SOC (%), (v) Power exchange with the grid (kW)

3.13 The practical impact of the proposed microgrid and A-ETR on the airport

An A-ETR system offers several benefits to the industry, but its main purpose in this study is to provide mobility as a service (MaaS) to replace the existing practice of engine-powered taxiing. Therefore, it is imperative to estimate the potential fuel savings from the new taxiing practices.

3.13.1 Fuel and emission benefit analysis

According to the collected data, the average number of aircraft taking off and landing at the operational Cranfield Airport on the day under consideration is around 15. The average taxiing time for each aircraft is 4.5 minutes, and every kilogram of jet fuel produces 3.156 kilograms of CO₂ [178]. Fuel consumption and emission for the datum aircraft B737 on the taxiway under unimpeded conventional taxiing were calculated and compared with SET and A-ETR in section 3.13.1. The thrust setting is set for double-engine and SET based on ICAO'S emission data bank [188],[189].

Here the fuel flow index is considered in terms of different APU modes for (B737), i.e., MES = main engine start mode = 0.038, NL = No Load = 0.021. The main engine fuel flow index for B737 = 0.124, and the average taxiing time = 270 sec. The fuel consumption and emission for any segment during the taxiing mission are expressed in (3-4)-(3-9)

3.13.1.1 Double engine taxiing

$$F_{eng} = t_{eng} * N_i * ffl_{eng} = (0.124 * 2 * 270) = 66.96kg \quad (3-15)$$

Emissions

$$E_{co2} = 66.9 * 3.156 = 211.33kg$$

$$E_{co} = 66.9 * 4.94 = 330.5kg$$

$$E_{Nox} = 66.9 * 7.64 = 511.12kg$$

3.13.1.2 Single-Engine taxiing

$$F_{eng} = ffl_{APU} * N_i * t_{eng} = (0.124 * 1 * 270) = 33.48kg \quad (3-16)$$

Emissions

$$E_{co2} = 33.48 * 3.156 = 105.7kg$$

$$E_{co} = 33.48 * 4.94 = 165.4kg$$

$$E_{Nox} = 33.48 * 7.64 = 255.8kg$$

3.13.1.3 On-board E-taxi. (EGTS &Wheel Tug)

$$F_{eng} = ffl_{APU} * t_{eng} = (0.038 * 270) = 10.3kg \quad (3-17)$$

Emissions

$$E_{co2} = 10.3 * 3.156 = 32.5kg$$

$$E_{co} = 10.3 * 4.94 = 50.8kg$$

$$E_{Nox} = 10.3 * 7.64 = 78.6kg$$

3.13.1.4 Off-board A-ETR

$$F_{eng} = t_{eng} * F_{Apu} = 0.021 * 270 = 5.67 kg \quad (3-18)$$

Emissions

$$E_{co2} = 5.67 * 3.156 = 17.9kg$$

$$E_{co} = 5.67 * 4.94 = 28kg$$

$$E_{Nox} = 5.67 * 7.64 = 43.3kg$$

Table 3-5 Emission of aircraft (B737) under four taxiing modes

Mode		Double Engine	Single-Engine	EGTS	E-ATR
B737	Fuel (kg)	66.9	33.48	10.3	5.67
	CO2 (kg)	211.3	105.7	32.5	17.9
	CO (kg)	330.5	165.4	50.8	28.0
	NOx (kg)	511.12	255.8	78.6	43.3

The preheating or cooling time of the engines should be set to 5 minutes if the aircraft's taxiing time (t_{eng}) is longer than 5 minutes. For taxiing times under 5

minutes, preheating or cooling times of the engines are used [189]. Although the aircraft engine is switched off when the E-ATR tows the aircraft, the APU still provides the aircraft's power and ventilation needs [181].

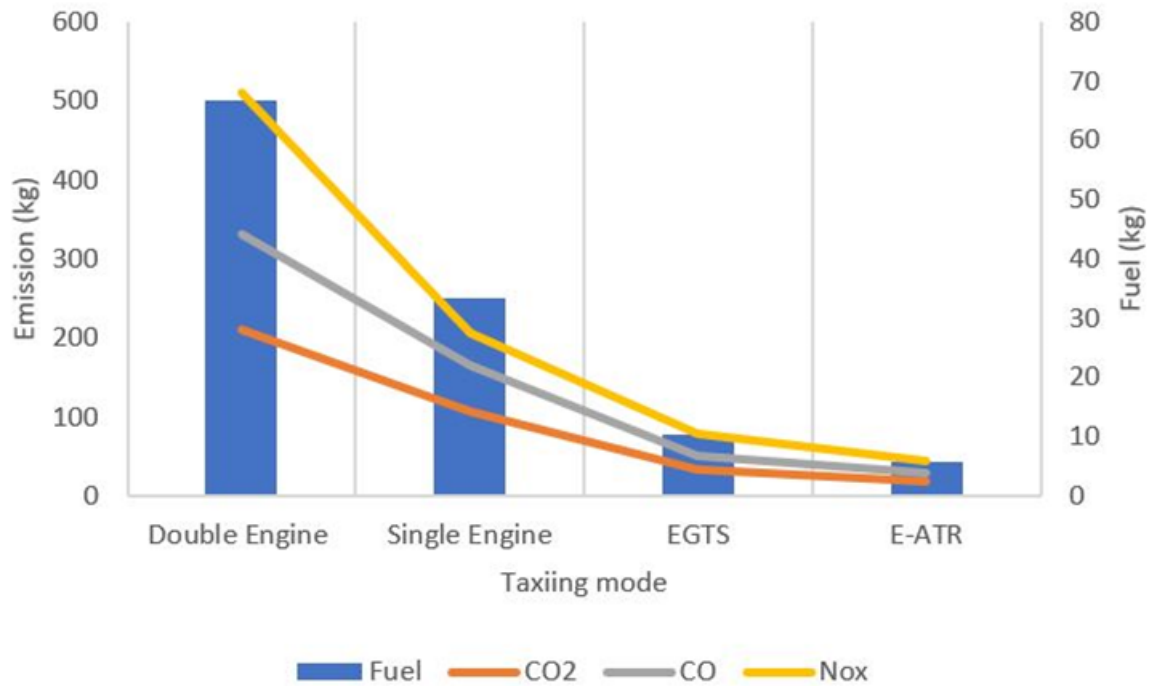


Figure 3-20: Comparison of fuel consumption and emission for the four scenarios

The emission index and fuel consumption table for aircraft types, fuel flow and emission indexes of the APU are given in [189] and [188]. By comparing the results in

Table 3-5 and **Figure 3-20**, the fuel consumption and emission of the aircraft under double-engine taxiing are 92% higher than the A-ETR, and NO_x emission is also reduced by 73% under A-ETR taxiing. Thus, nearly 0.92 tonnes of fuel, 4.75 tonnes of CO₂ and 2.26 tonnes of NO_x have been saved on a typical day at the airport by implementing the proposed microgrid with the A-ETR mobile interface strategy. Also, based on the most recent Jet-A price in the United Kingdom on 29th March 2022 of £928.22 per metric ton, the average flight spends £56.83 on taxi operation in Cranfield Airport. Based on the available air traffic movements and landing operations at Cranfield Airport, there is an average of

16,000 flights per year. Based on this number and average taxiing costs, a preliminary estimate of £910,893.23 is calculated as an estimated saving per annum. These results illustrate how innovation in aircraft ground movement operations can significantly decrease emissions and costs.

The environmental and economic benefits of the airport are significantly improved, and noise reduction is achieved through daily aircraft's engineless ground movements at the airport. In addition, since the PV system produces the most power when the sun is at its peak, instead of exporting the excess power to the grid directly, the BESS is charged to be used when solar energy is unavailable. Thus, the microgrid can take advantage of the time of use (TOU) market price for peak and off-peak hours to optimally charge the batteries in readiness for the early morning taxiing load the next day.

3.14 Conclusion

This study investigates the feasibility of developing a zero-emission aircraft taxiing system towards a green airport by implementing PV- A-ETR interfaces in a microgrid ecosystem to meet its electric taxiing load demands under some realistic taxiing scenarios. This is achieved by a novel A-ETR concept, which serves as a mobile charging and discharging interface to the microgrid. Typical flight data from Cranfield Airport and its B737 are used to create realistic taxiing scenarios to validate the utility of the proposed concept. Fuel consumption, NO_x and CO₂ emissions of the aircraft under A-ETR are compared with two conventional taxiing modes. The results show that the proposed A-ETR has the potential to save fuel and reduce emissions in the airport. These savings are, on average, 91% for fuel consumption, 73% for NO_x emission and 86.5% for CO₂ emission for a typical taxiing operation. Furthermore, by implementing the proposed E-ATR and microgrid interface, 4.75 metric tonnes of CO₂ and 2.26 metric tonnes of NO_x are saved on a typical day at the airport.

Although Cranfield Airport's aircraft traffic may be relatively small compared with a commercial one, it should be noted that the A-ETR concept is readily scalable.

Therefore, this study demonstrates a promising step towards meeting the target of FlightPath 2050's zero-emission ground operations at the airport.

As evident in the scenario studies in this chapter, the capacity of the storage system and the intermittency of renewable energy sources influence the microgrid's operational cost and service availability. These necessitate the optimisation of the microgrid operations to minimise operational costs and maximise service reliability. As a result, the feasibility of using machine learning-based optimisation models to forecast PV output and optimise battery energy storage to support microgrid operations is investigated in the next chapter.

4 .Machine Learning-Based Optimisation of Grid-tied PV system for Zero-emission Taxiing in Airport

4.1 Chapter Summary

Optimising aircraft ground movement is one of the key strategies for reducing aviation fuel consumption and contributing toward a greener airport. The average aircraft consumes 5% to 10% of its mission fuel and emits considerable pollutants when moving on the ground. Furthermore, the emitted pollutants adversely contribute to global climate change and are equally harmful to human health. Therefore, the electrification of ground movements in the airport has attracted a lot of interest, intending to reduce the worldwide proportion of pollution caused by airport operations. In response to the ACARE's FlightPath-2050's goal of zero emissions for all aircraft ground movements, this chapter proposes the optimisation of airport taxiing operations by using an airport-based solar photovoltaic system to supply the required energy as a novel and viable solution. The proposed smart solution minimises operating costs by analysing certain core information, such as flight data, the energy requirements of ETS, the availability of solar power and TOU market price. First, we forecast PV output power through various machine-learning regression models, followed by optimising the size of the BESS required to support the microgrid. Adjusting the battery's charge and discharge cycles with the available solar resources and electricity tariff can help minimise operating costs. Based on two taxiing load profile scenarios derived from Cranfield Airport's real-world data, the simulation results show that the support vector regression performs better than others in accurately forecasting the PV output power. Additionally, the combined optimisation of BESS capacity and charge/discharge cycles against TOU market prices minimises operational costs while still achieving ground-zero emission operation in the airport. The optimal capacity of the BESS for scenarios one and two are found to be 816.7 kWh and 593 kWh, at a total cost per day of £547 and £397, respectively.

Keywords— PV-battery system, optimal sizing, Genetic algorithm, Smart decision system, Machine learning

4.2 Introduction

Net-zero emission aviation is a necessity of the hour, which can be achieved largely by decarbonising the air transportation sector through electrification. A number of technological advancements have been made in aeronautical technologies to attain net-zero emissions, such as the deployment of superconducting machines for airborne electric propulsion and the use of electric taxiing systems for ground movement by aircraft [223],[224], [20],[21],[225]. The adoption of electrified ground operations and on-site renewable energy production are among the many options for achieving net-zero emissions in the airport. Majority of the emissions during ground movement in airports are due to aircraft engines, ground handling equipment, and service vehicles [226].

However, these emissions could further be reduced if the aircraft's ground movement is powered by low-carbon or renewable electricity. The Photovoltaic (PV) system is considered one of the most dependable renewable energy options for airports due to the availability of large expanses of land and their biodiversity and simplicity [114]. Nevertheless, the PV system will face challenges in adoption due to its reliance on current weather conditions, which present the PV as non-dispatchable units. Furthermore, solar radiation and ambient temperature constantly fluctuate, making the PV power generation intermittent and stochastic, resulting in unstable output power and reduced installation benefits. Therefore, an accurate forecast of the solar power output is essential to ensure its safe operation and economic integration and increase its share in the airport energy mix. Different artificial intelligence (AI) and machine learning (ML) based solutions are already available for PV power output forecasting [227],[228]. In [229], support vector regression (SVR), a time series prediction algorithm derived from support vector machines (SVMs), is described. [230] employed SVR to forecast the solar power output of a 1MW PV plant, considering weather variables. The results show improvement in prediction

accuracy. [231] constructed two separate SVR models based on cloud cover conditions to achieve a more accurate solar irradiance forecast. In [227], the effectiveness of PV system power forecasting was measured with the help of a long-term memory recurrent neural network (LSTM-RNN). Three different forecasting models have been compared to demonstrate the model's efficiency. The result shows that the proposed method gave the least forecasting error compared to the other methods. [228] present an improved solar energy forecasting algorithm based on ANNs with fuzzy logic pre-processing. The three-layer feed-forward model was trained via the back-propagation approach. The simulation results show a higher forecast accuracy. [232] investigated the performance of three ML techniques: decision tree (DTR), multiple linear regression (MLR) and k-nearest neighbour (KNN). The performance prediction results show that KNN performs better than the other model.

Furthermore, in support of net-zero emission operations in the airport, the aviation industry has shifted attention toward microgrid technology as a dependable and instantaneous supplementary power source in airports [40]. Although diesel generators are used as a backup power source in most airports, their operation is characterised as a failure during disasters and has high maintenance requirements with considerable environmental implications.

Microgrids (MG) are local electrical systems built to generate their power while operating parallel with the utility (grid-connected) or separated from the utility (island mode). In the grid-connected mode, excess energy is either stored in a BESS or sold to the main grid at a TOU market price. In this way, the upstream grid can be viewed as a two-way generator that produces positive power when sending energy to the MG and negative power when transferring power from the MG to the upstream grid.

The operating cost of MG is influenced by the capacity of its BESS, as its price impacts the initial capital cost and operation of the microgrid [233]. Therefore, the optimal sizing of the BESS for the proposed ASPV-based microgrid operation is essential and should be selected to minimise the MG's operational cost.

However, the installation of a BESS in a microgrid is only economically justifiable if the benefits provided exceed the investment cost [234].

Most of the reviewed articles formulate the BESS sizing problem as an optimisation problem to reduce overall operating costs or maximise the total benefits [235],[236],[231]. [237] developed a linear program (LP) optimisation algorithm to optimise the battery dispatch of a grid-connected photovoltaic system in a building to minimise the net-peak load. Load demand and PV production data are taken as inputs to the model. However, electricity prices were not included in the optimisation. [238] have used mixed integer programming (MIP) scheduling to determine the optimal size of energy storage that minimises the total planning cost of a microgrid. The study concluded that a large energy storage system does not necessarily produce greater economic benefits. [239] have proposed an energy management system based on operator decisions to determine the BESS capacity, but the optimal operation of the microgrid was not taken into account, which has affected the accuracy of the BESS sizing. [240] have proposed an optimisation method based on a genetic algorithm (GA) for BESS sizing. To maximise their economic benefit, they have used the annual energy cost of the households to investigate the problem of optimal sizing PV and BESS.

[241] have used the dynamic programming (Dp) approach to optimise the size of the BESS in a microgrid while considering the BESS capacity and power output under isolated and grid-connected scenarios. The goal is to minimise the capital cost and optimally schedule the microgrid operation. [242] have proposed a dual constraint-based iterative optimal sizing approach to optimise the component size of a hybrid photovoltaic - wind power generation with BESS. The objective is to improve the system's reliability and minimise the cost of operation. The simulation result shows the efficacy of the proposed approach. The whale optimisation algorithm (WOA) has been used to optimise the size of the hybrid microgrid system in [239]. Comparing the simulation result with other algorithms indicates a higher accuracy and faster convergency time that validates the efficiency of the proposed approach. [24] have proposed an interior search

algorithm (ISA) to solve the optimisation of a microgrid system with varying load conditions and minimise total operational cost. The results indicate a higher possibility of savings for the total operating cost.

This study investigates the output power forecasting and sizing of the BESS in a grid-connected ASPV that is designed to implement a net-zero-emissions ground operation at a proposed green airport. Different ML models have been used to forecast PV output power and analyse its correlation with weather conditions such as temperature, radiation, and time, and the best model is selected based on performance metrics. In the second stage, a G.A-based optimisation algorithm has been proposed to optimise the size of the BESS in the MG based on daily energy cost, load demand, and forecasted PV output.

4.3 System modelling

Mathematical models of different parts of the microgrid have been developed to set the optimal power flow within the system. The mathematical model is used to simulate the average hourly PV power output and two typical weekday taxiing load demands representing the airport's current and projected taxiing load demand profiles. In addition, the weather data and solar irradiation from the year 2018 to 2019 have been collected from the Kisanhub weather station' situated at Cranfield University. The collected data provides 11088 measurements and has been carefully reviewed to find the missing data instances and transform the attributes into features used to train the machine learning model.

The taxiing load demand model is based on a typical weekday flight schedule for Cranfield Airport (scenario 1) with an average taxi time of 4.5 minutes based on [178] and a projected flight schedule for commercialised operation of Cranfield Airport using the flight schedule data of Luton Airport in (scenario 2) [243]. The datasets are divided in a ratio of 70:15:15 for training, validation and testing of the model.

4.3.1 Prediction model and features

Generating electricity through solar PV is promising as solar radiation is abundant, requires minimal maintenance, and provides highly reliable energy. In addition, the availability of a large and sufficient land area in most airports supports the implementation of the solar-powered system in airports. However, the efficiency of the PV output largely depends on some crucial factors, such as the inverter efficiency, the angle of the panel, weather conditions such as irradiation, temperature and age etc. [244].

In real-world conditions, the temperature and irradiance tend to fluctuate within hours. For example, in overcast weather conditions, the whole prediction process becomes more complex [245]. Hence, such complex behaviour requires more intelligent algorithms for predicting the PV output value than classical methods. The distribution of the real-time PV output power (W) with respect to the variation in the temperature ($^{\circ}\text{C}$) and irradiance (Wm^{-2}) values are illustrated in Figure 4-1. From Figure 4-1. It can be asserted that the distribution of the PV output is neither overlapping nor strictly linearly correlated, which suggests that in the real-world scenario, the panels of the PV system encounter variability and unpredictability while producing the output power. To assess the role of dependency of the three core factors, namely temperature, irradiation, and time on the variability of PV output power, well-known regression-based machine learning algorithms, namely support vector regression, regression trees, linear regression, and neural networks with varying kernel functions are considered in this study.

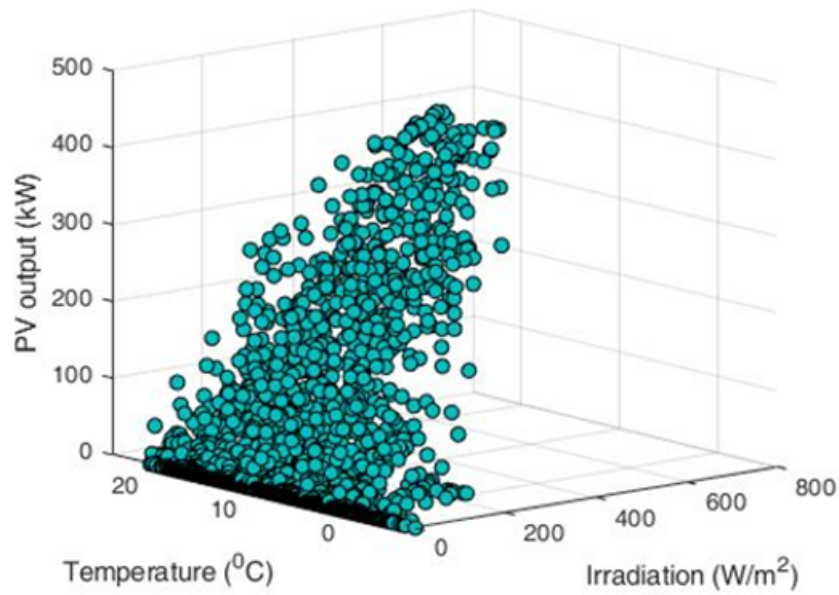


Figure 4-1: Scatter plot of the PV output with respect to irradiance and temperature

4.3.2 Pearson linear correlation coefficient

Before developing a machine learning model for estimating the PV output power, it is desirable to analyse the correlation of each input variable with the output variable. Figure 4-2 depicts the correlation between the PV output power, time, and irradiance. While Table 4-1 describes the correlation between the PV output power, temperature, irradiance, and time of recording instances, including the p-value as a measurement of the strength of the correlation. Pearson's linear correlation coefficient (PLCC) is a well-known function that evaluates the normalised covariance of the variables ranging from -1 to +1. Ideally, the extreme negative and positive values (i.e., -1 and +1) indicate the perfect negative and positive correlation, respectively, while zero indicates no correlation between the input-output variables [246]. In machine learning, if the absolute value of the PLCC of any variable is close to unity, then it can be deemed as a good feature for developing a regression model.

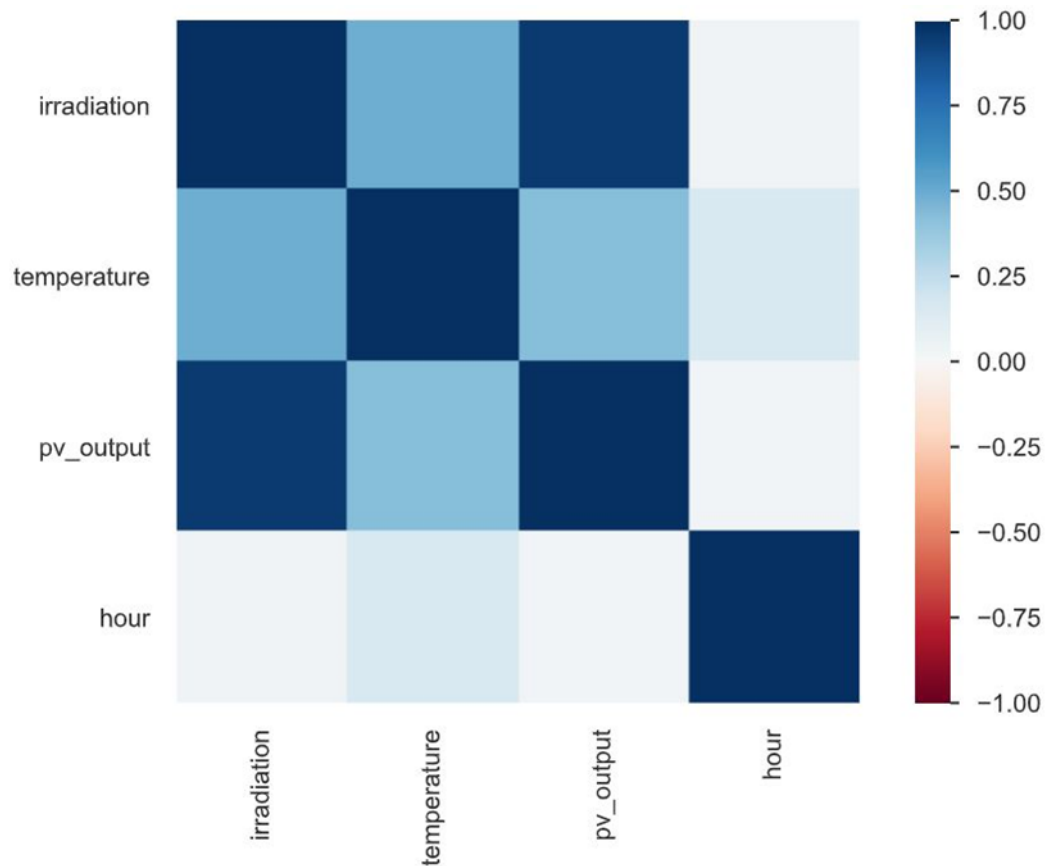


Figure 4-2: Feature correlation

Table 4-1: PLCC Between input variables and PV output power.

	Irradiation (w/m2)	Temperature(0C)	Timespan (hr)
PV output power	0.9450 (p-value<0.05)	0.4273 (p-value<0.05)	-0.2906 (p-value<0.05)

Table **4-1** describes the PLCC relation between the generation of PV output power for irradiation, temperature, and recording time. Table **4-1** shows that irradiation is one of the significant features that must be included in developing a machine-learning model due to its high correlation value. While the PLCC value for time suggests a negative correlation, which asserts that the PV output power is likely deteriorating as time progresses. Furthermore, a significant correlation between temperature and PV output value is established by rejecting the null hypothesis.

The PLCC analysis has indicated that the irradiation and temperature define the positive relation of PV output power, while timespan (age) is inversely contributing, suggesting that the PV panel's output power is likely to decline with age. Hence, in this sub-section, the extent of the variable mentioned above as an individual feature in developing an accurate forecasting model will be investigated by regression-based machine learning algorithms, namely support vector regression, regression trees, linear regression, and neural networks with varying kernel functions for predicting the PV output value [247],[248],[249].

4.4 Regression techniques

4.4.1 Linear regression

Linear regression is a modelling technique which can identify the linear relationship between independent and dependent variables. In a model, assume that $(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)$ are realisations of random variable pairs $(X_1, Y_1), (X_2, Y_2) \dots, (X_n, Y_n)$. The line equation is given by [250],

$$\bar{y}_i = \beta_0 + \beta_1 x_i \quad (4-1)$$

Where, $\bar{y}_i$ represents the mean expected value, and the subscript i represents the i^{th} unit in the population.

$$f(x) = w \cdot x + b \quad (4-2)$$

The support vector regression aims to find the value of (4-2) that minimises the following equations:

$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^N (\xi_i^* + \xi_i) \quad (4-3)$$

Subject to the constraints:

$$y_i - w \cdot x - b \leq \varepsilon + \xi_i \quad (4-4)$$

$$w \cdot x + b - y_i \leq \varepsilon + \xi_i^* \quad (4-5)$$

$$\xi_i, \xi_i^* > 0 \quad (4-6)$$

where, w is the weighting factor and b is the biasing factor, respectively, and can be calculated from [251] :

$$\text{Min } R_{SVR} = \frac{1}{N} \sum_{t=1}^N \theta_{\varepsilon} (y_t \cdot W^T \varphi(x) + b) \quad (4-7)$$

$$\theta_{\varepsilon}(y_t \cdot f(x)) = \begin{cases} |f(x) - y| - \varepsilon : & |f(x) - y| \leq \varepsilon \\ 0 : & \text{otherwise} \end{cases} \quad (4-8)$$

where $\theta_{\varepsilon}(y_t \cdot f(x))$ is a penalty loss function for wide support vectors. The combinatorial approach of minimising the training error and keeping a hyperplane on the model complexity is expressed in (4-9).

$$\text{Min}_{w, b, \xi^*, \xi} R_{\varepsilon}(w, \xi^*, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{t=1}^N (\xi_i^* + \xi_i) \quad (4-9)$$

The first term in (4-9) represents model complexity, and the second term represents the training error. ξ_i is the training error below $-\varepsilon$ and ξ_i^* represents the training error above $+\varepsilon$. The introduction of these two non-negative slack variables controls the sensitivity of SVR to overcome the problem of possible outliers.

The linear regression function is insufficient to represent the behaviour of the data in many cases; mapping to a higher dimension space $\varphi(\cdot): \mathcal{R}^n \rightarrow \mathcal{R}^{nh}$ generates a linear function f representing the relationship between the input (x_i) and output (y_i) as follows [252]:

$$a^2 f(x) = w^T \cdot \varphi(x) + b \quad (4-10)$$

Therefore, a nonlinear SVR solution is obtained by applying kernels which are nonlinear mappings that can be used in mapping the data into a higher dimensional feature space where linear regression is performed. The radial basis function (RBF) kernel is used in SVR to obtain nonlinear regression models.

$$(x, x') = \exp\left(-\frac{\|x, x'\|^2}{2\sigma^2}\right) = \exp(-\gamma\|x, x'\|^2) \quad (4-11)$$

4.4.2 Artificial neural network

A neural network is a sort of artificial intelligence that models function using the brain's response to stimuli. It can also solve real-world problems, regardless of their complexity. A neural network (ANN) is a computational system that establishes a correlation between input features and output by utilising our understanding of brain response to stimuli. An artificial neural network uses artificial neurons to solve complex, nonlinear problems like the brain uses interconnected neurons. The function in (4-12) can be used to represent an artificial neuron with n input dendrites [253].

$$y(x) = f\left(\sum_{i=1}^n w_i x_i\right) \quad (4-12)$$

There are n numbers of x inputs, and w_i are the weights that allow each of the n number of x input signals to contribute to the sum of the input signals. As a result, the activation function $f(x)$ returns the corresponding signal $y(x)$, modelled as the output axon. Feedforward neural network (FFNN) is used in the turning; it includes two inputs (G_i and T_{amb}), four hidden nodes, and an output layer (P_{out}). Network performance between the training set and the validation set are compared, and the process (epochs) is repeated until the acceptable result is obtained while preventing the network from overtraining, which may result in overfitting. The tuned ANNs were evaluated based on the stated performance assessment metrics with the test input variables and comparing the actual measured power to the predicted power.

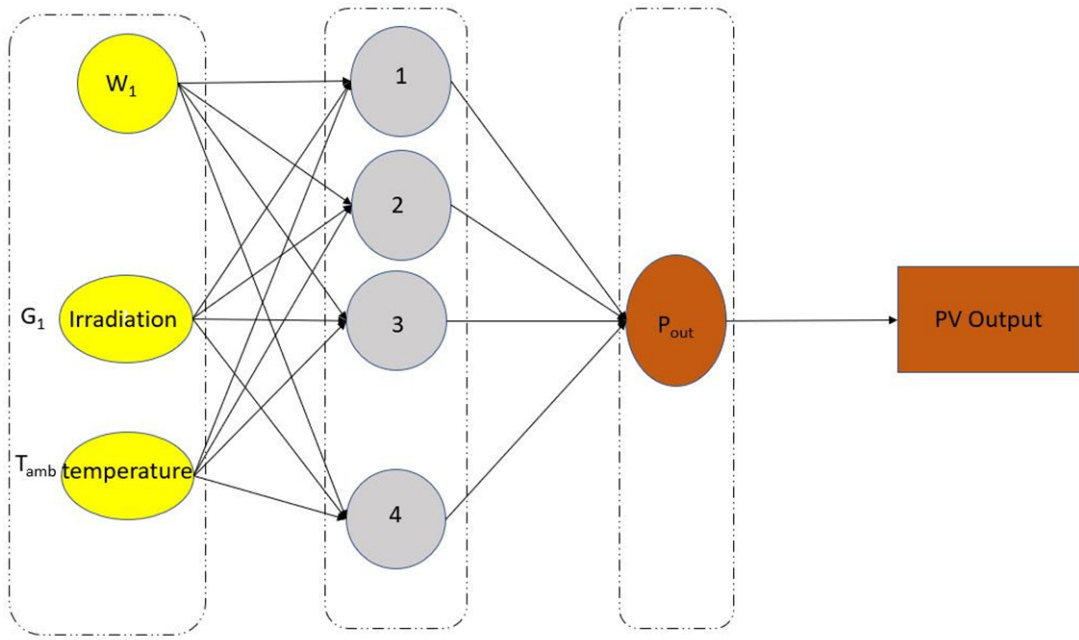


Figure 4-3: Network interconnection diagram of an FFNN ANN

4.4.3 Random forest regression (RF)

In RF regression, several decision trees are created, and each tree acts as its own regression function. The RF regression output is an average of all the decision trees. Decision trees, also known as classification and regression trees (CART), are statistical models developed by [254] in 1984. A decision tree is a non-parametric model without any previous class densities or tree structure parameters. The intricacy of the data used as input determines how the tree grows during the learning phase [255]. Decision trees consist of leaf nodes and decision nodes. Each fed-in sample is evaluated by a test function in a decision node and directed to a different branch based on its characteristics. Consider X as the input vector with m features, i.e., $X = x_1, x_2, \dots, x_m$, consider Y as the output vector and S_n as the training set containing n observations, which can be expressed as [256].

$$S_n = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}, X \in \mathcal{R}^m, \quad Y \in \mathcal{R}. \quad (4-13)$$

Splitting the input data at each node allows the parameters of split functions to be optimised for S_n . The first step of a decision tree is to decide which split is best between all variables. As the split process begins at the root, each node applies its split function to the new input X . Recursion repeats until a terminal node (also known as a leaf) is reached. When the levels reach a given number, or a node consists of fewer observations than the predefined number, then the tree is generally stopped. The training process is followed by constructing a prediction function $\hat{h}(X, S_n)$ based on S_n . Each observation is randomly selected from n observations with replacement from S_n , resulting in a bootstrap sample with a probability of $1/n$.

Breiman's bagging algorithm [255] has been used to lessen prediction-related variation and enhance prediction accuracy. The bagging algorithm builds q -prediction trees $\hat{h}(X, S_n^{\theta_1}), \dots, \hat{h}(X, S_n^{\theta_q})$ by applying the previous tree decision algorithm to several bootstrap samples $(S_n^{\theta_1}, \dots, S_n^{\theta_q})$. As a result, the ensemble produces q outputs for each tree which can be expressed as:

$$\hat{Y}_1 = \hat{h}(X, S_n^{\theta_1}), \hat{Y}_2 = \hat{h}(X, S_n^{\theta_2}), \dots, \hat{Y}_q = \hat{h}(X, S_n^{\theta_q}) \quad (4-14)$$

Afterwards, all trees are averaged to obtain an aggregate output. Therefore, the approximation $\hat{Y}$ of the output can be given as:

$$\hat{Y} = \frac{1}{q} \sum_{l=1}^q \hat{Y}_l = \frac{1}{q} \sum_{l=1}^q \hat{h}(X, S_n^{\theta_l}), \quad (4-15)$$

where $\hat{Y}_l$ is the output of l^{th} tree, and $l = 1, 2, \dots, q$. A framework for RF regression prediction is presented in Figure 4-4

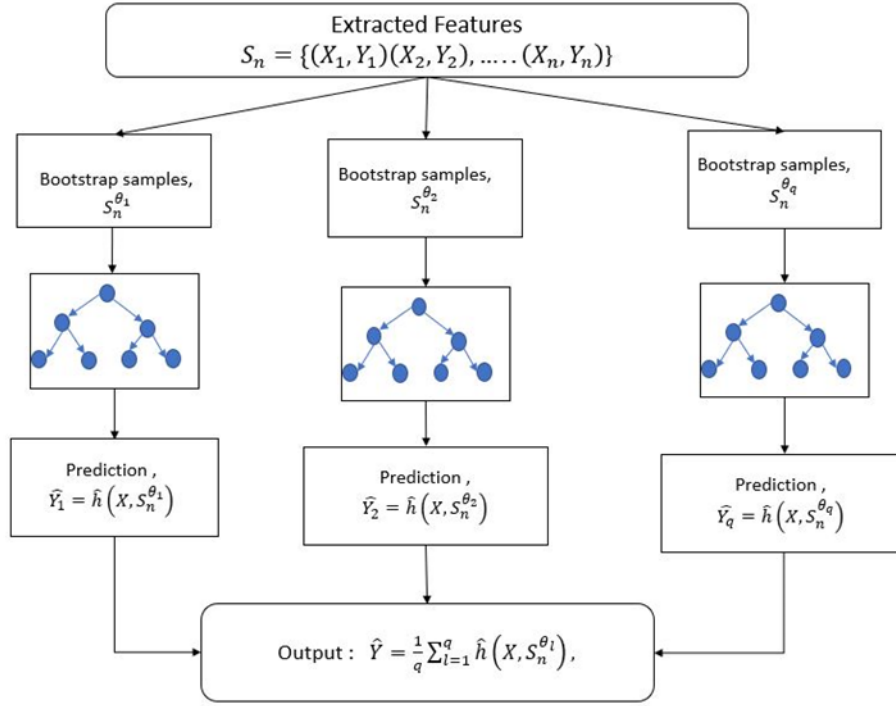


Figure 4-4: Demonstration of random forest regression construction [256]

4.5 Performance indexes

The preferred forecasting model is the one that produces the least error. Suppose that $P_{fcs,t}$ is the power forecast at time t and $P_{msd,t}$ is the measured power value for t . Four metrics, namely, root mean square error (RMSE), R-squared value [257], mean square error (MSE) [258], and mean absolute error (MAE) [259], with ten-fold cross-validation, have been considered to evaluate the performance of the regression models. The errors have been calculated using (4-16) - (4-18).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{fcs,i} - P_{msd,i})^2} \quad (4-16)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |(P_{fcs,i} - P_{msd,i})| \quad (4-17)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (P_{fcs,i} - P_{msd,i})^2 \quad (4-18)$$

Table 4-2 shows the performance of optimised machine learning algorithms for predicting the PV output value when time is not considered a dependent variable. Out of all the machine learning models considered, the best two performers are support vector regression (with radial basis function) and random forest (with leaf size = 9, learners = 127). [260], [261]. A similar trend is also observed in Table 4-3 when the age factor is introduced in the learning process.

Table 4-2 Performance of regression models for predicting PV output value using the daily dataset (Excluding age feature)

Machine Learning Model	Kernels	RMSE	R-squared	MSE	MAE
Linear Regression	Linear	34.247	0.89	1172.90	14.110
Regression Tree	Leafs=32	29.719	0.89	882.71	12.454
Support vector Regression	Linear	30.238	0.89	914.32	16.708
	RBF kernel scale:2.8061 constant:53.9391 Epsilon:5.7282	27.180	0.91	823.25	12.550
Random Forest	Leaf =9, learner =127	27.485	0.91	828.76	12.685
Neural Networks	Bilayer(size=10:10)	29.689	0.90	870.16	14.318
	Trilayer(size=10:10:10)	29.604	0.90	876.41	13.071

However, the performance error has drastically changed due to the introduction of the time factor in the learning process. These results suggest that the machine learning models are efficiently able to predict the PV output power when the age of the PV panel is considered in the learning process, as shown in Figure 4-10

and Figure 4-11. The best-performing metrics are highlighted in italic-boldface in Table 4-2 and Table 4-3.

Table 4-3: Performance of regression models for predicting PV output value using the daily dataset (Including age feature)

Machine Learning Model	Kernels	RMSE	R-squared	MSE	MAE
Linear Regression	Linear	29.50	0.90	870.31	14.32
Regression Tree	Leafs=8	26.00	0.92	676.08	11.25
Support vector Regression	Linear	29.21	0.90	853.37	12.83
	RBF kernel scale:437.7466 Box constant:993.7545 Epsilon:4.9584	15.750	0.97	248.31	7.68
Random Forest	Leaf =9, learner =497	18.216	0.96	331.83	8.1475
Neural Networks	Bilayer(size=10:10)	27.704	0.91	767.51	12.720
	Trilayer(size=10:10:10)	28.305	0.90	801.15	12.766

4.6 Battery storage system

In optimal decision-making, a BESS in a microgrid can be considered either a generator source when it discharges or a load when it charges, depending on the variation of electricity price and amount of power generated or consumed at the time. Therefore, the installed PV power output and size/rating of the BESS must match to maximise the benefit for users while increasing the lifecycle of a battery and minimising its maintenance. According to one of the recent studies on the available battery technologies [262], lead-acid-based batteries have the lowest investment cost but have a lower depth of discharge and life cycle than lithium-

ion- batteries. Therefore, we consider lithium-ion (Li-ion) batteries in this study due to their superior characteristics, including high energy and power density, lightweight design, absence of memory effect, very low self-discharge, and high efficiency [222], [263]. As a result, it is among the most widely used batteries and is utilised in many applications, such as microgrid storage systems [222]. The rate of charge and discharge of the battery system is expressed as follows:

$$\frac{dE_B(t)}{dt} = P_B(t) \quad (4-19)$$

where, $E_B(t)$ (Wh) is the quantity of electric energy stored in the battery at time t , and $P_B(t)$ (W) is the rate of charging and discharging of the battery, which can be defined as $P_B(t) > 0$ if the battery is charging, $P_B(t) < 0$ if the battery is discharging. The quantity of electric energy in BESS at any instance depends on its previous state of energy and the mode of charging/discharging. The charge and discharge equation is shown in (3-12) in which. $D_{BESS}(t)$ is the battery discharged power at the time (t), $P_{BESS}(t)$ is the power charged to the battery, $c(t)$ is the current state charge SOC at the time (t), and $c(t-1)$ is the previous SOC at the time ($t-1$) [198].

The cost of BESS includes the one-time fixed battery investment cost (FC) in £/kWh, which comprises of battery's capital, installation cost, and annual maintenance cost (MC). The annual maintenance cost is proportional to the size of the BESS. Therefore, the total cost of BESS is given as:

$$(FC + l * MC) * CB \text{ (£)} \quad (4-20)$$

Where CB is the BESS size, and l is the number of years. If the interest rate of financing the BESS is r , then the annual one-time cost of the energy storage (AOTC) in £/year for BESS is expressed in (4-21)

$$AOTC = \frac{r(1+r)^l}{(1+r)^l} FC * CB \quad (4-21)$$

Where, $\frac{r(1+r)^l}{(1+r)^l}$ is the capital recovery factor (CRF). The installed BESS total cost per day (TCPD) in £/day is expressed in (4-22).

$$TCPD = \frac{1}{365} (AOTC + CB * MC) \quad (4-22)$$

4.7 Battery degradation cost

Repeated charge and discharge cycles tend to degrade the service life of batteries, with the extent of degradation varying depending on the battery class and chemistry, as well as storage conditions such as temperature and cycling characteristics, including charge/discharge rate and state of charge. The impact of these factors on battery life varies, with Lithium batteries showing sensitivity to the total number of cycles and the depth of discharge during those cycles [264]. The cost of battery degradation for a charge and discharge cycle of nKWh can be estimated by either cycle-life performance characteristics or the cycle-life against the depth of discharge[265]. The cycle-life performance characteristic is used in this model [264].

$$C^n = \left| \frac{k}{100} \right| \frac{n}{B} C^B \quad (4-23)$$

Where k represents the slope of the battery degradation cost optimisation curve in Figure 4-16, which represents the linear approximation of the battery life as a function of the cycles, B represents the battery capacity, C^B is the battery cost, and C^n is the degradation cost.

4.8 Battery storage constraints

(a) State of charge constraints

$$C_{min}(t) \leq C(t) \leq C_{max}(t) \quad (4-24)$$

(b) Charging and discharging power constraints

There are three possible states for the battery status at any given time: charging, draining, or idle. Therefore, we assign two binary variables $\delta_{bch}(t) \in [0,1]$ and $\delta_{bdis}(t) \in [0,1]$ to formulate the status of the battery.

$$\delta_{bch}(t) + \delta_{bdis}(t) \leq 1 \quad (4-25)$$

The equation (4-25) prevents the battery from charging and discharging at the same time during the optimisation. The charging and discharging constraints for the storage battery could be formulated as follows [266].

$$\delta_{bch}(t) \cdot P_{bchmin}(t) \leq P_{bch}(t) \leq \delta_{bch}(t) \cdot P_{bchmax} \quad (4-26)$$

$$\delta_{bdis}(t) \cdot P_{bdismin}(t) \leq P_{bdis}(t) \leq \delta_{bdis}(t) \cdot P_{bdismax} \quad (4-27)$$

4.9 Electric grid

Due to the intermittency of the RE, the condition can arise when RE source output power and BESS become insufficient to supply the required load demand. The utility grid then acts as a backup and sells power to the microgrid to meet the load demand. Electricity can be bought from or sold back to the utility grid at the TOU ($E_{mkt}(t)$ (£/kWh) at time t). The TOU $E_{mkt}(t)$ can be ≥ 0 depending on the time (t) as it varies across a typical day. Therefore, $P_g(t)$ (kW) is used to represent the electric power exchanged with the grid and $E_{cb}(t)$ as the energy cost such that:

$$E_{cb}(t) = E_{mkt}(t) * P_g(t) \quad (4-28)$$

The power transfer limit (D) between the utility grid and the MG is set to 2500kW in the model based on the maximum power carrying capacity of the line connecting the airport, which is 5MW, $P_L(t)$ is the load demand, $P_{pv-out}(t)$ is the output PV power, $P_B(t)$ is the battery power.

(i) $P_g(t) > 0$ if electric power is purchased from the grid, and

(ii) $P_g(t) < 0$ if electric power is sold to the grid

The equation (4-28) can be expanded for the net power readings as:

$$E_{cb}(t) = \{[E_{mkt}(t) \times P_{g(net1)}(t) + [E_{mkt}(t) \times P_{g(net2)}(t)]\} \quad (4-29)$$

where, $P_{g(net1)}(t) > 0$ denotes the cost of purchasing power from the grid and $P_{g(net2)}(t) < 0$ denotes the expected benefit of selling excess power to the grid.

4.10 Solar PV model

The power measured by the photovoltaic array is influenced by the temperature and radiation, as shown in section 4.3.2. The PV power output is given by (3-11). The balance between supply and demand is the main problem facing the power system; the expression for power flow balance in the microgrid at each time step can be expressed using (4-30).

$$P_g(t) = P_L(t) - \sum (P_V(t), P_{BESS}(t)) \quad (4-30)$$

where, $P_L(t)$ is the taxiing load demand, P_{pv-out} is the output PV power, $P_{BESS}(t)$ represent the battery power, $P_g(t)$ is the power injected by the utility grid. The power exchange with the grid ($P_g(t)$) depends on the situation, i.e. the active and reactive power exchanges would either be sold or bought, and there may be no exchange at all.

4.11 Aircraft taxiing load

The model considers the forces acting on the aircraft during ground movement operation, such as traction force, linear acceleration force (F_{LA}), the rolling resistance force of the tire (F_r), aerodynamic drag force (F_{drag}) and grade resistance force (F_{grade}) based on the interaction between the aircraft mass, wheel, and tarmac as represented by a two-dimensional longitudinal dynamic model expressed in (3-1) - (3-8) [201]. The flight schedule of the airport showing the number of departure flights per hour used in the simulation and the taxiing load demand is shown in Table 4-4 and Figure 4-5, respectively.

4.11.1 Case one: Taxiing load demand of Cranfield Airport

Partial flight information from a typical weekday flight schedule of Cranfield Airport that is used in the simulation of the taxiing load demand profile for scenario one is given in Table 4-4:

Table 4-4: Partial flight information (scenario one)

No.	Flight number	Aircraft type	STAi/STDi	Flight attribute
1	G-BRTX	Fixed-wing single engine	18:08	Departure
2	G-BDGM	Fixed-wing single engine	17:26	Departure
3	G-BRTX	Fixed-wing single engine	17:18	Departure
4	G-BNVB	Fixed-wing single engine	17:16	Departure
5	G-BRTX	Fixed-wing single engine	15:22	Departure
6	G-LCTO	Fixed-wing single engine	11:43	Arrival
7	G-LDGH	Fixed-wing single engine	14:21	Departure
8	G-BDGM	Fixed-wing single engine	13:04	Departure
9	G-LCTO	Fixed-wing single engine	11:43	Departure
10	G-LCTO	Fixed-wing single engine	09:29	Arrival

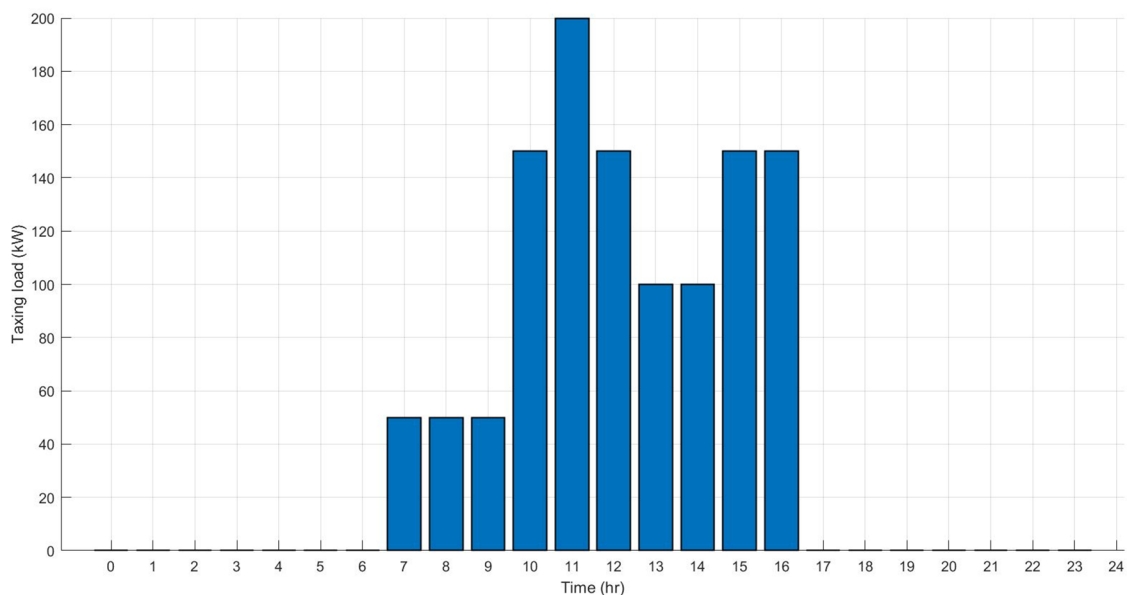


Figure 4-5 Aircraft taxiing load profile scenario one

4.11.2 Case two: Taxiing load demand Luton Airport (representing Cranfield Airport's future flight schedule)

Partial flight information for the flight schedule of London Luton Airport [267] that is used in the simulation of future taxiing load demand profile for Cranfield Airport in scenario two is given in Table 4-5 and Figure 4-6

Table 4-5 Partial flight information (scenario two)

No	Flight number	Aircraft type	STAi/STDi	Flight attribute
1	WZZ3654	A320	23:10	Departure
2	WZZ1054	A21N	22:42	Departure
3	WUK4009	A21N	22:29	Departure
4	WZZ3008	A320	22:23	Departure
5	WZZ1608	A321	22:01	Departure
6	RYR5456	B738	23:25	Arrival
7	WZZ4504	A320	21:52	Departure
8	WZZ3306	A321	21:49	Departure
9	WUK1476	A320	21:41	Arrival
10	RYR5456	B738	21:57	Arrival

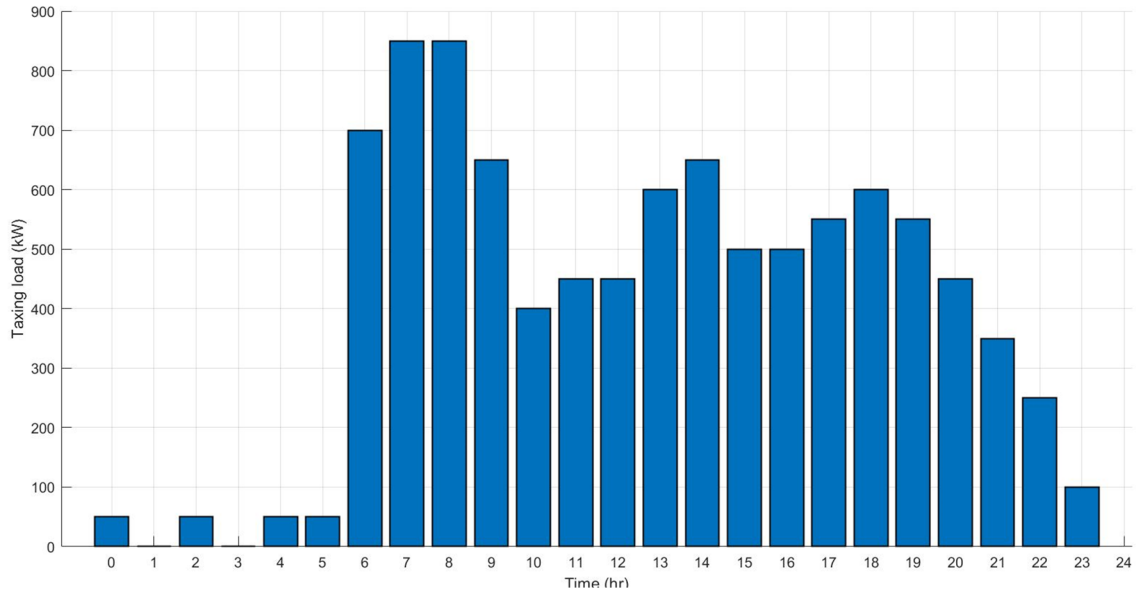


Figure 4-6 Aircraft taxiing load profile scenario two

4.12 Problem formulation and cost minimisation

In this section, we aim to determine the ideal storage size for a grid-connected PV system. The system's output is constrained by the transmission line that connects it to the upstream grid, as it operates as a bidirectional generator. For this reason, we have chosen to consider 24-hour operation in our study. This allows the optimizer to utilize all available solar power while minimising the import of grid power.

$$\text{Min } F = \sum_{t=0}^T E_{cb}(t) + TCPD(t) + C_{PV}(t) \quad (4-31)$$

Constraints [268]:

$$P_B(t) = \begin{cases} \frac{P_{BESS}(t)}{\eta_B} & \text{if } P_B(t) < 0 \\ \eta_B P_{BESS}(t) & \text{otherwise} \end{cases} \quad (4-32)$$

$$P_{B \min} \leq P_B(t) \leq P_{B \max} \quad (4-33)$$

$$0 \leq P_g(t) \leq D \quad (4-34)$$

$$0 \leq C_B \leq C_{B \max} \quad (4-35)$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (4-36)$$

where, $C_{PV}(t)$ is the cost of solar PV dispatched [269], SOC_{min} is the minimum state of charge of BESS, SOC_{max} is the maximum state of charge of BESS. The goal is to reduce the overall cost (TC) in (4-31). The GA computes the different costs under different sizes of BESS between the minimum size CB_{min} and maximum size CB_{max} . The optimum size can be found at the minimum cost point of (4-31).

4.12.1 Proposed optimisation methodology (GA)

The Genetic Algorithm (GA) is a stochastic global search and optimisation algorithm used to solve constrained and unconstrained optimisation problems. The GA is inspired by the principle of genetic and natural selection. The process starts by generating a random set of potential solutions (chromosomes) to a given problem. The GA repeatedly modifies the population of individual solutions (chromosomes). At each iteration, individuals are chosen at random from the current population in accordance with the chosen fitness function. These individuals are used as parents to generate the offspring of the next generation [270], [271]. The G.A. is used in this study due to its effectiveness in handling multi-objective optimisation problems and can provide a solution that balances the different requirements of the system. Additionally, the GA-based optimisation method can be readily adapted to accommodate any modifications or changes in the microgrid system, enabling the design to be updated and optimised to meet the new system requirements [272].

Generally, GA uses three operators, namely selection, crossover, and mutation, to imitate the natural evolution processes; these are applied to the members of the potential solutions to create new solutions. The evaluation and new population generation process are continued until a satisfactory solution subject to specific termination conditions has been satisfied. Genetic algorithms sometimes suffer from a premature convergence problem in populations where

high-rated individuals' genes quickly gain dominance, causing the population to converge to a local optimal. However, this study has used the genetic clustering method [273] to prevent premature convergence. The population size is 500, with a cross-over rate of 0.9 and a mutation rate of 0.001. The optimisation model is implemented in the Matlab simulation platform.

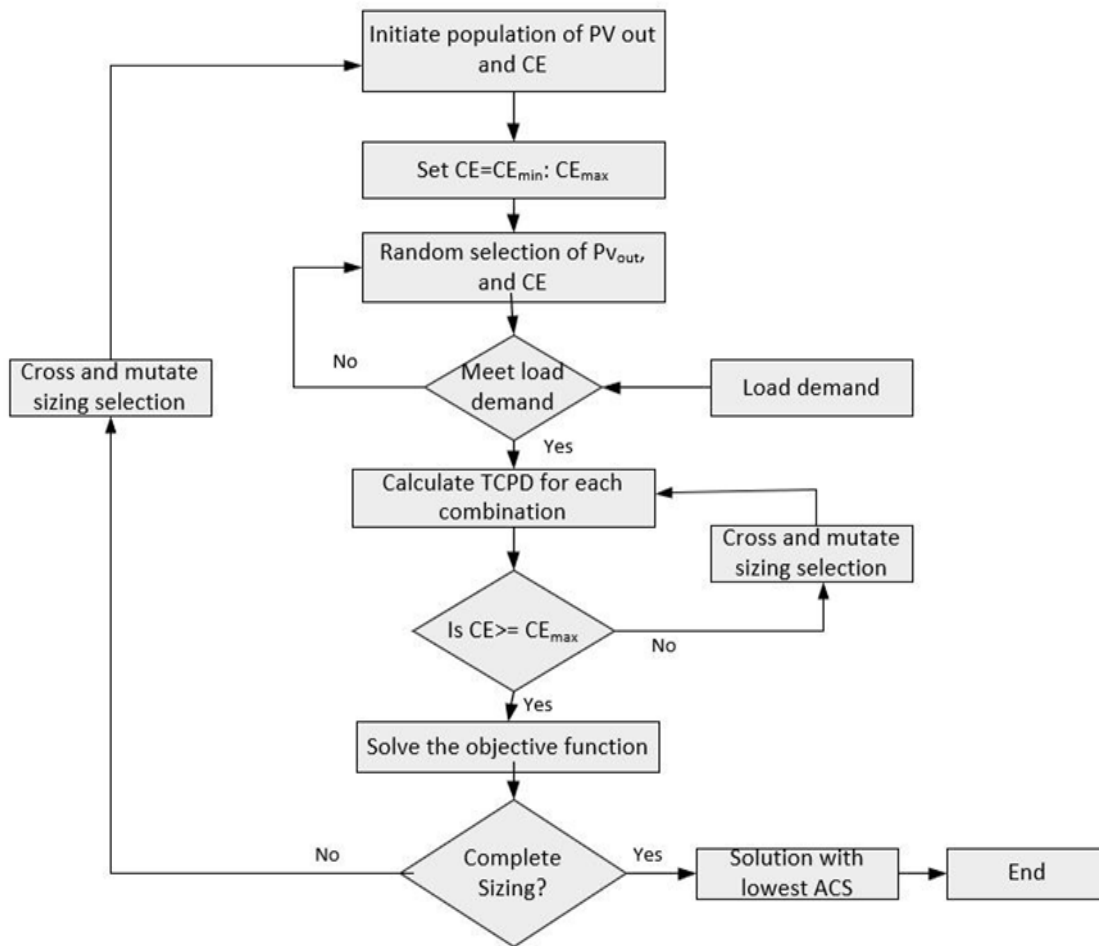
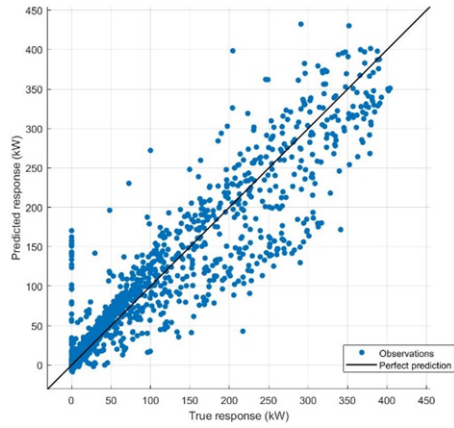


Figure 4-7: Flow chart of the optimal sizing model using GA

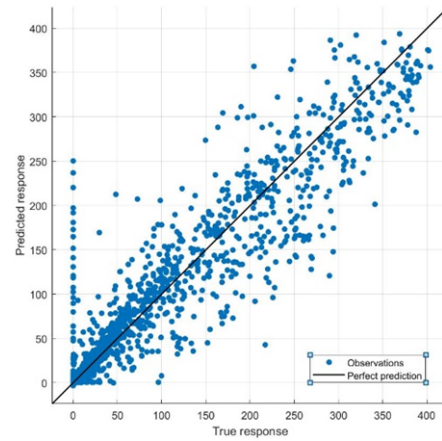
4.13 Results and discussion

The optimisation algorithm computes the optimised battery size and corresponding daily operational cost. The different values are generated and compared for two scenarios: (i) with the current taxiing load demand in Cranfield Airport and (ii) with Cranfield Airport as a commercial airport considering the

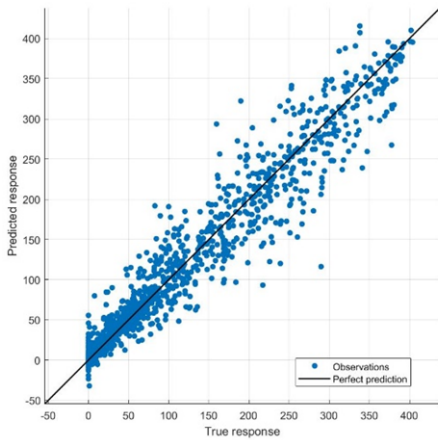
taxiing load demand of Luton Airport. The parameters of the PV source are efficiency (η) = 17.6%, $S = 5858.4 \text{ m}^2$, $P^{STC} = 1000$, $I_{ref} = 1000 \text{ W/m}^2$, and $k_t = (-3.7 \times 10^{-3} (1/^\circ\text{C}))$. Solar radiation and temperature obtained from the site have been recorded in a span of every half-hour for one year and are used to model the power output. The simulation was performed using the Matlab platform for computational analysis. The response plot performance of the ML model with and without age factor consideration in the optimised learning process is illustrated in Figure 4-8 and Figure 4-9. The wider area of the observed data points in Figure 4-8 (a), (b) compared to (c) and (d) suggests that the ML model is likely to create a large error in the prediction process in linear regression and neural network than the random forest and support vector regression models. Ideally, the observation points should lie on a perfect prediction line resulting in a unity R-squared value and zero RMSE, MSE, and MAE values.



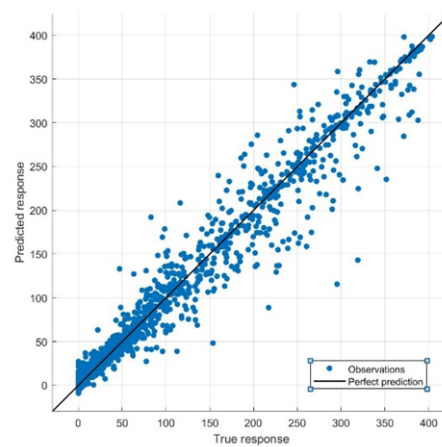
(a)



(b)



(c)



(d)

Figure 4-8: Prediction response plot of PV output value without age feature by (a) Linear regression, (b) Neural network, (c) Random Forest, (d) Support vector regression (RBF)

In contrast, Figure 4-9 (a) - (d) illustrates the response plot of the ML models when the age feature is included in the optimised learning process.

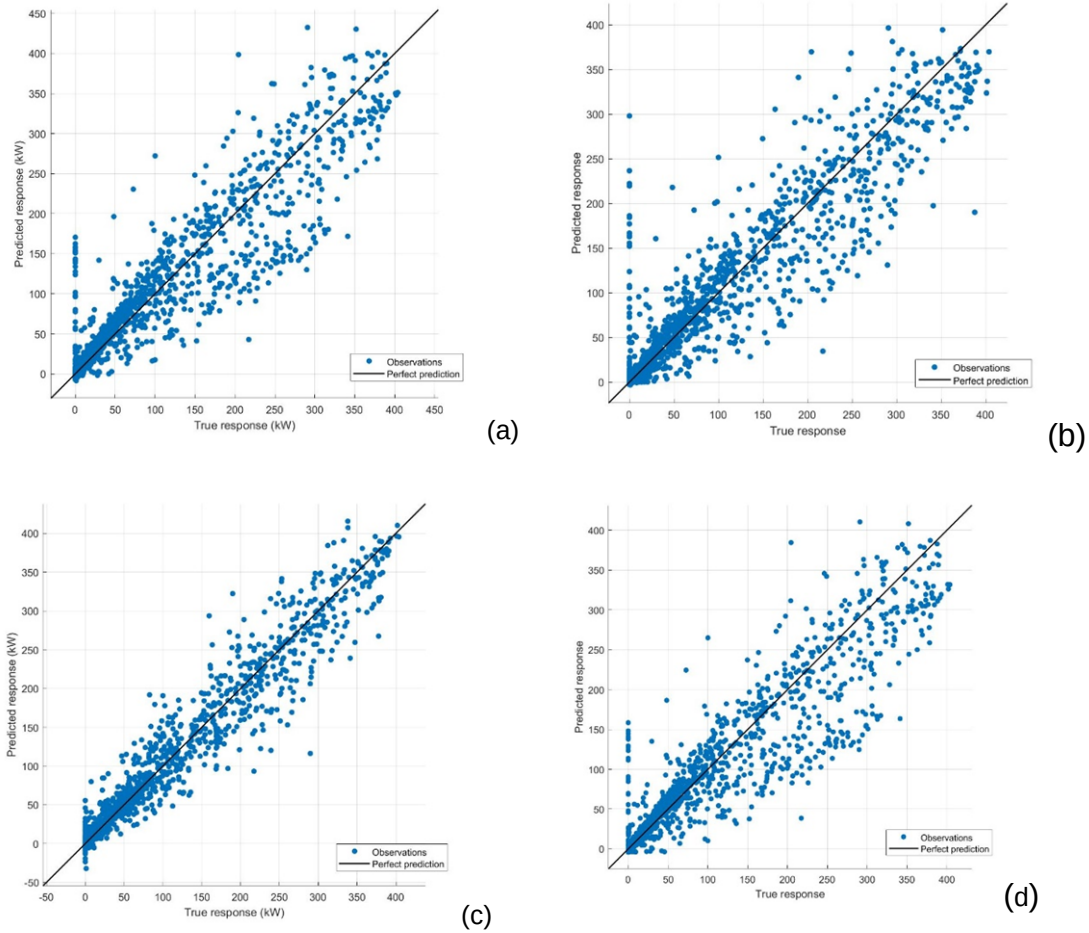


Figure 4-9: Prediction response plot of PV output value with age feature by (a) Linear regression, (b) Neural network, (c) Random Forest, (d) Support vector regression (RBF)

Based on the comparative analysis of Figure 4-8 and Figure 4-9, as well as the results presented in Table 4-2 and Table 4-3, we can confidently conclude that incorporating the age factor into the learning process has resulted in a substantial improvement in the accuracy of PV output power predictions. Furthermore, both the support vector regression and random forest models have demonstrated exceptional performance, exhibiting minimal error and higher R-square values. The performance of the various ML algorithms in terms of the performance

indices (RMSE, MAE, R-squared and MSE) are shown in Figure 4-10 and Figure 4-11.

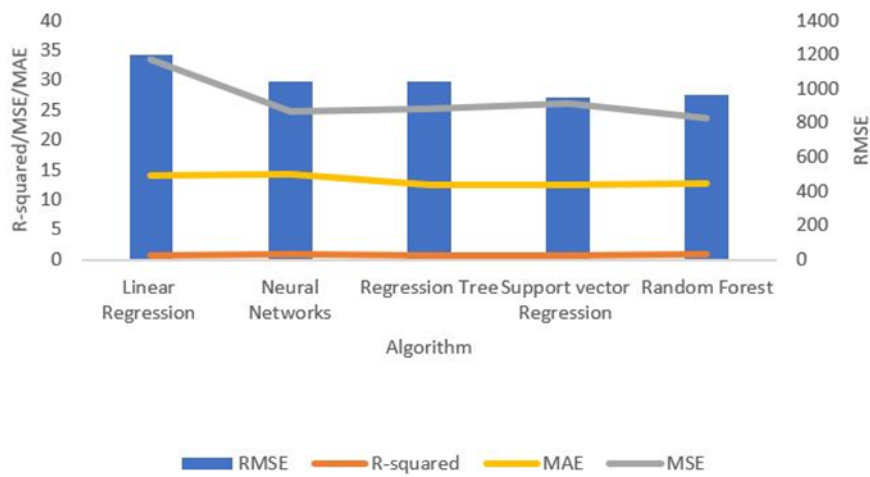


Figure 4-10 Performance of regression models for predicting PV output value without age consideration

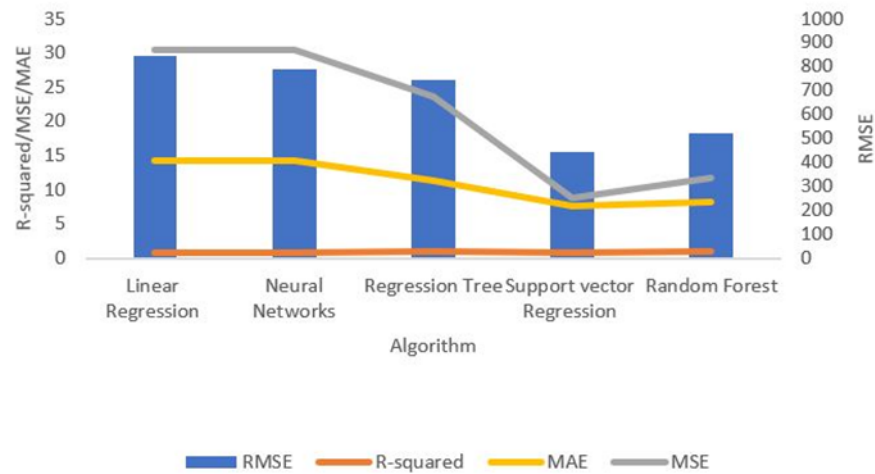


Figure 4-11 Performance of regression models for predicting PV output value with age consideration

4.13.1 Cost benefit-analysis (case studies)

These case studies attempt to determine the optimal rating of BESS for the PV-based grid-connected MG. Two scenarios have been considered here: (i) The optimum BESS capacity problem for the MG under the present taxiing load condition is addressed in scenario one, and (ii) The second scenario considers a commercial airport operation taxiing load profile.

BESS finance is set to a 6% interest rate, and the cost for 100 kWh is about £60000, based on [124] [197]. In general, the interest rates for battery energy storage finance in microgrid cost-benefit analysis can range from around 4% to 12%, depending on the specific circumstances. However, it's important to note that interest rates are subject to change over time and can vary depending on market conditions and other factors. These rates are used as an estimate of the cost of capital, which considers factors such as inflation, risk, and the opportunity cost of investing in alternative projects. It helps to determine the net present value (NPV) of the microgrid investment, which is a widely used financial metric for assessing the profitability of a project over its lifetime [124] [268].

The maintenance cost is £2000, the BESS lifetime is set to 3 years, the maximum BESS capacity is set at 3000kWh, and the charge and discharge rate is set at 90%, respectively. The minimum and maximum charge power are set at 50% of its full capacity. This means that the battery can be charged to full capacity or discharged completely in 2 hours.

4.13.1.1 Scenario one

The optimiser finds the optimal BESS size for the MG in this scenario as 816.7kWh at a minimum cost per day (TCPD) of £547. As shown in Figure **4-12** (a), the incremental cost of BESS per 100kWh per day is £70. The degradation cost is £53.7 per 100kWh. Meanwhile, the market benefit at the optimum BESS is £259.3, and it decreases by £13.1 for every 100kWh increase in capacity. Thus, the total benefit (TB) is £57 per day (loss).

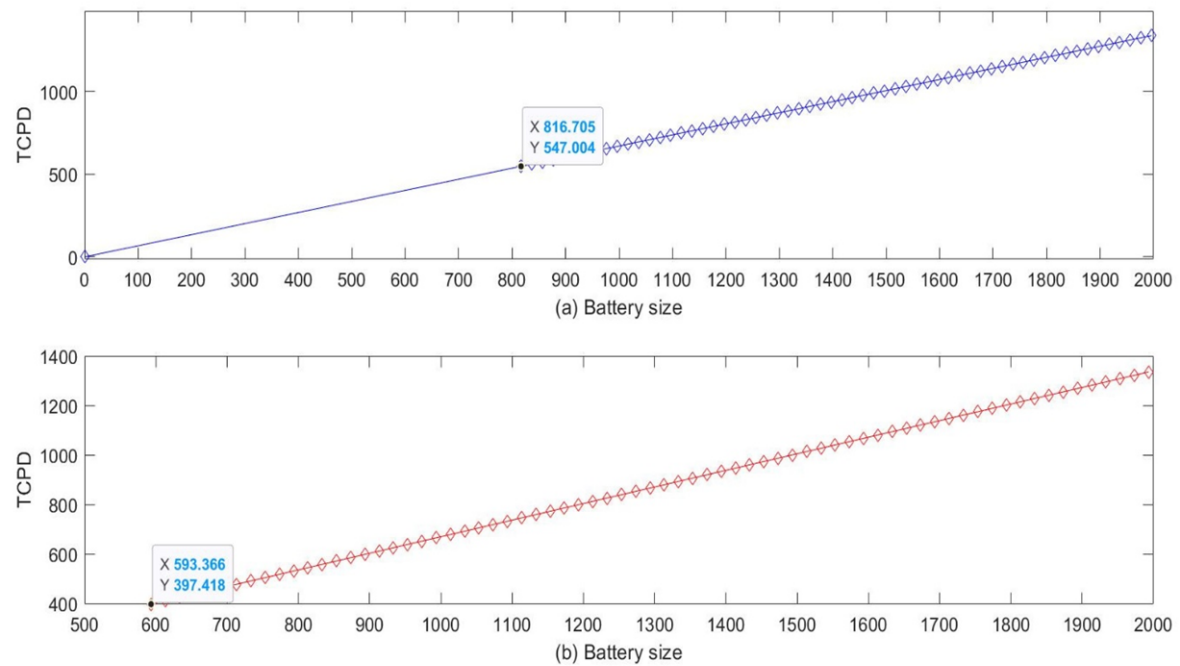


Figure 4-12 Optimum battery size (a) Scenario one (b) Scenario two

4.13.1.2 Scenario two

Simulation of the MG is based on the taxiing load demand for Luton Airport. It can be observed that during the off-peak hours (00:00 to 07:00), both the load demand and the battery charging depend on the grid. Battery charging occurs between 01:00 and 03:00 (2 hours) as specified in Section 4.13.1 because it is cheaper as the market price is at a minimum value (0.049£/kWh) compared to the degradation cost of 0.78£/kWh when supplied by the battery.

A peak load demand of 2800kW occurs at 07:00, in which the grid supplies 2500kW while the battery supplies the remaining 300kW despite the market price at a minimum value because 2800kW is above the transmission line limit stated in the constraint in Section 4.9 since the PV power is not available yet. The BESS recharge between 08:00 and 09:00 using the PV power that begins at 08:00 to keep the battery fully charged. Excess PV power is fed to the grid to profit at 09:00, 10:00, and 13:00 as the battery is fully charged, and PV power output is greater than the load demand. The optimum battery capacity for the microgrid in this scenario was found as 593kWh, and the total cost per day (TCPD) at the

optimal size is £397, as shown in Figure 4-12 (b). The TCPD increases with battery size; the incremental cost of BESS is £70 per 100kWh in one day, which is the same as case one. However, the degradation cost is £78.8 per 100kWh, representing a higher value than in scenario one because there is a higher load and higher charge/discharge cycles in scenario two, as shown in Figure 4-13 (c) compared to scenario one in Figure 4-13 (b).

4.13.2 Optimal charging and discharging schedule of the BESS

Figure 4-13 (a)-(c) illustrates how the BESS charges and discharges to its maximum active power and how the algorithm handles the constraint of SOC and TOU. According to Figure 4-13 (b), the battery charges up during the valley period from 01:00 to 02:00 until its state of charge reaches its maximum when the TOU is minimum. The battery remains steady at a maximum charge but inactive for three hours (03:00 to 06:00), then the battery releases its energy at 07:00 in scenario two (refer to Figure 4-13 (c)) to supply the deficit of 300kW above the 2500kW power transfer limit of the upstream grid to meet the peak load demand. The BESS charges from the PV from 08:00 to 09:00.

Finally, the battery discharges to the grid at 19:00 in scenario one and 16:00 in scenario two, as shown in Figure 4-13 (b) and Figure 4-13 (c), respectively, when the TOU is maximum. The optimiser successfully reduces the overall operating cost or raises the MG profit by scheduling the charging and discharging operations of the system.

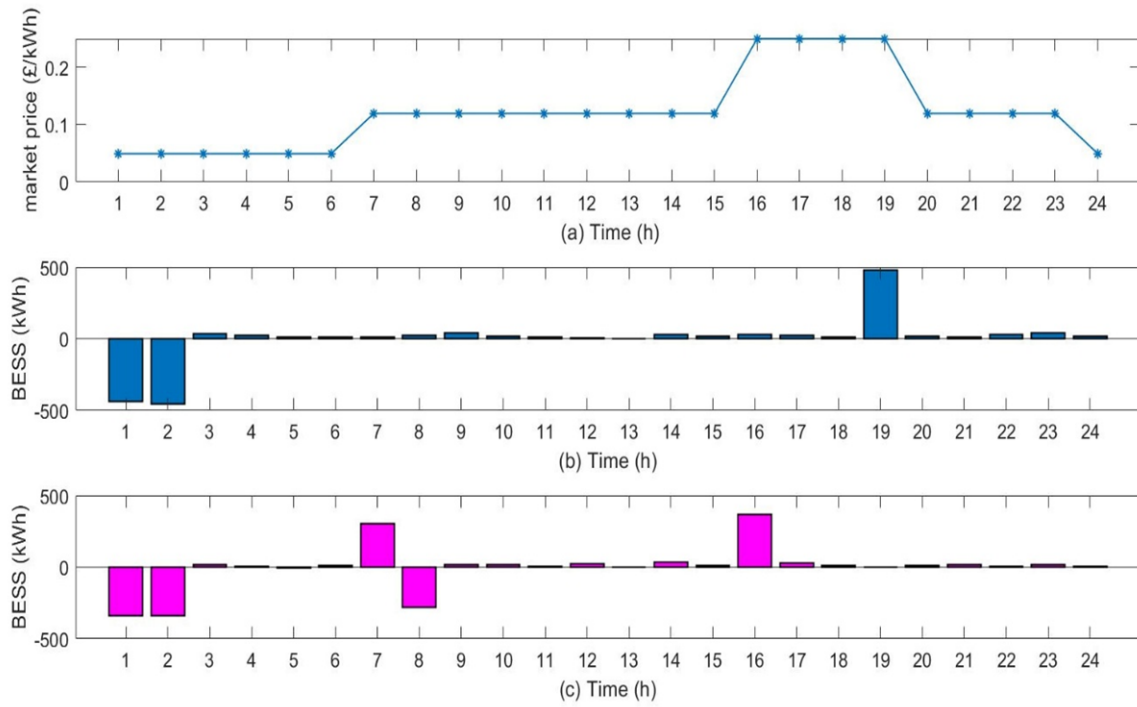


Figure 4-13 : (a) market price (£/kWh) (b) battery charging/discharging profile scenario one (c) battery charging/discharging profile scenario two

4.13.3 Optimal exchange of active power with the upstream grid

Figure 4-14 (a) and (b) illustrate active power exchange with the utility grid. It could be observed that the MG purchased active power from the utility grid at hours 01:00-02:00 to charge the battery system and at 09:00,10:00,11:00,12:00,15:00,16:00 to compensate for the deficit in the PV and BESS discharge to meet the load demand.

For the same purpose, active power is sold to the grid by the MG during peak hours (08:00, 13:00,14:00,17:00) when the PV output power exceeds the taxiing load demand and at hours 18:00-19:00 when the TOUs have high values to maximise the profit. In scenario one, for the same purpose, the MG sell power to the grid at 09:00,10:00,13:00 when PV output power is greater than demand in scenario two.

The exchange of active power between the utility grid and the MG varies dynamically due to the nature of taxiing load demand in the airport, while the

model adjusts to meet the objective of the optimisation. As shown in Figure 4-15, the amortisation period for the investment on the BESS at optimal capacity is found as six years.

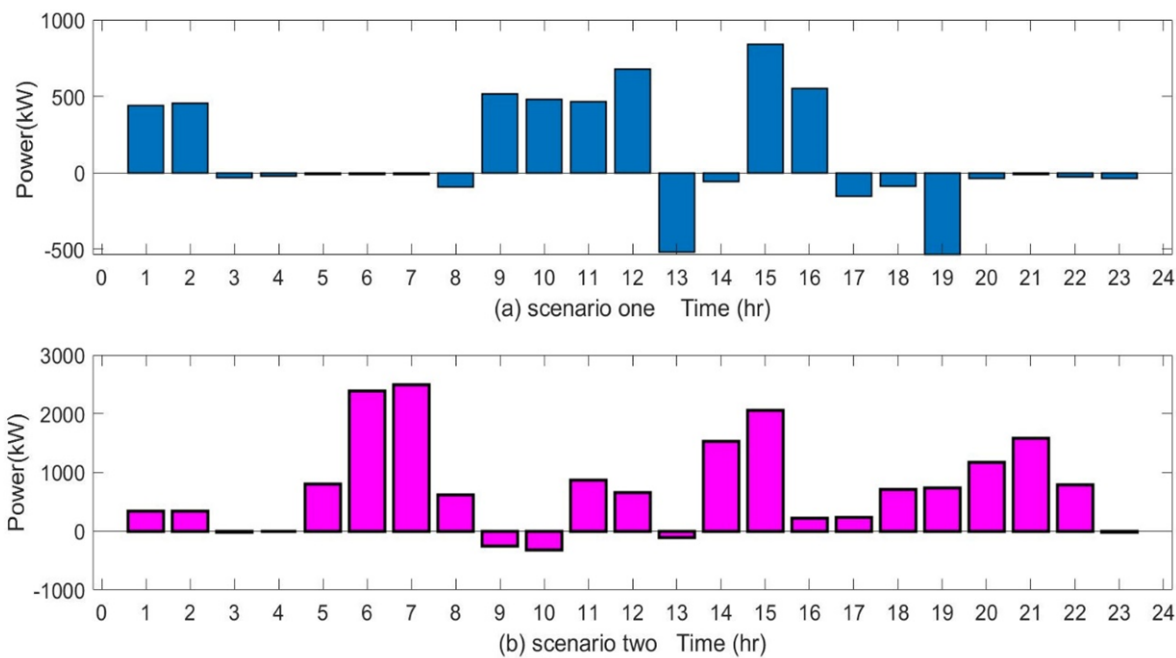


Figure 4-14: Optimal exchange of active power with the utility grid (a) Scenario one (b) Scenario two

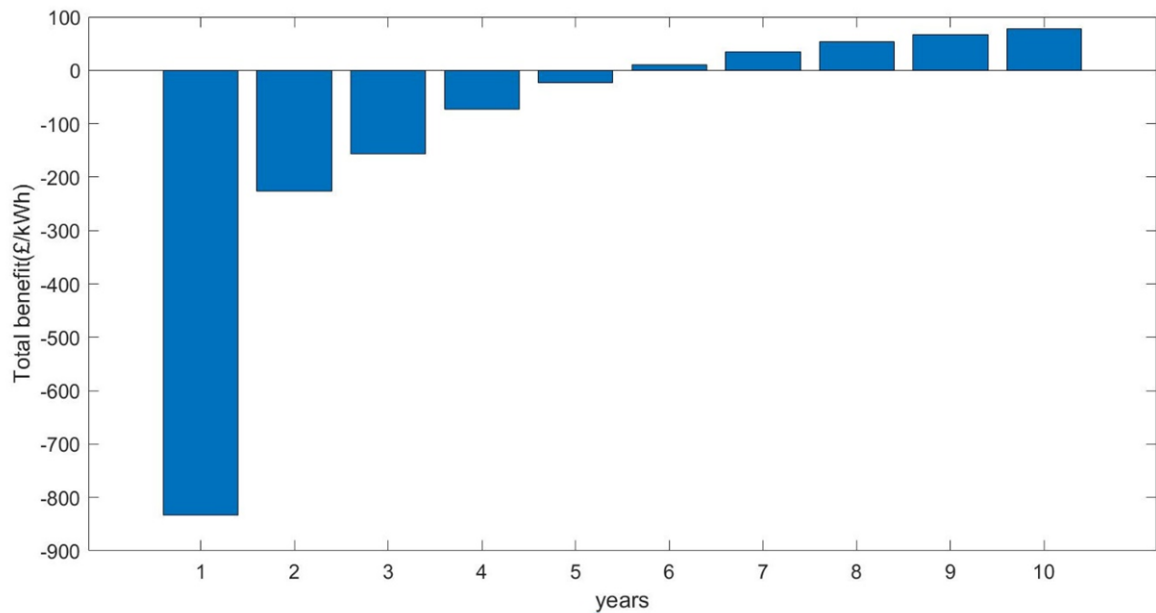


Figure 4-15: Amortization period

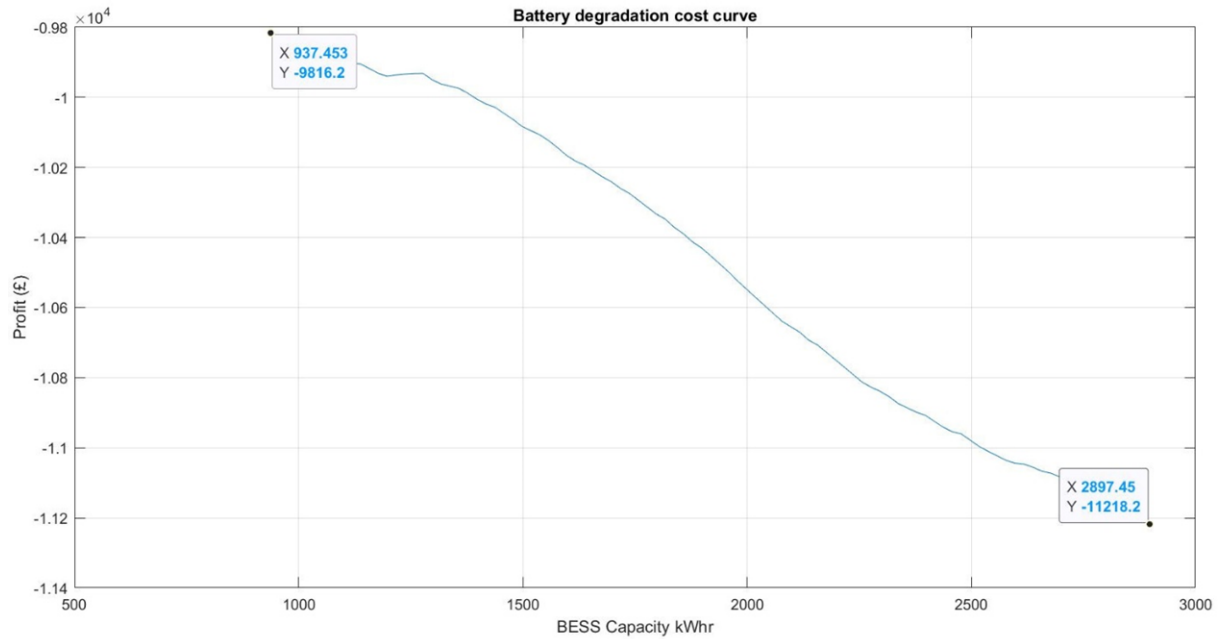


Figure 4-16 Battery degradation cost optimisation curve from

4.14 Conclusion

This study investigates the feasibility of optimising the BESS in the microgrid using a combination of regression models and GA. The BESS is optimised based on the forecasted PV power output by the best-performance regression model combined with the charge and discharge cycles of the A-ETR according to the airport electric taxiing load profile and time-of-use market price. The microgrid has been simulated under two taxiing load profile scenarios, representing the airport's current and future taxiing load demand profiles, to validate the utility of the proposed concept. The results indicate that the proposed MG has the potential to minimise operating cost and reduces emissions due to aircraft taxiing operations in the airport.

Based on the best performance model above, the optimal capacity of the BESS for scenarios one and two are found to be 816.7 kWh and 593 kWh, and the TCPD are £547 and £397 for scenarios one and two, respectively. Although the aircraft taxiing load is a small fraction of the total load in the airport, it is historically fossil fuel-intensive, and it is to be ensured that it should be powered from a renewable energy source to meet the requirement of future green airports.

Therefore, this study demonstrates a promising step towards meeting the target of FlightPath 2050's zero-emission ground operations at the airport.

According to the scenario studies in this chapter, the efficiency of PV systems declines with age. For this reason, it is vital to constantly balance energy supply and demand to compensate for the deterioration of the PV system in critical infrastructures such as airports. Therefore, a robust predictive energy management system must continuously match the airport's supply and demand over a predetermined horizon. This will enable adequate compensation for any deficit or surplus in net energy in the system. Subsequently, the next chapter investigates the feasibility of future net energy forecasts incorporating more representative days for ground movement operations at the airport using machine learning-based time series analysis to develop an energy prediction model for ground movement operations in the airport.

5 . Machine learning-based energy prediction model for ground movement operation in airport

5.1 Chapter Summary

Aviation has played a key role in expanding economic growth and fostering international understanding over the past century. But because of its enormous contribution to GHGs and propensity to contribute to climate change, it is currently the subject of considerable controversy. Airports frequently employ oil-based ground support vehicles and tugs, which have large carbon dioxide emissions. Transforming these fuel-based airport service vehicles into electric vehicles and charging through a renewable energy source can dramatically reduce emissions and save the cost of energy. However, the ground support operation depends on the flight data, and renewable energy output is stochastic and requires accurate forecasting to optimise energy management to achieve emission-free ground movement operation in the airport. This chapter proposes a novel data-driven machine learning-based energy prediction model using the Facebook Prophet algorithm to develop univariate and multivariate time series models to forecast ground operation net energy demand in the airport using historical flight data and an onsite (ASPV). The result proves the efficacy of the model and its usefulness for airport operators and planners in making more energy-efficient plans and provide predictions with adequate accuracy for realistic ground movement energy demand and clean energy production at airports.

Keywords— Multivariate, energy prediction, prophet, renewable energy, Machine learning

5.2 Introduction

Green airports have become increasingly popular in recent years as the aviation industry aims to reduce its carbon footprint and improve sustainability [155]. Energy forecasting is an essential task in green airports, as it helps to optimise energy production and consumption, reduce costs, and improve energy efficiency [274]. Also, electric utilities and energy management systems, such as grid operators, use energy forecasting models to predict the electricity demand required to balance the generation and load demand [275]. This process involves estimating the future load demand to ensure the reliable operation of the electric grid. Energy forecasting is essential for power system planners and grid operators to guarantee sufficient electricity generation to meet the increasing demand in the future [276].

Moreover, load forecasting is essential for other participants in the electric energy generation, transmission, and distribution systems. It helps in capacity expansion, better grid operation, budget planning, maintenance scheduling, and fuel management [277]. Forecasting is also employed in various fields, such as finance to predict stock exchange courses, business to manage inventory and forecast demand, medicine to monitor the spread of diseases, and meteorology for weather forecasting [278]. Forecasting is the process of predicting future outcomes by analysing trends in past and present data [279]. It comprises three main components: input variables (past and present data), forecasting/estimation methods (analysis of trends), and output variables (future predictions), as illustrated in Figure 5-1

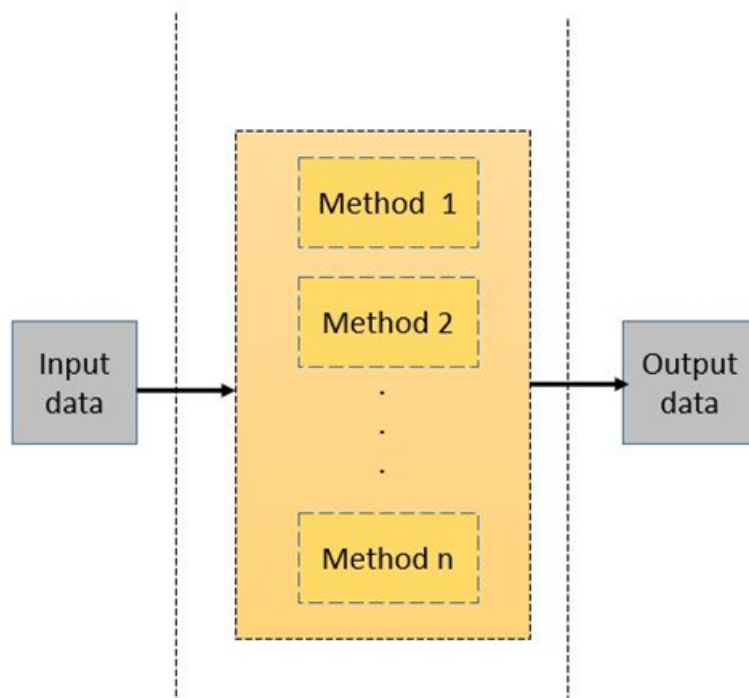


Figure 5-1 Structure of a basic model for forecasting or estimation [280]

Forecasted models can cover a range of time frames, from a few hours to as long as 100 years [280]. [281] proposed that short-term forecasts cover a period of five years or less, medium-term forecasts range between three to fifteen years, and long-term forecasts span ten years or more. However, this categorisation can confuse medium- and long-term projections because of their overlapping time frames. To avoid this confusion, [280] defines time span or modelling horizons as follows: short-term ($t < 3$ years), medium-term (between 3 and 15 years inclusive), and long-term (more than 15 years), where t represents the time span in years.

Forecasting techniques used for trend analysis can be broadly classified into two main types: stand-alone and hybrid. Stand-alone methods use a single technique for trend analysis, while hybrid methods integrate more than one stand-alone technique. Stand-alone methods can be further classified into statistical, computational intelligence (CI), and mathematical programming (MP).

Hybridisation is typically used to improve the reliability and accuracy of forecast output[278]. Hybrid methods are divided into four categories: statistical-statistical, statistical-CI, CI-CI, and statistical-MP methods. In addition, some studies in the literature use multiple stand-alone and/or hybrid methods for comparison and critique purposes [280].

Past research on forecasting methods in energy planning has traditionally been divided into either application areas or categories of underlying techniques. However, the evolution of application areas and new techniques have made these categorisations inflexible and incomplete [282]. For example, application-based categorisations have not fully accommodated the importance of behavioural energy conservation in the climate and energy debate. Similarly, dividing forecasting methods into statistical and AI-based approaches is inaccurate and insufficient, as hybrid methods that combine both approaches are increasingly common [280].

Research has indicated that hybrid methods are more effective in forecasting non-linear and discontinuous data, especially when the relationship between variables is unknown and difficult to handle statistically [[283], [284], [285],[286]. However, it's worth noting that hybrid methods that utilise machine learning can be more complex in both learning and application compared to statistical methods. Consequently, the learning complexity of a method can influence the choice of forecasting technique [287]. In addition, data availability is also a crucial factor to consider when choosing a forecasting method. For example, Artificial neural networks (ANNs) are data-driven and require a large dataset for higher forecasting accuracy [288]. In incomplete data sets, fuzzy logic may be more suitable. However, the level of accuracy with fuzzy logic may not always be satisfactory [288]. Grey prediction is another useful method, particularly when dealing with uncertainty problems, small sample sizes, and incomplete or discrete data [286] [289].

Many researchers advocate for the use of hybridisation methods to improve the accuracy of forecasting models [290] [291]. [292] discusses the challenges faced

by various country-driven sectors due to the COVID-19 pandemic, highlighting the lessons learned from these challenges. The paper provides a roadmap for future forecasting in these sectors, emphasising the importance of accurate data and the use of appropriate forecasting methods. The sectors covered in the paper include healthcare, tourism, education, finance, and trade.

The authors propose a hybrid approach combining machine learning and statistical methods to improve the accuracy of forecasting models. However, they note that this can increase the complexity of the models. The paper concludes by stressing the need for effective communication and collaboration between researchers, policymakers, and stakeholders to develop resilient and sustainable strategies for the future.

5.2.1 Time series forecasting

Time series algorithms have been widely used in energy forecasting tasks due to their ability to capture the patterns and trends in time series data. The technique is used to predict future values of a variable based on its past behaviour. Popular models for time series forecasting include Autoregressive Integrated Moving Average (ARIMA) [293], Exponential Smoothing (ETS) [294], Vector Autoregression (VAR), Seasonal Autoregressive Integrated Moving Average (SARIMA) [295], and Long Short-Term Memory (LSTM) [296]. These models can handle both stationary and non-stationary time series data and have been widely used in various fields such as finance, economics, energy and weather forecasting [297], [298].

[299] presents a study on energy consumption forecasting in China using an ARIMA model. The research aims to provide accurate predictions of energy consumption to support energy management and decision-making. The study uses historical data on energy consumption in China from 1995 to 2019 and employs the Box-Jenkins approach to build an ARIMA model. The model is then used to forecast energy consumption from 2020 to 2025. The results of the study show that the ARIMA model is an effective tool for energy consumption

forecasting in China and can provide accurate predictions with a high degree of confidence.

[300] evaluates the accuracy of prediction models for airport passenger throughput using a hybrid method. The research aims to identify the most effective model for predicting airport passenger traffic, which is important for airport management and planning. The study uses historical data on passenger throughput at an international airport in China from 2015 to 2019 and compares the performance of four prediction models: ARIMA, LSTM, SVM, and a hybrid model combining ARIMA and LSTM.

The results of the study show that the hybrid model outperforms the other models in terms of prediction accuracy, with a lower mean absolute percentage error (MAPE) and higher correlation coefficient (R).

[301] proposes a machine-learning approach for predicting the energy consumption of ships in port, taking into account the concept of green ports. The method considers various factors that influence energy consumption, such as weather, traffic, and operational characteristics of the ship, and uses data from port monitoring systems and ship sensors. The proposed model uses a random forest algorithm for prediction and is validated using real-world data from Jingtang Port in China. The results show that the model has high accuracy and can be used to support decision-making for energy-efficient operations in green ports.

[302] proposes a hybrid model for predicting water levels in the Red Hills Reservoir using a combination of seasonal autoregressive integrated moving averages (SARIMA) and artificial neural network (ANN) models. The approach uses time series analysis to identify trends, seasonality, and noise in the data and capture the seasonal patterns in the data. The hybrid model is evaluated using real-world data from the Red Hills Reservoir in India and compared with several benchmark models. The results show that the proposed model outperforms other models in terms of accuracy and can be used for real-time water level prediction and management. However, traditional time series

forecasting methods, such as ARIMA and exponential smoothing, have limitations in handling the complexity of energy data, which is often characterised by non-linear relationships, seasonality, and multiple variables.

In addition, traditional time series forecasting methods require expert knowledge and manual tuning of hyperparameters to achieve accurate results, which can be time-consuming and error-prone [303]. Therefore, further research has focused on developing new algorithms and improving existing ones to handle more complex time series data.

The Facebook Prophet algorithm addresses these limitations by incorporating a flexible Bayesian framework that automatically selects the appropriate model parameters, allowing non-experts to use it easily. It also includes a customisable seasonal component that can capture multiple seasonal patterns and a robust regression model that handles outliers and missing values [304]. Furthermore, the algorithm provides interpretable results that help users understand the drivers of change in their data and make informed decisions. As a result, it has been shown to outperform traditional time series methods in various applications, including retail sales, energy demand, and financial forecasting [305],[303]. Its ability to handle multiple seasonalities, user-friendly and easily interpretable nature, robustness to missing data and outliers, flexibility in modelling trend changes, and scalability make it a valuable tool for optimising energy usage in green airports. The Facebook Prophet algorithm takes into account various factors, such as holidays, seasons, and events, that affect the predicted variables, resulting in more accurate forecasts. However, from the literature review above, there is no work in the scientific literature on forecasting the energy consumption of ground support equipment operations at airports.

This study developed an energy prediction model using machine learning-based Facebook's prophet algorithm tools in Python to forecast future ground operation energy demand in the airport. The model's time series multivariate algorithm forecasts and merges the EGSVs and E-ATR charging load demand with the onsite PV power system output to optimise the power flow in the airport.

5.3 Electric ground support equipment

Aircraft LTO emissions have received much attention in research because they contribute significantly to air pollution from aviation activities [28]. Still, the GSE units at the airside that support aircraft operation, maintenance, and management could significantly contribute to airport-related emissions. The GSEs are responsible for servicing aircraft during turnarounds. Several tasks are performed during this period, such as loading and unloading passengers and baggage, cleaning and maintaining aircraft, and refuelling and refilling provisions. The aircraft's function is complete once loaded and ready for take-off. A total of nearly 20 different activities many of which take place simultaneously require between 40 and 90 minutes to complete for narrow-body aircraft and the largest aircraft, respectively.

Therefore, the operation of the GSE is expected to be fast, efficient, and punctual to minimise aircraft turnaround time. The management of this operation is crucial to make the service profitable due to the airport fees and the airline's logistical needs. In addition, their prompt arrival helps ensure the efficient use of airport resources. GSE emission in the airport has been estimated to be approximately 60% of total airport emissions at McCarran International Airport in Las Vegas [306] and around 11% of the emission in London Luton Airport. The issue of airport GSE cannot be avoided, as airport accreditation requires the airport to address transport-related emission concerns [307].

However, many challenges are associated with the electrification of ground support vehicles, including the considerably longer charging time than refuelling conventional fossil fuel vehicles. In addition to these issues, the electric grid faces an increased burden, steady-state loads, and dynamic disturbances [308]. Therefore, comprehensive system planning and future demand forecast are necessary to meet the charging load of the GSE and minimise the effect of the load on grid components. Some of the existing work in this area include stochastic optimisation-based models for EV fleets and renewable generation joint operations are presented in [309] and [310]. The results demonstrate that

technology solutions can reduce the energy costs associated with direct current fast charging (DCFC) at high energy and/or demand charges, thus lowering the average electricity costs associated with DCFC applications.

[311] used the benefit-cost ratio method (BCR) to analyse the benefit of using GSE in the aerospace industry. The study compared the cost of using diesel-driven GSE and EGSE. The results show that the investment in diesel and EGSE are feasible because they both have a net present value greater than one, but in terms of useful life, the diesel-operated GSE is better than the investment in EGSE. [158] have proposed a technique for using EGSE to participate in a day-ahead frequency regulation market based on flight schedule data of the airport. The result indicates that in addition to providing frequency regulation ancillary services, the E-GSE makes a significant profit through the V2G capability.



Figure 5-2: Ground support equipment and vehicles servicing aircraft (Luton airport)

The vehicles and ground support tools are used in aircraft maintenance. Some examples include galley service vehicles, baggage carts, bulk cargo loaders, jet bridges, lavatory service vehicles, cabin cleaning vehicles, potable water vehicles, and conditional air vehicles.

5.3.1 Energy demand per GSE/Aircraft

Table 5-1 illustrates how much energy is required to service a small aircraft and a narrow-body aircraft during turnaround based on the power and capacity of each EGSE (information from suppliers) [307] [312], and the service time [313]. A section of the A-ETR energy demand according to the flight schedule on the basis of the maximum payload capacity of each aircraft is shown in Table 5-2, and Table 5-3 illustrates the total energy demand for 40 flights with different penetration levels of narrow and small-body aircrafts

Table 5-1 Energy consumption per GSE/Aircraft

Service	Company	Model	Power (kW)	Capacity (kWh)	Narrow body aircraft (min)	Energy demand kWh	Small body Aircraft (min)	Energy demand kWh	
Tractor	Trepel	Challenge r 280e	92	168	7	10.7	5	7.6	conservative Assumption
Ground power unit	ITW GSE	7400eGPU	90	160	40	60	40	60	
Catering	Kamag	E-catering wiesel	156	80	17	44.2	6	15.6	
Transporter	Mulag	Pulsar 7E	24	74.4	41	16.4	0	0	
Baggage tractor	Mulag	Comet 6E	40	124	45	30	27	18	
Belt Loader	Charlattel	CBL150E	1.3	28.8	41	0.88	23	0.49	
Lavatory vehicle	Charlattel	CIT200E	30	40	14	7.0	0	0	
Water truck	Charlattel	CWT300E	30	40	14	7.0	0	0	
						176.2		47.69	

Table 5-2 A section of A-ETR schedule load demand according to the flight schedule

Flight number	Aircraft Type	Departure/Arrival Time	Flight attribute	Max Payload (kg)	Number of-ETR trips	No of aircraft/ hour	Energy demand (kWh)
EZY2396	A320	23:04	arrival	16600	6	04	78.4
EZY2086	A320	23:44	arrival	16600	6		
RYR7785	B738	23:09	arrival	20540	7		
BN15T	C525	23:11	departure	1400	1		
WZZ3306	A321	22:59	arrival	21540	7	09	231.2
RYR342	B738	22:54	arrival	20540	7		
RYR7785	B738	22:58	arrival	20540	7		
WUK4009	A21N	22:41	arrival	21200	7		
WZZ3654	A320	22:36	arrival	16600	6		
WZZ3306	A321	22:26	departure	21540	7		
WUK1476	A320	22:21	departure	16600	6		
VJT449	CL35	22:04	departure	16600	6		
LEU401	BE20	22:37	departure	16600	6		
WZZ4039	A320	21:19	departure	16600	6	14	234.8
JC07X	FA7X	21:16	departure	1996	1		

Table 5-3 Daily Ground movement energy demand from flight data

Scenarios	Narrow body Aircraft (%) penetration	Small body aircraft (%) penetration	Energy demand (kWh)
1	50	50	4478
2	30	70	3449.84
3	10	90	2421.68

5.4 Methodology

5.4.1 Design and setting

Historical data has been collected for PV output from the solar farm and flight activities at the Cranfield Airport. Cranfield Airport has a 1MW solar farm onsite with an installed ground array covering 5,858 m², 3,508 panels, and 285 W PV modules capable of generating 1,000 MWh of electricity annually.

5.4.2 Data collection

5.4.2.1 PV output data collection.

The daily energy production by the ASPV serving the airport is documented in the solar farm energy record. The observation period is from 14 August 2018 to 01 April 2019. It contains PV output, irradiation and temperature collected at 30-minute intervals, providing a total of 11088 data values. Upon preprocessing, using the Pandas date time module to increase time granularity from hourly to daily basis and down-sample the data to make it suitable for the autoregressive model (i.e., Facebook Prophet), the total data points have been reduced to 231.

5.4.2.2 Flight data collection.

The flight data contains hourly records of the number of flights at Cranfield Airport for 11 years, from 01 January 2011 to 01 December 2021. The dataset has been indexed according to the dates within the observation period, while the columns record the number of flights every hour of the day with a total of 3515 observations. The total number of flights per day has been calculated by taking a

row-wise sum of the number of flights per hour and stored in a new variable, namely flight total. The Flowchart of the modelling steps for the Facebook Prophet evaluation algorithm is shown in Figure 5-3.

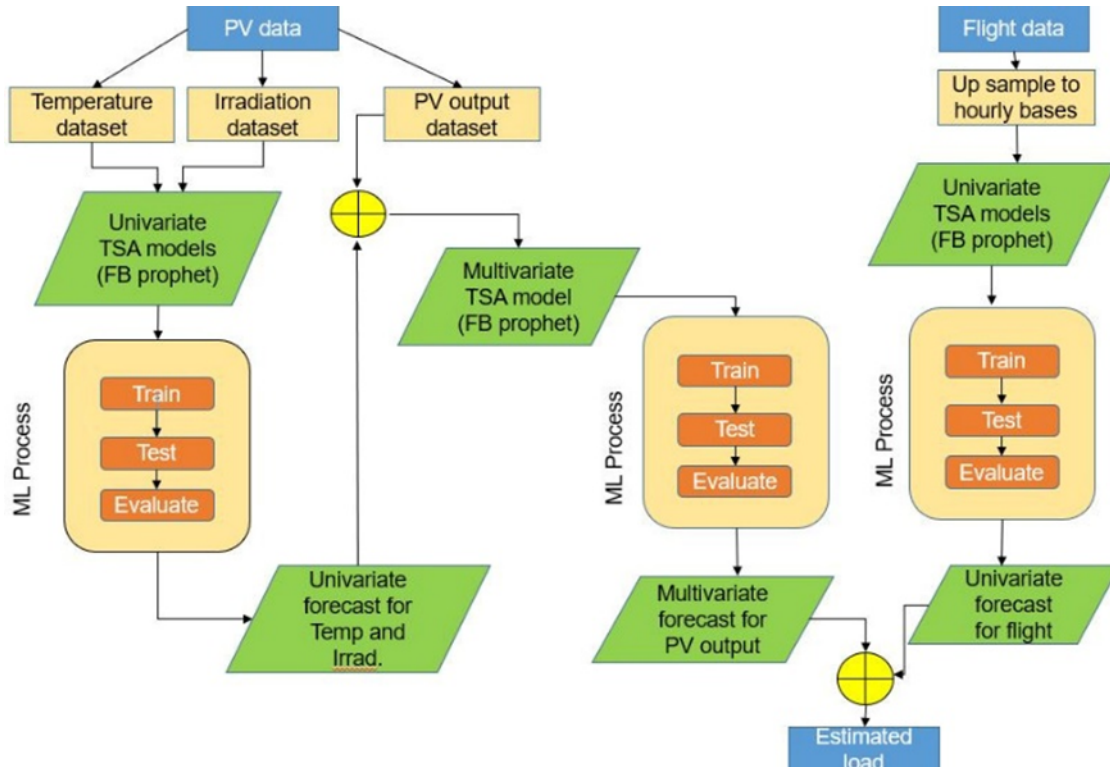


Figure 5-3: Flowchart of the modelling steps for the prophet evaluation algorithm

5.5 Forecasting method

5.5.1 Prophet: Time series forecasting tool

The Prophet algorithm is a time series model with inbuilt adjustable parameters that can suit the peculiarities of regular time series data, especially business time series. It is an open-source programme created by Facebook's data science team for forecasting time series data that can fit nonlinear patterns with annual, monthly, and daily seasonality as well as holiday effect based on an additive model [314],[315]. It performs better with time series data having strong seasonal variation. Unlike most other predictive models, prophet handles missing data well, as well as trends that shift over time and outliers. According to Taylor and Letham, the prophet algorithm performs better than many other approaches for producing

reliable forecasts across Facebook [316]. In this study, Facebook's prophet tool is used to model energy forecasts for ground movement operations in the airport to generate daily, weekly and monthly energy demand forecasts. It is based on a time series model that can be broken down into three primary parts: trend, seasonality, and holidays. They are combined in the following equation [317]:

$$y_t = g(t) + s(t) + h(t) + \varepsilon(t) \quad (5-1)$$

Where, $g(t)$ is the trend function which is used to model non-periodic changes in the value of time series, $s(t)$ is used to model periodic changes (e.g., weekly and annual seasonal changes), and $h(t)$ is used to model the effects of holiday breaks over a few days. The error term ε_t refers to any change in characteristics that the model cannot accommodate.

Although flight schedules can provide some information about the expected demand for energy during ground movement operations at an airport, they may not account for certain variables that could impact energy consumption. For example, unexpected changes in weather conditions, delays, or cancellations can impact the energy demand and require adjustments to be made in real-time. So also is the effect of holiday breaks on the energy demand, which is one of the component parts of the Facebook Prophet algorithm used in the forecasting model.

The data is read using Python's Pandas data analysis module [318]. After loading the file, the pandas create a table with rows and columns (data frame). Another library used in support of the prophet model is Matplotlib, which displays graphs. This library helps to fit individual forecasts from the prophet to the requirement of the operators. Pandas' library is used to load the CSV data to Matplotlib and assign appropriate columns (ds, y).

5.5.2 Forecast accuracy metrics.

Four major forecast accuracy metrics have been used to evaluate the univariate and multivariate time series models, i.e., mean absolute error (MAE), mean absolute percentage error (MAPE), median absolute percentage error (MdAPE)

and Symmetric mean absolute percentage error (SMAPE). The predictive power of the model is measured by summarising the magnitudes of error in predictions across time. The mean absolute error is the mean between the value predicted by a model and the actual observed value [319], [259].

$$MAE = \frac{1}{N} \sum_{l=1}^N |(P_{ft} - P_{mt})| \quad (5-2)$$

MAPE is calculated as the average percentage difference between the model's predicted values and observed values [320]. Due to its scale independence, it is frequently used for comparing forecast performance across a variety of data sets. The MAPE can be expressed as follows:

$$MAPE = \frac{1}{n} \times \sum_{t=1}^n \left| \frac{P_{ft} - P_{mt}}{P_{ft}} \right| \quad (5-3)$$

However, the disadvantage of MAPE is that it is prone to extreme values and that positive errors are penalised more severely than negative errors when a training set observation is close to zero or negative value. SMAPE has been proposed to overcome the asymmetry in MAPE and to give a better evaluation of errors [321]. SMAPE is the average across all forecasts made for a given horizon. Due to its interesting properties, SMAPE is gaining popularity in the machine-learning community [322],[323].

$$SMAPE = \frac{1}{n} \times \sum_{t=1}^n \frac{|P_{ft} - P_{mt}|}{P_{ft} + P_{mt}} \quad (5-4)$$

MdAPE is found by arranging the absolute percentage error (APE) in ascending order and using the number's middle value, or if the total is even, the average of the two mid values.

$$MdAPE = median\left(\frac{P_{ft} - P_{mt}}{P_{ft}}\right) \quad (5-5)$$

where P_{mt} is the measured value, P_{ft} is the forecasted value, and n is the size of the sample.

5.6 Result and discussion

5.6.1 The component of a decomposed time series Prophet model

The decomposition of time series data into its individual components, namely trend, seasonality, and residual, is a widely used technique for analyzing time series data. Facebook Prophet is a popular tool for time series forecasting that utilizes a decomposable time series model.

The trend component of a time series represents the overall direction or pattern of change in the series over time. A negative trend indicates a decreasing pattern or trend over time, while a positive trend represents an increasing pattern or trend. Factors such as changes in economic conditions, market trends, or social factors can influence the trend component. Seasonality is another important component of time series data and refers to the recurring pattern in data, such as daily, weekly, monthly, or yearly patterns. A negative seasonal component indicates a decreasing pattern or trend during a particular season, while a positive seasonal component represents an increasing pattern or trend [303].

In the context of a decomposed Facebook Prophet model, a negative sign in the trend or seasonal component indicates a decreasing pattern or trend. For example, a negative trend component would indicate a decreasing trend over time, while a negative seasonal component would imply a decreasing pattern during a particular season. Daily and weekly seasonality can have positive or negative signs depending on the direction of the pattern. For instance, a positive daily seasonality component would represent an increase in Irradiation on sunny afternoons during the day, while a negative daily seasonality component would indicate a decrease in Irradiation at sundown. Similarly, a positive weekly seasonality component would represent higher Irradiation on weekdays, while a negative weekly seasonality component would indicate lower Irradiation on weekdays [316].

5.6.2 Exploratory data analysis (EDA) on PV output variables

5.6.2.1 Irradiation.

Irradiation is one of the two exploratory variables from the PV output dataset, defined as a numerical variable. Zero irradiations account for 50% of the variable, which explains the daily seasonality in the time series, stretching between evenings and early hours of the morning when there is a scarcity of sunlight. The components graph Figure 5-4 shows a constant decrease in irradiation, with a trough in December 2019. This is followed by a steady rise in January 2019 throughout the observation period. Irradiation is an important factor in the PV output of solar grids, as shown in section 4.3. This is because solar panels depend on rays from the sun to generate electricity. Hence, the irradiation-PV output time series shows a strong correlation between irradiation and PV output.

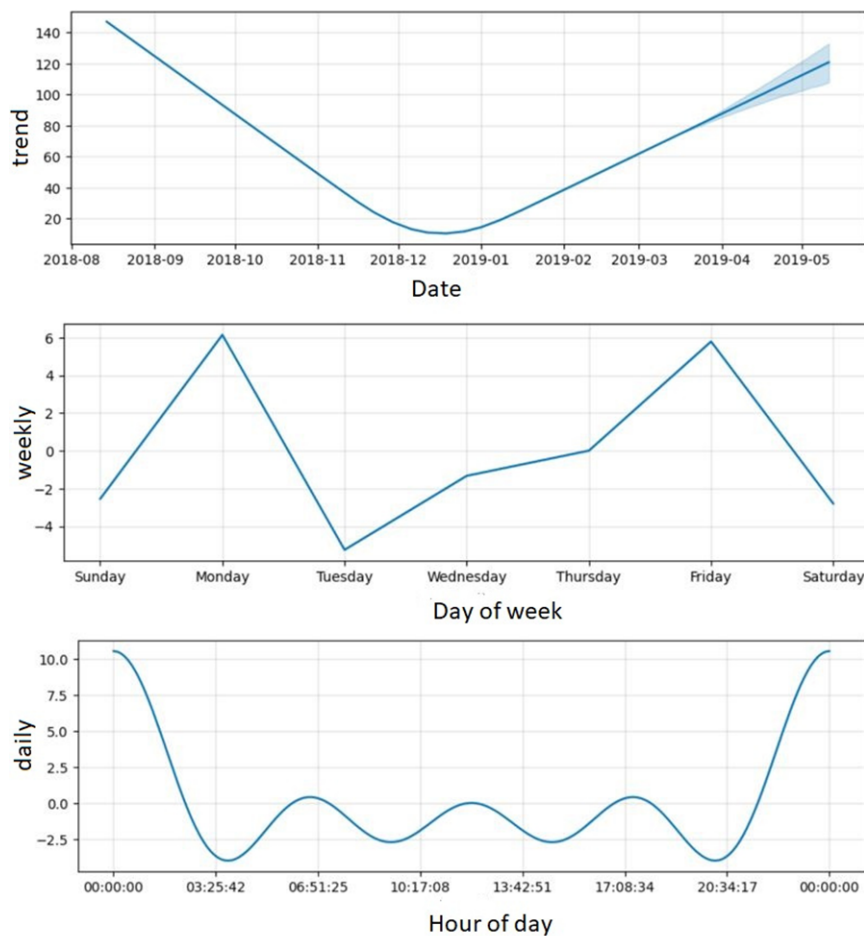


Figure 5-4: Component of the Prophet forecast for Cranfield Airport ASPV (*irradiation*)

5.6.2.2 Temperature

Temperature is the second exploratory variable in the PV output dataset. Negative values account for 2.7% of the variable, corresponding to periods of temperature drop. The components plot Figure 5-5 shows a trend in the steady decline in temperature.

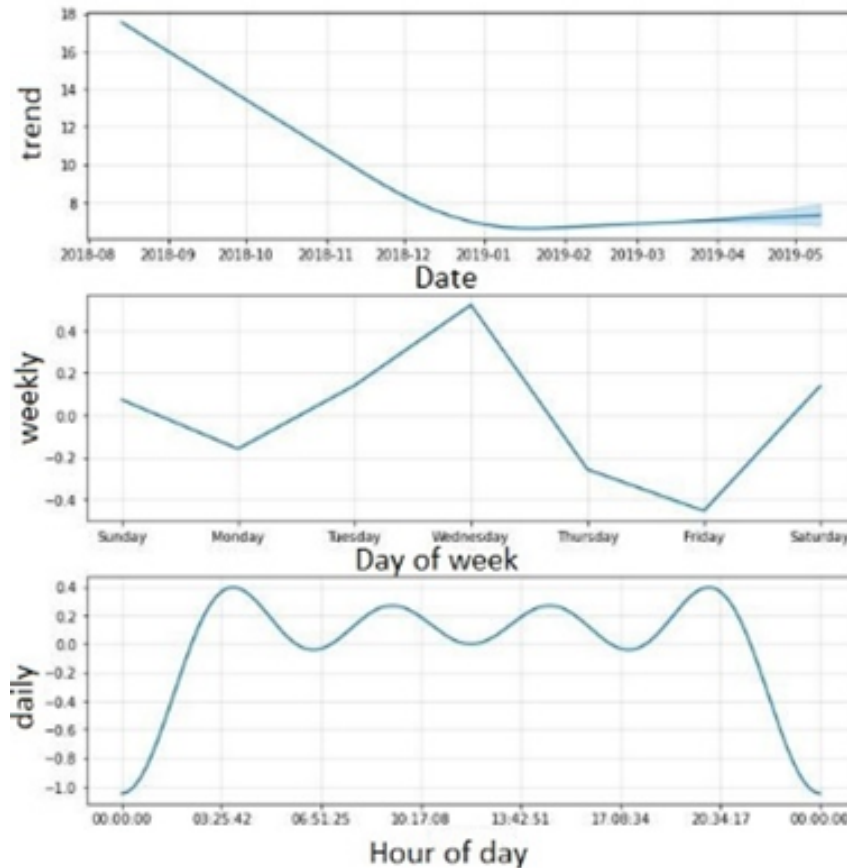


Figure 5-5: Component of the Prophet forecast for Cranfield Airport ASPV (*temperature*)

5.6.2.3 PV output

PV output is the target variable in the PV output dataset, which is a numerical variable. Zeros account for 55.1% of the variable. This is due to periods of poor irradiation, which can be seen in the component plot Figure 5-7 between PV output and irradiation. This also accounts for the seasonality in the PV time series graph. The trend in the components plot shows a steady rise in PV output and a weekly peak on Tuesdays and a trough on Thursdays.

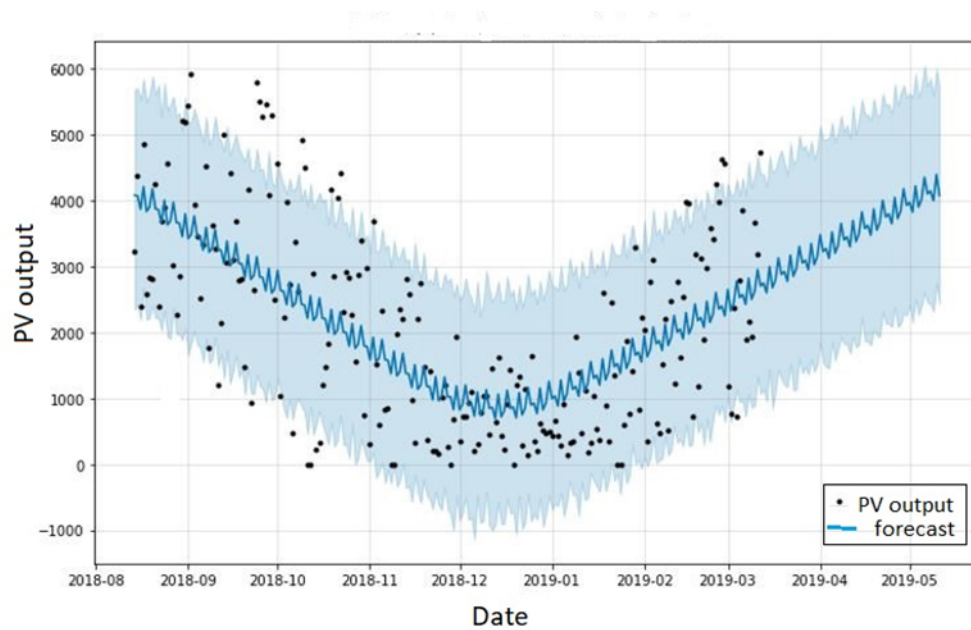


Figure 5-6: Daily PV output forecast in the ASPV

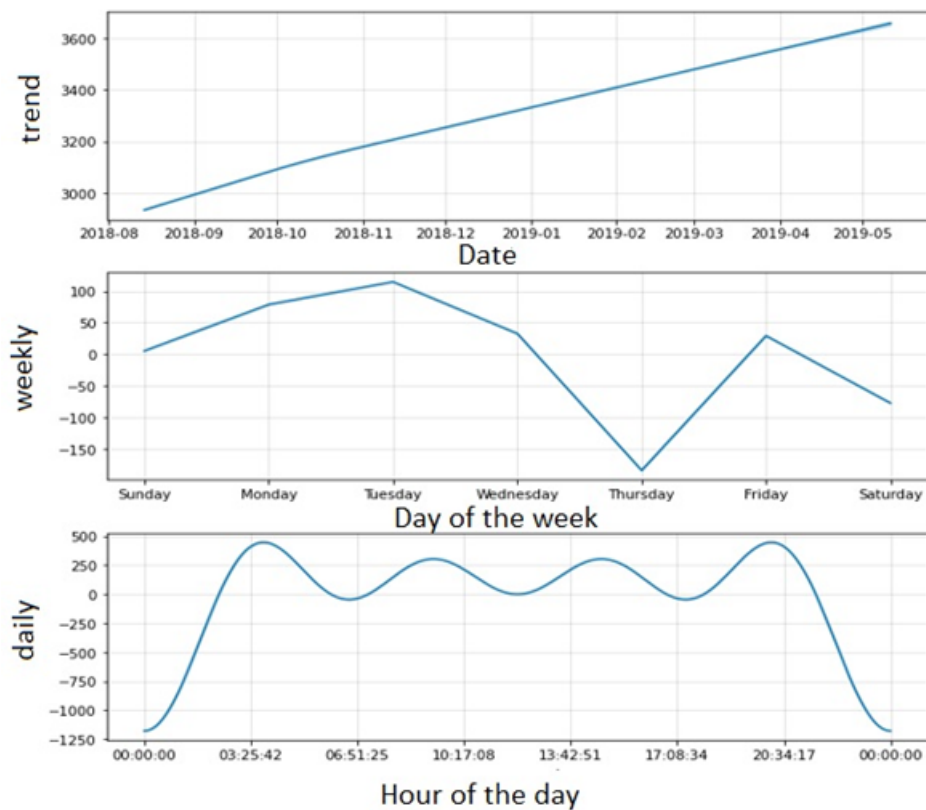


Figure 5-7: Component of the Prophet forecast for Cranfield Airport ASPV

5.6.3 EDA on flight data

The components plot Figure 5-8 reveals a continuous decline in the number of flights from 2012 to 2018, followed by a steady rise from 2018 to 2020. The weekly number of flights declines between Sunday and Monday; there are fewer flights overall every week, which then gradually increases until the next Sunday.

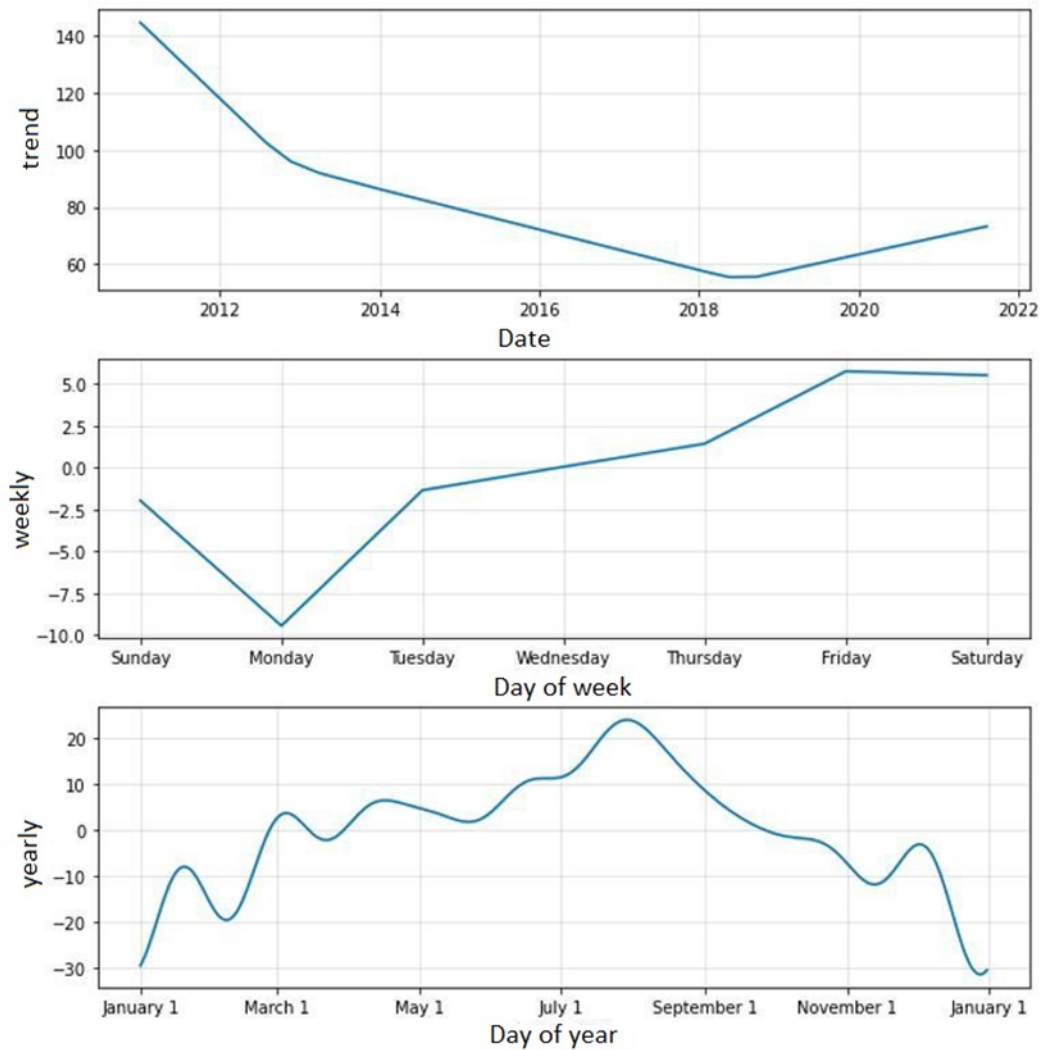


Figure 5-8: Component of the Prophet forecast for Cranfield Airport flight schedule

5.7 Forecast results for univariate and multivariate models on PV output data.

Irradiation recorded at the ASPV within the observation period ranged between 345 and 10496, with a mean value of 3478.56. The MAE value is 2460.82, corresponding to an average difference of 0.56% MAPE between predicted and actual irradiation values at the ASPV. The temperature ranged between -0.88 and 19.99°C, with a mean value of 8.96. The steeping in Figure 5-5, which corresponds to a steady drop in temperature over the next 20 days, is consistent with the data observation period. The MAE is 7.20, corresponding to an average difference of 0.90% MAPE. PV output ranges between 0 and 5928.69, with a mean value of 2136.84. Figure 5-7 shows consistency in the forecast within the 20-day forecast horizon. This gives an MAE of 1114.94, corresponding to an average difference of 0.58% MAPE between the predicted and actual values.

Table 5-4: Model error measures for PV data variables

Variable	MAE	MAPE	MdAPE	SMAPE
Irradiation	2460.82	0.56	0.58	0.83
Temperature	7.20	0.90	0.90	1.64
PV output	1114.94	0.58	0.42	0.47

5.8 Forecast results for univariate model on flight data

The number of flights recorded at the airport within the observation period ranged from 1 to 366, with a mean value of 81. The MAE is 38.87, which corresponds to an average difference of 3.44% MAPE between the predicted and actual number of flights. The graph gives a consistent representation of the observations and the forecast within a 20-day forecast horizon.

Table 5-5: Model error measures for Flight data variables.

Variable	MAE	MAPE	MdAPE	SMAPE
Total flight	38.87	3.44	0.56	0.74

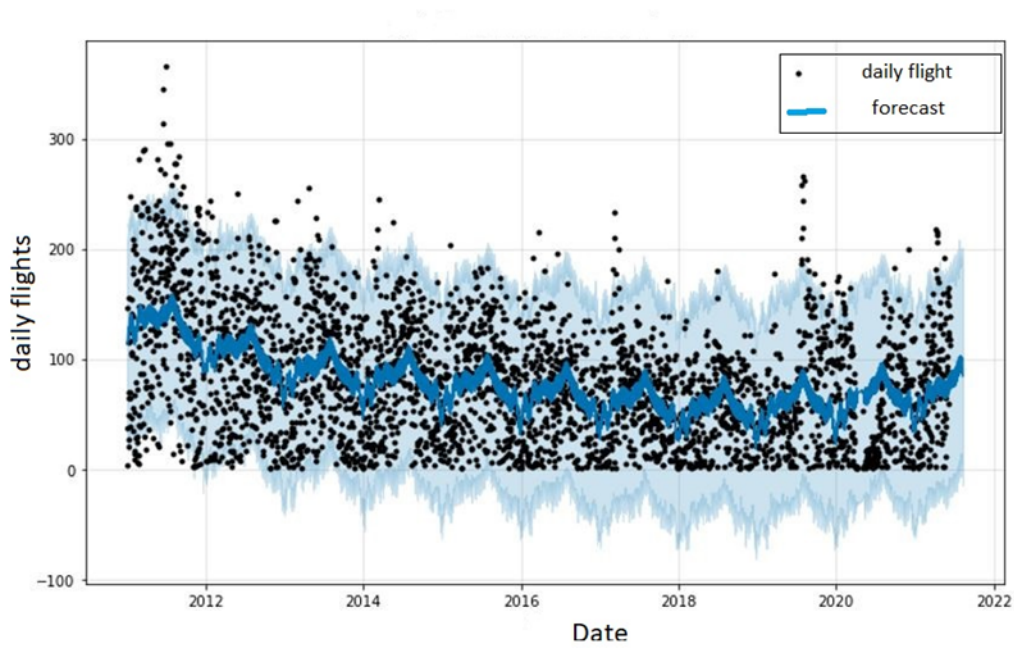


Figure 5-9: Daily flight forecast in the airport

5.9 Estimating airport ground movement energy requirement.

To estimate the future cumulative available energy E_T , the actual ground movement energy demand at the airport has been subtracted from the forecasted PV output. For our purposes, the actual energy demand has been calculated by multiplying the energy demand of each EGSE and A-ETR, servicing the predicted total number of flights on the specified future dates within the forecast horizon. Then, the actual value from the forecasted PV output is subtracted to obtain the available energy. The cumulative energy requirement for the forecast horizon can be calculated by using (5-6)

$$E_T = \sum_{i=1}^n \rho_i - (u * f_i) \quad (5-6)$$

where,

E_T = Cumulative energy requirement, n = number of days within forecast horizon, ρ = forecasted PV output,

f = forecasted number of flights, and u = energy required by a single E-GSE.

Table 5-6: A section of forecasted daily PV output, total flight, and net energy demand.

	date	pv_output	total_flight	available_energy(kwh)
0	2022-09-07	34430.368520	87.0	-492267.631480
1	2022-09-08	34280.930526	88.0	-498471.069474
2	2022-09-09	34677.999709	92.0	-522290.000291
3	2022-09-10	34358.379381	91.0	-516555.620619
4	2022-09-11	34473.528114	83.0	-468008.471886
5	2022-09-12	34809.443066	75.0	-419240.556934
6	2022-09-13	34559.246823	83.0	-467922.753177
7	2022-09-14	34604.477547	84.0	-473931.522453
8	2022-09-15	34455.039554	85.0	-480134.960446
9	2022-09-16	34852.108736	89.0	-503953.891264
10	2022-09-17	34532.488409	89.0	-504273.511591
11	2022-09-18	34647.637142	81.0	-455726.362858
12	2022-09-19	34983.552093	73.0	-406958.447907
13	2022-09-20	34733.355850	81.0	-455640.644150

5.9.1 Scenario one:

The worst case during this forecast horizon occurred on Friday (09 September 2022), when the energy deficit required to sustain ground movement operation was 789.27kWh. On that day, the airport reaches the highest deficit between the EGSV energy demand and solar PV generation. That day corresponds to the airport's peak traffic, as indicated in Figure 5-8, which resulted in higher demand for E-GSE and A-ETR and increased energy demand. On the following day of the week, net daily energy demand declined gradually. The day with the lowest energy deficit during the prediction horizon is on Mon (12 September 2022), which corresponds to the beginning of the gradual decline in traffic in the airport, as shown in Figure 5-8



Figure 5-10: Daily Optimised energy demand (10 days prediction forecast).

5.9.2 Scenario two:

The minimum amount of energy required to ensure continuity of operation under this scenario is 583.286kWh on the worst day within the forecasting horizon.



Figure 5-11: Daily optimised energy demand (20 days horizon forecast)

5.9.3 Scenario three:

The minimum energy required on the worst day within the 30 days forecast horizon is 522.29 kWh.



Figure 5-12: Daily optimised energy demand (30 days horizon forecast)

The models have been used to forecast the daily total number of flights, PV output and evaluate for accuracy using suitable metrics. In the univariate models on the PV output dataset for temperature and irradiation, MAPE ranged between 0.58 to 0.90, while SMAPE ranged between 0.83 and 1.64, accounting for MAPE of 0.58 and SMAPE of 0.47 in the multivariate model forecasted PV output. The univariate model for total flights per day showed a MAPE of 3.44 and SMAPE of 0.74. Based on these error metrics and the forecast results, it can be stated that the models provide a useful estimate for predicting daily available energy.

The overall number of flights at any given moment is crucial in predicting ground movement. This has been used alongside estimated energy requirements by one EGSV to service a unit flight to estimate actual energy demand ahead. Hence, the total number of flights and energy generation has been treated as a time series problem. Univariate and multivariate time series models have been developed, using Facebook Prophet to forecast PV output at the ASPV and the total number of flights. The three scenarios illustrate how the energy forecasting model offers operators the chance to schedule the airport's available energy sources economically and optimally. By merging decomposition, forecasts, and accuracy measures data into a single model, the model has streamlined the operators' work and allowed direct output interpretation.

In general, it allows the operators to forecast the days with the highest energy demand and more efficiently plan the scheduling of the energy sources. Finally,

the fundamental pattern of the projection indicates that on September 9, 2022, within the forecast horizon, the airport under examination has the most significant energy deficit.

5.10 Conclusion

For proper planning and budgeting, airports depend on energy projections and optimisation to help airport operators plan and allocate resources more effectively. This includes the efficient use of airport infrastructure, such as runways, gates, and terminal facilities, which can help reduce energy consumption and carbon emissions. Hence, airports that accurately forecast their future traffic and energy demand can better anticipate the needs of their operators and thus will be in a better position to plan for strategic changes in the energy demand. In addition, this could include expanding airport infrastructure or implementing new technologies to improve operational efficiency. The proposed study provides useful predictions for clean energy generation at airports and helps airport administrators plan energy usage more efficiently. Other benefits of this approach are capacity assessment, which could give insight into how much storage would be needed to further support the use of clean energy in airports. Although this analysis is based on ground movement operation, it can be extended to the overall airport energy demand. This chapter provides insight into how to optimally plan the increased electric load demand in the airside of the proposed future green airport to meet the zero-emission ground operation target of the FlightPath 2050 policy.

As a further extension of the concept and broader analysis, the next chapter explores integrating additional energy sources in the airport, such as vertical wind turbines and V2G concepts, to complement solar PV production.

6 Smart Energy System Design for Green Airport Electrification: A wind-solar-storage integrated microgrid

6.1 Chapter Summary

An attractive approach for zero carbon emissions in the aviation sector is the electrification of the airport energy system as a microgrid. The technical assessment of integrating wind energy, solar energy, tugging, and electric ground support vehicle batteries (EGSVBs) into the electrified green airport energy system has been examined using a case study of London Luton Airport (LLA). Mixed integer linear programming (MILP) algorithm is used to optimise the power flow between sources in microgrids, such as solar, wind, and EGSVBs, which deliver surplus power to the utility grid and charge and discharge EGSVBs based on demand. Furthermore, the stochastic behaviour of renewable power generation and airport flight schedules is integrated with airport energy management solutions. In this study, a novel approach, known as the stochastic model predictive control-based cascade feedforward neural network (SMPC-CFFNN), is used to reduce the computing complexity of the system based on the CFFNN training approach. The outcome demonstrates that the suggested power flow management architecture is capable of minimising optimisation time and achieving a zero emissions-based microgrid for a resilient green airport.

Keywords— Stochastic, model predictive control, neural network, cascade feed-forward, green airport,

6.2 Introduction

6.2.1 Airport Electrification

The global coronavirus pandemic's travel limitations have dramatically decreased carbon emissions in the aviation sector over the past three years. Nonetheless, this pandemic has temporal effects on low carbon emissions caused due to aviation-based people and cargo transportation. Furthermore, compared to other transportation sectors, the aviation industry consumes a lot of fossil fuels, making decarbonisation difficult. However, many initiatives have been taken globally to decarbonise the aviation industry. In addition, developed nations and organisations have devised various countermeasures and policies to resolve environmental challenges caused by the aviation industry [324]. For example, ACARE's FlightPath 2050, a pan-Europe aviation vision, has been introduced. FlightPath 2050 requires the aviation industry to achieve a 75% reduction in CO₂ emissions per passenger in a mile 90% reduction in NO_x emissions to achieve an emission-free aviation system by 2050 [325].

In order to attain low-carbon aviation goals, electrification of the air transportation industry is considered a promising approach. In addition, many aircraft manufacturers and airlines have set an agenda to design eco-friendly electric and hybrid-electric aircraft [326].

Nonetheless, passenger and cargo aircraft electrification is constrained by technical issues, i.e., the low electrical power density of energy storage systems (batteries). Additionally, it is challenging to generate high-torque electric motors when carrying a heavy load of passengers and cargo. Hence, many airports equipment, primarily GSE, are electrified as a commencement of the electrification in the sector, which can be seen majorly in these two areas: (i) Vehicles used for ground operation such as forklifts, freight trailers, vehicles used as a guide for aircraft, vehicles providing auxiliary services, aircraft tractors, passenger shuttle buses, etc. (ii) Aircraft ground power unit (GPU) which replaced APU operation during aircraft turnaround at the apron.

However, fulfilling the emission-free objective of the aviation industry comes with different challenges: (i) increased electric demand in the airport due to an increase in the airport flight operation, (ii) need for infrastructure up-gradation and reconfiguration where necessary. These operations require a timely update in the capacity of the connected electric grid to supply the necessary power for the electrification of ground service vehicles and airplanes. Additionally, the airport energy system must provide the electricity needed for charging EGSV as well as energy to augment aircraft APU when at the gate. In order to balance the supply-demand relation of the airport electric systems, typical capacity expansion schemes of the connected electric grids are less viable because of long construction cycles, land and resource restrictions, and high capital investment costs [327], [328]. Hence, such power generation expansion methods will ultimately increase airport electricity costs with additional power distribution and transmission capacity. Simultaneously, higher CO₂ emissions and transmission losses are caused by the power industry during power grid expansion [31].

The main goals of electrifying airport facilities are to reduce their carbon footprint and improve power flow between connected sources and loads, which will lead to a significant drop in operating costs. However, if the upstream grid is expanded to supply the electricity demand, the sources of pollution will be indirectly shifted from the airport facility to the power generation facility. Consequently, this study further supports the onsite generation of renewable energy as an alternative to producing clean, sustainable and self-sufficient energy to meet airport energy needs. The concept is further supported by the large expanses of areas available in airports, car parking, and terminal roof for solar and wind energy generation installation. As reported in [329], wind energy accounts for 47% of the energy used by airport facilities globally. At the same time, the stochastic and intermittent nature of solar energy production requires additional installation for energy storage to smoothen the output [330]. Furthermore, the small life cycle of a BESS, which generally lies between 8–15 years, is not optimal for installation at airport facilities that typically have a lifespan of 20–25 years as it will require a high replacement cost for the BESS [31]. Hence, flexible electric power generation is

required for airport facilities to ensure a resilient power supply to the electric load demand.

Moreover, many aircraft manufacturers are working on designing electric propulsion systems for electric aircraft (EA) as automotive electrification is becoming a reality [331], [104], [332]. However, designing all-electric aircraft is not impossible, but such innovation requires electrified airport infrastructure [333], [334]. The electrification of the airport infrastructure will increase the data repositories that are mandatory to process so that a knowledge database of different dynamic parameters in the airport can be maintained. Power flow management requires a deep understanding of all the connected loads and key operations to understand the dynamic system. Additionally, it helps develop optimizers that can handle specific actions for improved system performance. Different data processing techniques can be used to process the database for useful implementation and actuation, such as cloud computing, machine learning and ANN, including dense and convolutional neural networks [335],[336].

6.2.2 Existing airport electrification methods

Most of the existing research works on energy management in the airport are carried out to minimise the electric energy consumption of the airport facilities regarding airport energy system planning [337],[338],[339],[167]. However, very little research has been done to analyse the electric power consumption of the loads associated with air transportation outside the airport terminal building. In order to maintain cabin comfort, the AC supply connected at the bridge or onboard APUs is utilised by the aircraft parked at the airport gates. But this energy supply is considered inefficient and expensive [154]. [340] have conducted a case study of the airport facility in Aydin, Turkey, where microgrid architecture has been integrated with renewable sources and an energy storage system. [341] studied the feasibility of implementing EVs at Amsterdam Airport Schiphol on a large scale. [308] proposed a simulation-based experimental strategy for a synthesized airport model that used Monte Carlo simulation to manage different parameters to minimise operating costs and optimise vehicle

performance within the airport model. [31] have proposed a techno-economic solution that includes the MILP optimisation method, a life cycle theory-based method designed to help size solar energy, battery storage, and hydrogen energy systems. Additionally, it aims to reduce the airport microgrid system's overall financial costs while taking into account its advantages from an economic and environmental standpoint.

Nevertheless, the study is not capable of replacing all fuel consumption with green energy, and it does not consider battery capacity degradation due to frequent charging and discharging of batteries when participating in V2G. Although handling the several variables in MILP techniques is difficult, it is not insurmountable.

On the other hand, some researchers focused on utility in providing a balanced load profile for optimised control and power system stability. While some works consider both utility and the end-user simultaneously, there might be some trade-offs in managing the resources of both sides. [342] developed a new optimisation architecture for the smart-community microgrid, which has been proposed based on the Lyapunov optimisation theory. For handling complex physical constraints, a model predictive control (MPC) based framework is used that forecasts any system uncertainty. Additionally, by utilising MPC architecture, the efficiency of the available resources can be improved. MPC has been mostly used for DR-related applications and smart grids, as depicted in [343] and [344]. [345] proposed an MPC scheme for Multi microgrid energy management via the coordination of individual energy management operations to economically balance system-wide supply and demand.

The Work described in [346] incorporated ANNs fixed by GA to employ demand-side management (DSM) controllers for residential consumers. A neural and scheduling network synchronised with the local PV generation and utilities make up the distributed domestic automation system, which aims to increase local energy output. Appliances in the system are fitted with the ANN controller, which

enables distributed local generation. These devices also have the freedom to arrange their output in accordance with priority and forecast.

The usage of ANNs additionally aids the execution of DSM programmes [347]. The classification characteristic of the ANN is used intelligently to categorise the load curves of each consumer from the pool of load data produced by dynamic networks. A classification of load data is used to optimise electrical systems based on customer behaviour data. Then DSM is applied to each class to make it more efficient and sustainable. In addition, using the ANN network facilitates the service providers to estimate the energy rates for future needs.

Therefore, because of its inherent nature, supervised learning in ANNs is used to cope with future irregularities and uncertainties in a power system. Furthermore, the usage of ANNs also aids in estimating wholesale market prices and predicting real-time unknown load demand instead of a day ahead to incentivise the active registered consumer [348].

6.2.3 Multi-energy microgrid system in airport electrification

A wind-solar-storage integrated microgrid system is introduced in this chapter for airport electrification to achieve complete zero-emission operation in the airport. The microgrid system is developed to power all the ground operation electric loads in the airport. Ground support vehicles, i.e. A-ETR, EGSV and EGSE, are integrated into the microgrid to provide V2G support in the case of emergency and peak load demand. The integrated microgrid also offers sufficient mobility and flexibility to the airport's power supply. Initially, optimisation is performed in the SMPC setting to cope with the uncertainties in the system due to the stochastic and intermittent nature of the RES and flight schedule. In the next step, the validity of the results is checked by training and testing neural networks with the optimiser's inputs and outputs. A connected neural network minimises the computing complexity for future prediction of optimiser outputs for the complex mathematical model of the wind-solar-storage integrated microgrid system. The primary contributions of this study are briefly illustrated as follows:

- Solar, wind, and EV batteries as energy storage system are integrated into the airport as a micro-grid that can generate sufficient energy for charging A-ETR and EGSV and supply power to all-electric loads while avoiding noise and CO₂ emissions. Additionally, the microgrid is also connected to deliver electricity to the airport in the event of sudden utility grid outages, changes in the weather, or crises.
- The airport electric and EGSV charging load models are developed based on flight schedules to manage airport power requirements. The flight schedule is also used to evaluate the number of available EGSVs to charge/discharge for this airport microgrid.
- An SMPC-CFFNN optimisation method is introduced, which aims to curtail the total load demand of the airport on the microgrid. In addition, this method manages power flow to support vehicle-to-grid (V2G) and grid-to-vehicle (G2V) operations.
- The CFFNN has significantly reduced the proposed methodology's optimisation time

The remainder of this chapter is organised as follows: section 6.3 illustrate the architecture of the proposed energy system for the airport. Section 6.4 presents the methodology of the proposed stochastic model predictive control based on an ANN for the management of airport energy systems. Results and a discussion are shown in Section 6.5, and the conclusion is in Section 6.6.

6.3 Architecture of airport microgrid energy system

A DC microgrid energy system is proposed for the airport to integrate various DC energy sources, such as PV and EV batteries. The schematic structure of the DC microgrid for the proposed airport electrification is presented in Figure **6-1**. This system integrates a number of distributed energy sources, various converters, energy storage, and distribution components that are arranged optimally to meet the airport's energy demand. Most converters convert DC power into AC power verse versa in a typical power grid. The energy conversion between DC and AC reduces the system's reliability and causes energy losses at both supply and

demand ends [349]. To ensure optimal energy supply and utilisation, the energy control centre automatically connects all system components operating within the microgrid. The operational voltage of the microgrid can be interfaced directly with the battery storage system, and its value is taken to be 600 V. This DC voltage is reduced to the output voltage required by loads (380 V/400 V).

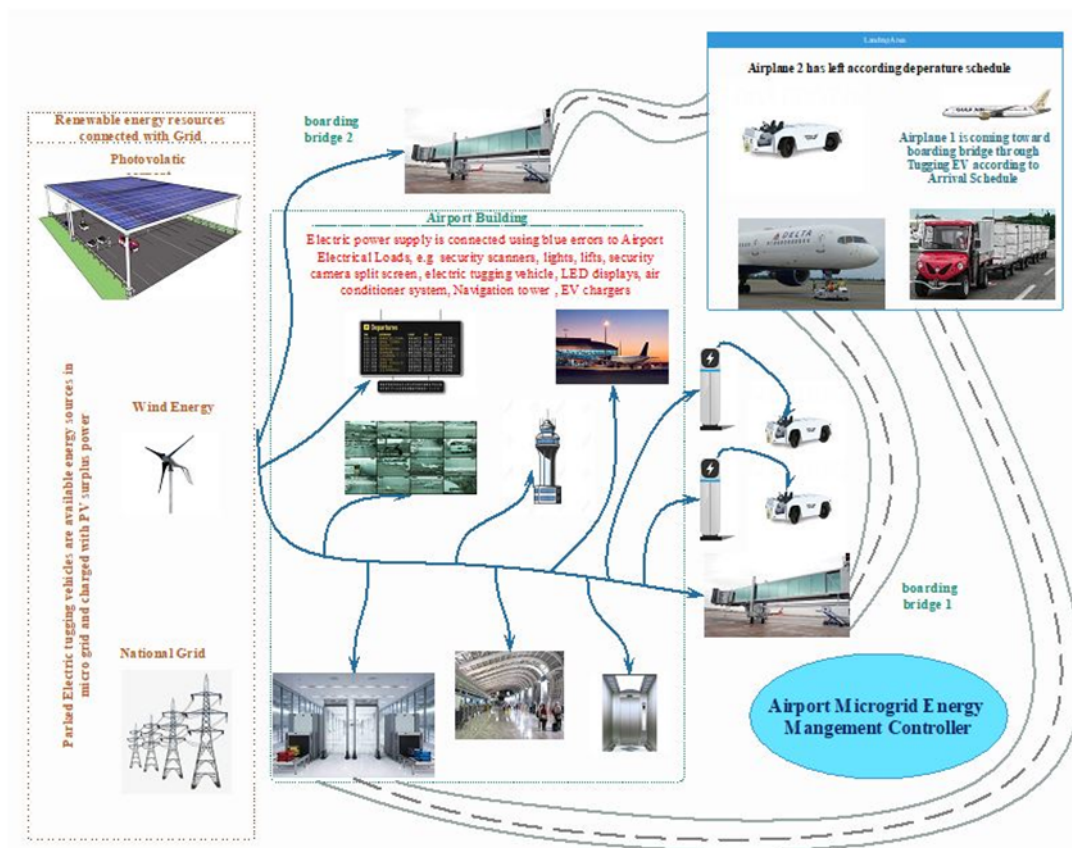


Figure 6-1 Schematics of the airport multi-energy microgrid structure

6.3.1 Modelling of DC Microgrid for Airport

6.3.1.1 Model of the Wind power system

Another renewable energy source considered is wind energy which is sustainable and eco-friendly. Solar panels are readily available at airports, whereas extracting wind energy near airports requires redesigning the existing turbines. Despite this source showing a lot of promise, there are significant technological obstacles to the safety of aircraft operations. A significant amount of energy need can be

fulfilled using wind turbines that convert kinetic energy into electricity. However, critical safety assessments are required before installing wind turbines close to airports because they cause interference issues regarding the safety of navigable airspace. Hence, surveillance infrastructure, navigation and communication about flight operations can be hampered by employing such turbines [329]. Therefore, an alternative design option, such as installing wind turbines with vertical axes, can be considered. To generate scenarios for using VAWTs in an airport environment, the following steps should be taken:

- Analyse the airport's current energy consumption and future energy needs to identify the energy requirements.
- Determine the feasibility of using wind turbines by assessing the wind resource at the airport site, including analysing historical wind data and using modelling tools to estimate wind speeds and energy yields.
- Ensure compliance with local and national regulations, including zoning laws, noise ordinances, and aviation regulations, to evaluate the regulatory framework and determine the permissibility of VAWTs and any height or setback restrictions.
- Consider site-specific factors such as available land, proximity to buildings, and potential impacts on wildlife when selecting the type and location of wind turbines.
- Select the most appropriate VAWT technology based on factors such as energy output, cost, and compatibility with site-specific factors identified in step 4.
- Develop a detailed installation plan that takes into account the selected VAWT technology, site-specific factors, and regulatory requirements, including the layout, electrical infrastructure, and foundation of the wind turbine installation.

- Conduct a cost-benefit analysis to evaluate the economic viability of the wind turbine installation by comparing the cost of the installation and maintenance against potential energy savings and revenue generated from selling excess energy back to the grid.
- Implement the wind turbine installation according to the design plan and conduct regular monitoring to ensure optimal performance, identify any issues that may arise, and carry out maintenance and repairs as needed to ensure the continued efficient operation of the VAWTs.

Savonius's vertical axis wind turbine is considered for this study. Savonius, a drag-based wind turbine, can be utilised close to airports while adhering to all applicable rules. Savonius turbine can be installed on the rooftops around the airport. Strategically placing these turbines around the airport can effectively harvest wind energy [25]. Vertical axis wind turbine (VAWT) is considered in this study because they are well-suited for power generation in airports due to their reduced noise production, compact design, and ability to generate electricity at lower wind speeds. The vertical axis rotation of VAWTs allows for quieter operation, and their smaller size enables installation in limited space areas common in airports. Additionally, VAWTs can generate power even in low wind-speed environments.

The rotational force of the wind forces the blades of the wind turbines to move. Mechanical power is captured by the aerodynamic design of turbines and can be calculated using (6-1). According to this description, it can be seen that the amount of energy that is delivered to the rotor relies on the air density (kg/m^3), the swept area (A) of the turbine blade, the wind speed V (m/s), and the power coefficient (C_p) (λ, β). Whereas C_p is the power factor, β and λ indicate blade angle and tip speed ratio. Furthermore, C_p lies in the range of 0.2–0.5 for wind turbines; however, for the fixed blade angle wind turbine, $\beta = 0$, and C_p changes only depending on λ [350].

On the other hand, λ , the relation between linear speed and wind speed in the blade, can be defined as in (6-2) [350]. Here, the terms R and W_m , respectively,

stand for the blade radius and rotational speed. A typical day output power of the wind turbine is shown in Figure 6-2

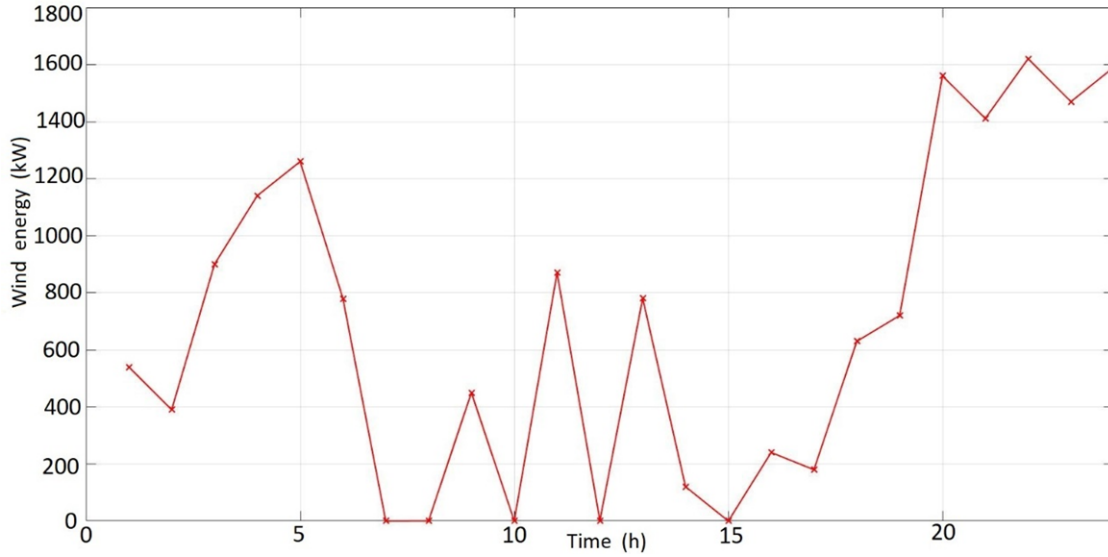


Figure 6-2 Wind energy on a typical day at the airport

$$P = \frac{1}{2} \rho A C_p(\lambda, \beta) V^3 \quad (6-1)$$

$$\lambda = \frac{R \omega_m}{V} \quad (6-2)$$

6.3.1.2 Model of PV System

The vast area of the airport provides enough land for installing solar power plants. The PV panels can be installed on the rooftop, car parking areas, and open spaces available at the airport. The output power of solar panels can be determined using the following expression in (3-11) [212].

The solar power output is intermittent and stochastic, so its energy varies daily. A typical day power output of the PV plant is shown in Figure 6-3. The peak solar energy production occurs around noon and is fed into the electricity system, as shown in Figure 6-3.

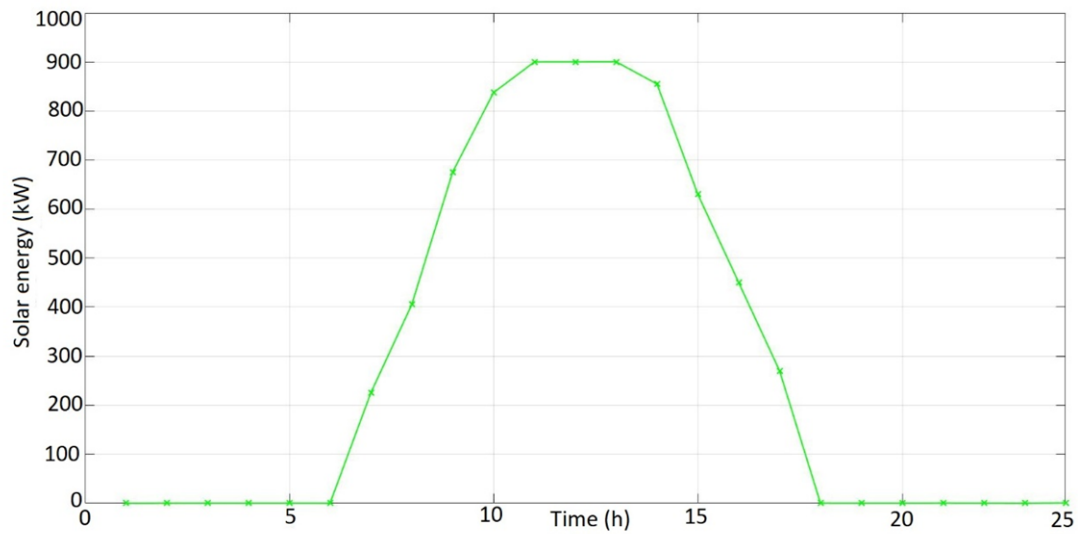


Figure 6-3: Solar energy production on a typical day at the airport

6.3.1.3 Model of Airport Electric Load

In order to maintain a comfortable cabin environment for the passengers and carry out the flight preparation work, the aircraft is powered by a ground power source before its departure. Therefore, an hourly-based load characteristic of the aircraft APU model is established according to the flight schedule, as presented in Figure 6-4, to obtain a new electric load profile. The provided flight schedule has been extracted from LLA's flight database for 2021. However, it is possible to estimate the electric load of aeroplanes at different airports using the load modelling method. Airport electrical loads include electric taxiing, transportation, luggage vehicles, security scanners, lifts, LED displays, security camera split-screen, lights, EV chargers, air conditioner systems, navigation tower etc.

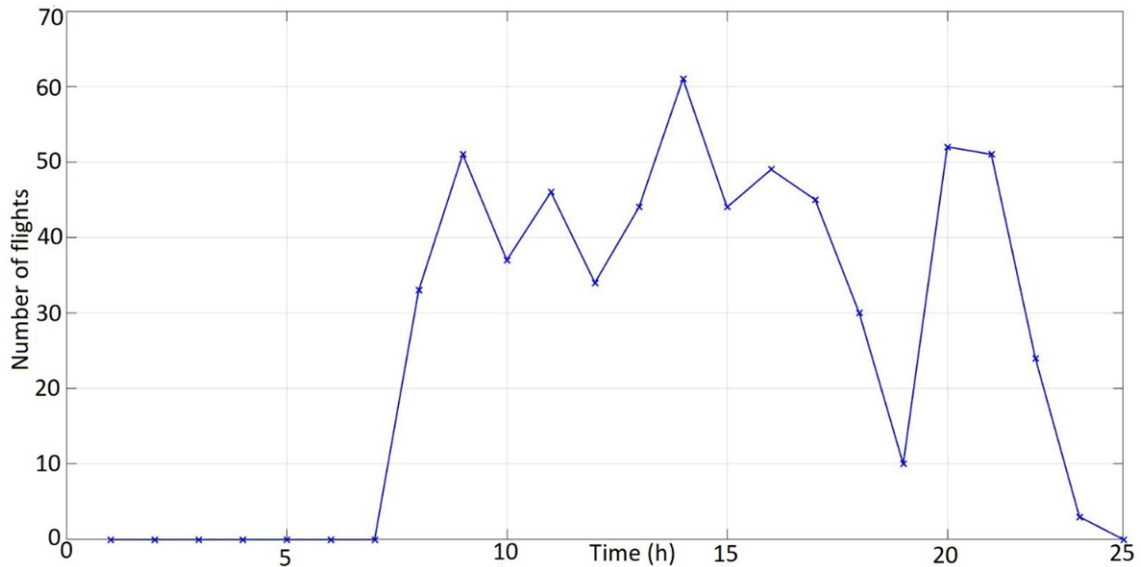


Figure 6-4: Number of flights on a typical day at Luton Airport

Generally, all the electric loads employed at the airport are categorised into three types based on their functions: fixed, variable, and opening loads [351]:

- Fixed loads: These types of loads include electric loads that remain in continuous operation and produce minimum base energy demand, which is required to maintain some critical airport operative facilities. These loads include the security camera, split-screen, security scanners and navigation tower.
- Variable loads: Such loads include electric loads that keep variable operation during airport opening hours based on aircraft operations or the number of passengers. These loads include airfield lighting, amenities for people and luggage, and electromechanical systems, all of which are dependent on the timing of outbound and incoming flights. It also depends on the standards set by the air traffic controller (ATC) service in the event of airport illumination. The profile of the cumulative electric load for all airport load categories is shown in Figure 6-5.
- Opening loads: They are the kind of electric loads that keep their operations while the airport is open, but they are mandatory to start the process of paying attention to travellers and aircraft. Additionally, they are

unaffected by the passenger count or aircraft operations. These loads include lighting and various other equipment.

6.3.1.4 Model of EGSV and A-ETR Charging Load

The proposed electrified airport model is comprised of a typical airport electrical load, the ground support vehicles, and their chargers. The use of vehicle chargers is governed to integrate flight schedules into the EVs operation at the airport.

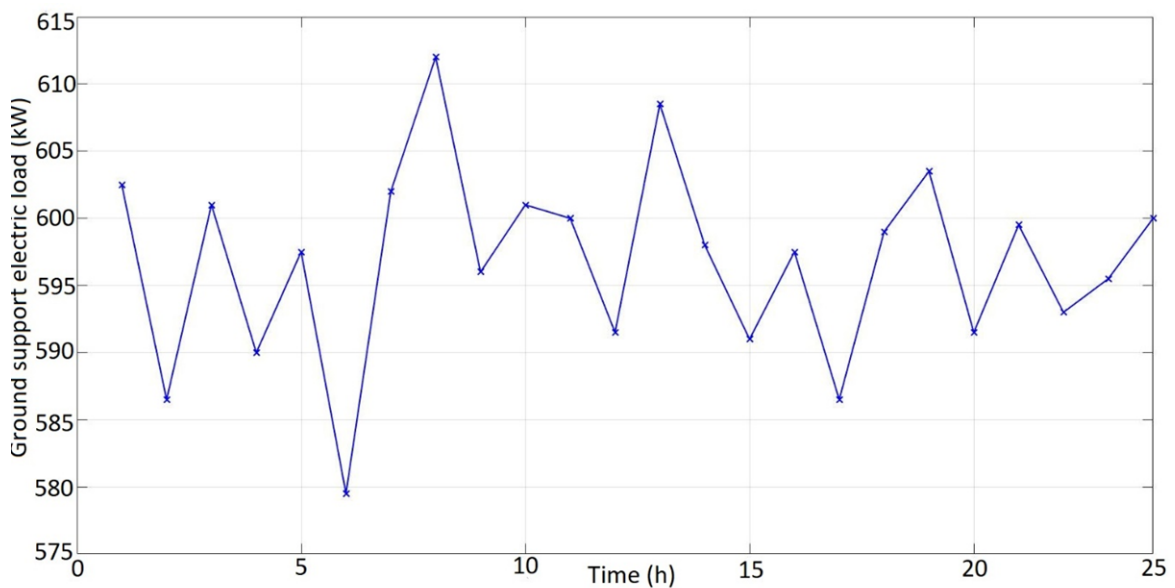


Figure 6-5: Airport ground support electric charging load on a typical day

The number of each type of ground support vehicle and the number of chargers make up this model's adjustable parameters. The system also contains a number of additional fixed elements that affect its operation. However, the most significant factor is the airport baseload, which comprises all electrical loads other than vehicle charging on the property, like heating and lighting. The charging load will maintain the facility's overall electrical load at or below the maximum desired load. There are two classifications of ground support vehicles: Classes A and B. Class A vehicles transport workers working at the airport as well as food, fuel, and deicing fluid. Unlike Class A vehicles, Class B vehicles are extremely powerful tug tractors to help push the plane back on its wheels from the gate.

Every vehicle in the system possesses many characteristics in the vehicle matrix, such as EGSV's availability, state of charge (SOC) and current state [308]. Initially, the value of SOC is set randomly through random uniform distribution, whereas the current state of EGSV indicates whether it is charging, idle or not charging.

Additionally, the required EGSVs can be calculated based on the anticipated number of flights. Mathematically, required EGSVs at a given time slot t can be determined as the number of flights in the current time slot multiplied by the average number of service vehicles needed for an aircraft. Each EGSV and AETR is updated and prioritised based on its characteristics within the vehicle matrix for every time slot. By ranking electric ground support vehicles and equipment based on their characteristics, airport operators can ensure that they have the right equipment available for each task and that the equipment is safe, efficient, and appropriate [352]. The number of EGSVs that are charged at any time is evaluated by the number of EGSVs not dispatched ($N_{udp}(t)$) and the number of charging piles N_{CP} . Afterwards, each EGSV SOC is refreshed at each time slot t . The SOC increases by the charging rate when the EGSV is charging, while it decreases by the discharging rate when the EGSV battery is discharging, as expressed in (6-3) and (6-4), respectively.

$$SoC_t^{fnl} = SoC_t^{int} + SoC_t^{ch} \quad (6-3)$$

$$SoC_t^{fnl} = SoC_t^{int} - SoC_t^{disch} \quad (6-4)$$

Figure 6-6 illustrates the hourly charging load profile for EGVS. It can be shown that the charging load is maximum between 01:00–07:00 hours. Due to the fewer flights scheduled during this period, 01:00–07:00 hours (all EGSVs are at charging), and the charging load is minimum in-flight peak hours at 09:00–17:00 hours (almost maximum EGSVs are dispatched).

6.4 Methodology

MILP method is used to formulate the airport microgrid energy model within the SMPC setting using CFFNN, in Matlab platform as illustrated in Figure 6-7

6.4.1 SMPC-Based Power Flow Management

SMPC can accommodate power system uncertainties by providing a receding horizon control. An important feature of SMPC is its inclusion of soft probabilistic constraints (or chance constraints, which require constraint satisfaction with only a certain probability), thus enabling a systematic trade-off between control performance attainable and constraint violation probability, in (6-5), ' δ ' is a probability distribution representing the airport's uncertain behaviour of load demand. This uncertainty can occur due to unexpected flight delays and cancellations because of adverse weather conditions, bird strikes, cyber-attacks, and IT issues. Although the power ('P') is dependent on a random variable $\delta(k)$, the scenario approach is used in this work to draw the S realisations of the uncertain element, $\delta(k)$, from the set Δ for each time step on the horizon to find the scenario approximation [353],[354].

To effectively manage and schedule consumption through a demand response (DR) scheme, a demand forecast of the airport in the management controller of the microgrid is required to control the flexible loads optimally. In this research work, DR has been implemented to model uncertainties interfering MG operations including failure of generation units and random outages of transmission lines and upstream line, error in load demand forecasting, uncertainty in production of renewable energies (wind and solar) based distributed generation units for airport system.

The objective function balances the airport's energy supply and demand. Mathematically, it is expressed as [354]:

$$\min_{U \in \mathbb{R}^{(M+L)T}} \sum_{k=1}^T (\hat{P}(k, U, \delta(k)) - \gamma)^2 \quad (6-5)$$

$$\hat{P}(k, \mathbf{U}, \delta(k)) = P_{re}(k) + P_{v_mg}(k) - P_{l_max}(k) - P_{sr}(k) \quad (6-6)$$

$$P_{re}(k) = P_w(k) + P_{pv}(k) \quad (6-7)$$

$$P_{v_mg}(k) = \sum_{i=1}^n P_i^{dch}(k) + \sum_{i=1}^n P_i^{ch}(k) \quad (6-8)$$

$$P_{l_max}(k) = \sum_{i=1}^n P_j^A(k) + \sum_{i=1}^n P_j^B(k) + \sum_{j=1}^m P_j^{app}(k) \quad (6-9)$$

where $P_j^{app}(k)$ represents the electric load of all-electric applications in the airport. $P_{v_mg}(k)$ denote bidirectional power flow from EGSVs to micro-grid to charge and discharge EGSVs to meet the load demand. $P_j^A(k)$ is the charging load of a class A electric ground support vehicle. $P_j^B(k)$ is the charging load of class B electric ground support vehicles. $P_i^{dch}(k)$ represents the sum of discharging power of vehicles of both classes in case of less power generation than demand. $P_i^{ch}(k)$ represents the sum of vehicles' charging power in both classes if extra power is available after meeting demand. $P_{sr}(k)$ represents surplus power generation fed to the utility grid after meeting charging and the electric load of the airport.

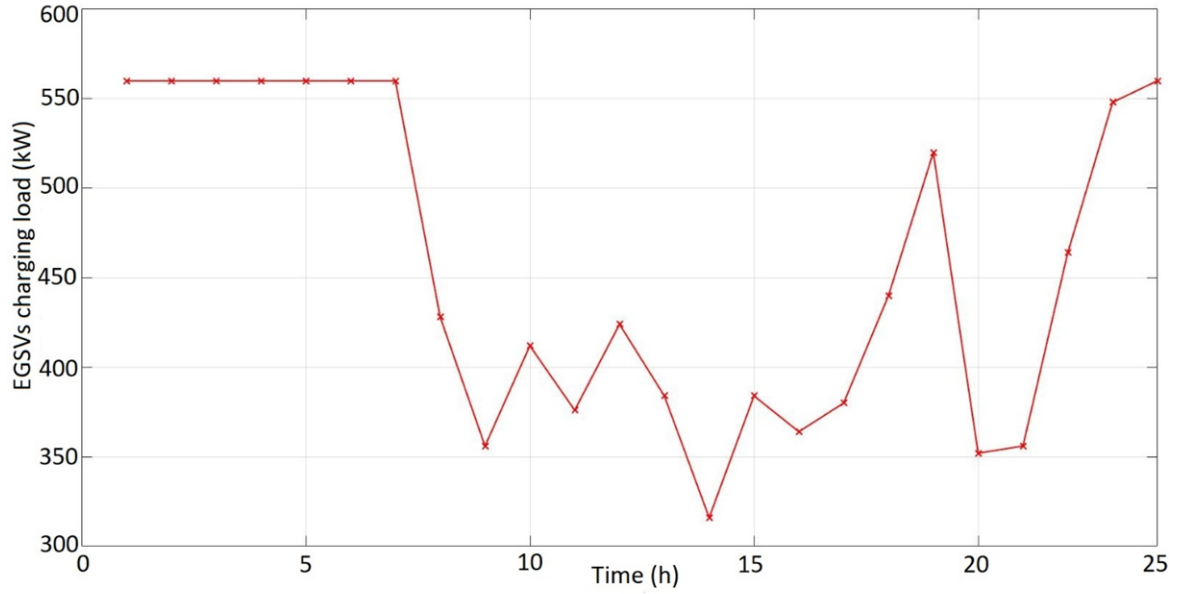


Figure 6-6 Hourly EGSVs charging load profile on a typical day

$P_{l_max}(k)$ is the overall maximum load demand of the airport. $P_{re}(k)$ is the accumulative power of renewable resources, i.e., the sum of wind power, $P_w(k)$ and PV power $P_{pv}(k)$.

Where $\mathbf{T}$ represents the length of a finite time horizon while $\mathbf{U} = [U^A(1), \dots, U^A(T), U^B(1), \dots, U^B(T)]_{(M+L)T \times 1}$ denotes the vector of controls over the finite planning horizon, which is $k = k = \{1, \dots, T\}$ in (6-5). γ is selected zero as the reference to minimise the difference between demand and supply at each instant. The minimisation in (6-5) will help avoid the peaks and dips in consumption, $\hat{P}(k, \mathbf{U}, \delta(k))$ by penalising the deviation of the consumption from the historical mean value $\delta(k) = [\delta_1(k) \dots \delta_N(k)]$, is the vector of uncertainties in the demand forecast, $P_j^{app}(k)$, where $j = \{1 \dots N\}$.

Hence, the proposed airport microgrid multi-energy system models are liable to operation and planning constraints. All such constraints are employed for each time interval within their optimisation time horizon. Available power at BSS is guaranteed in each time interval in (6-10) and (6-11), respectively. In and out power flow to BSS must persist within the maximum operating range, followed by each energy system's reliability and safety requirements (6-12). Power stored in

all the batteries at a specific instant is decreased by the total tugging power consumption and charging or discharging power from EGSVs to microgrids to fulfil power demand in (6-13). Power available in batteries must remain within the battery bank's minimum and maximum capacity when charged and discharged (6-14). The surplus power of the microgrid is delivered to the utility grid (6-15). The supply and demand of electricity are balanced at every time interval, in (6-16).

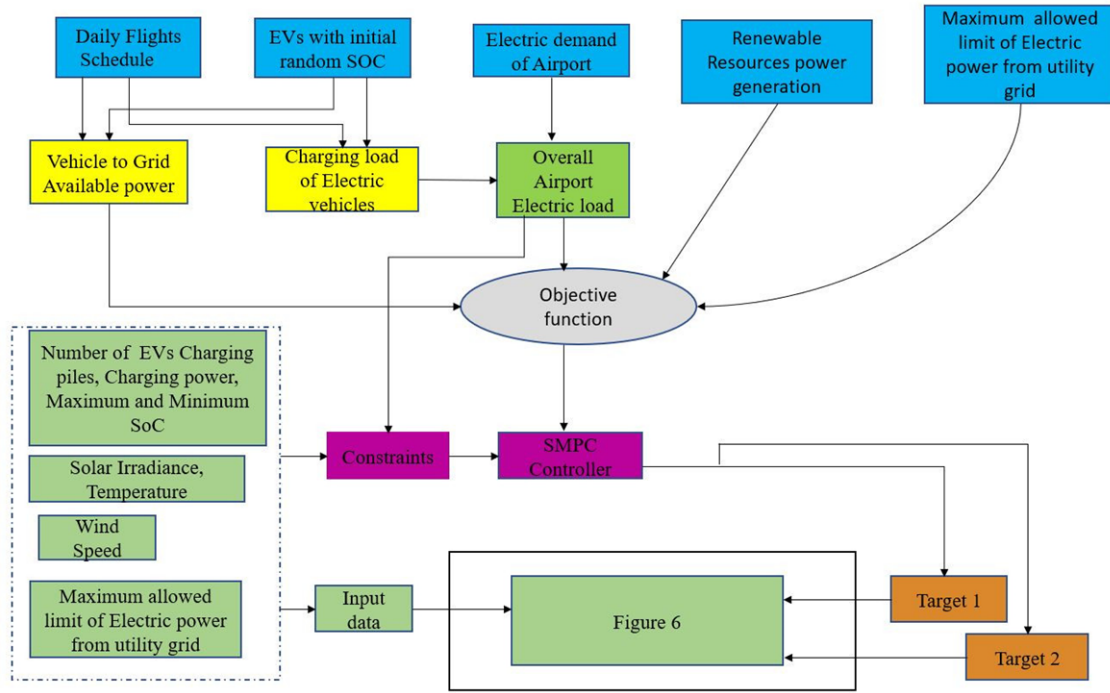


Figure 6-7: Methodology model of Airport microgrid with A SMPC -CFFNN controller

$$P_{BSS}^{Av}(k) \leq SoC_{BSS}^{Av}(k) * N_{udp}(k) \quad (6-10)$$

$$P_{BSS}^{Av}(k) = \frac{P_B^{Av}(k)}{N_{EGSVs}^T} * N_{BSS}^{EVs} \quad (6-11)$$

$$P_{BSS}^{Av}(k) - N_{CP} * P_B^{Av}(k) \leq P_{v_{mg}}(k) \leq P_{BSS}^{Av}(k) \quad (6-12)$$

$$P_B^{Av}(k+1) = P_B^{Av}(k) - P_{v_{mg}}(k) - P_B^T(k), \quad (6-13)$$

$$P_{BSS}^{min} \leq P_B^{Av}(k) \leq P_{BSS}^{max}, \quad (6-14)$$

$$0 \leq P_{sr}(k) \leq P_{re}(k) - P_{l_max}(k) \quad (6-15)$$

$$P_{re}(k) + P_{v_mg}(k) - P_{l_max}(k) - P_{sr}(k) = 0 \quad (6-16)$$

where $C_{BESS}^{Av}(k)$ is the available capacity at BSS at instant k ; $P_{BESS}^{Av}(k)$ is the available power at BSS at instant k ; C_B is the Electric ground support vehicle batteries (EGSVBs) capacity (in kWh), $P_B^{Av}(k)$ is the available EGSVBs power at instant k , N_{EGSVs}^T denotes the total number of vehicles for tugging and transportation, N_{BSS}^{EVS} denotes the number of vehicles left behind at BSS; $P_{v_mg}(k)$ is the in and out power flow of BSS batteries in the form of charging and discharging at microgrid, $P_B^T(k)$ is the total consumed power from EGSVBs for tugging and transportation. P_{BSS}^{min} and P_{BSS}^{max} are the lower and upper limits of available power in all EGSVBs.

6.4.2 SMPC-CFFNN

SMPC optimisation algorithm has operational superiority over the convectional MPC algorithm when addressing uncertainties [355]. However, these optimisation algorithms require high processing power and large optimisation time due to architectural complexity and iterative convergence to the optimal solution [356]. Due to intelligent architecture, Neural Networks (NN) provide a very reliable solution for this computational complexity of optimisation. NN does not require iterative convergence to the optimal solution, which helps decrease actuation time [357]. The dynamic behaviour of any system can be uploaded into NN by using the input and output patterns of any system. NN is trained using input and output sampled datasets that can be later tested and validated using a similar scenario. The advantage of this strategy is that it accommodates nonlinear relationships between input and output while leaving the linear relationship intact. The SMPC-CFFNN provides a comprehensive solution to overcome the computing limitations of classic SMPC due to its easy mathematical representation and excellent approximation capacity.

In this study, inputs and actuation parameters generated by the SMPC optimiser are logged into Microsoft Excel sheets from different scenarios. Five parameters, including solar energy, wind energy, airport electric load, EGSVs charging load and EGSVs SOC, were considered from the data and taken as inputs, as represented in Figure 6-8. Three stages were involved in designing this model: training, testing and validation, of 70%, 15%, and 15% data usage, respectively. In the first stage, the training criteria of the model are met, and then it moves to the second stage, in which it is tested to determine its performance for a given testing data sample; otherwise, the initial stage must be retrained.

More significantly, the elements of the CFFNNs are divided into various layers. The one-way connection (red line) from one layer to another is carried out to show their cascade link. While in general, all the neurons of the input layer and hidden layers are inputs of all neurons of their output layer. The input layer in the network carries information from the external environment directly to the cells in the intermediate layers without altering the external environment.

The output of the network is compared with the result when the input is given to the network. Therefore, the resultant difference from this comparison determines the error value. The sole aim of determining the backpropagation is to create an appropriate output by minimising this error [358]. Additionally, the network receives this error across all weight ratings for each iteration. Unlike recurrent networks used to simulate dynamic relationships, CFFNNs can emulate static nonlinear relationships. Therefore, the CFFNNs would be easier to use because static relationships are required [359]. Hence, SMPC-CFFNN possesses unique merits, such as excellent approximation capacity, simple mathematical expressions, and a general solution to the computational complexity challenge of employing SMPC in electronic power uses.

SMPC can also be abstracted into a function as the SMPC controller inputs can be considered independent variables, whereas their outputs can be considered dependent variables and control signals. Thus, this control process is considered a complex nonlinear problem: [359].

$$y(t) = f(x(1), x(2), x(3), \dots, x(n)) \quad (6-17)$$

SMPC-CFFNN uses the same input as conventional SMPC. Thus, the dimension of $\mathbf{X}$ is equal to the number of the SMPC controller's input elements. Each input element is normalised into a suitable range such as [-1,1] with the help of SMPC-CFFNN controller to achieve a better distribution of data, using (6-19) as given below:

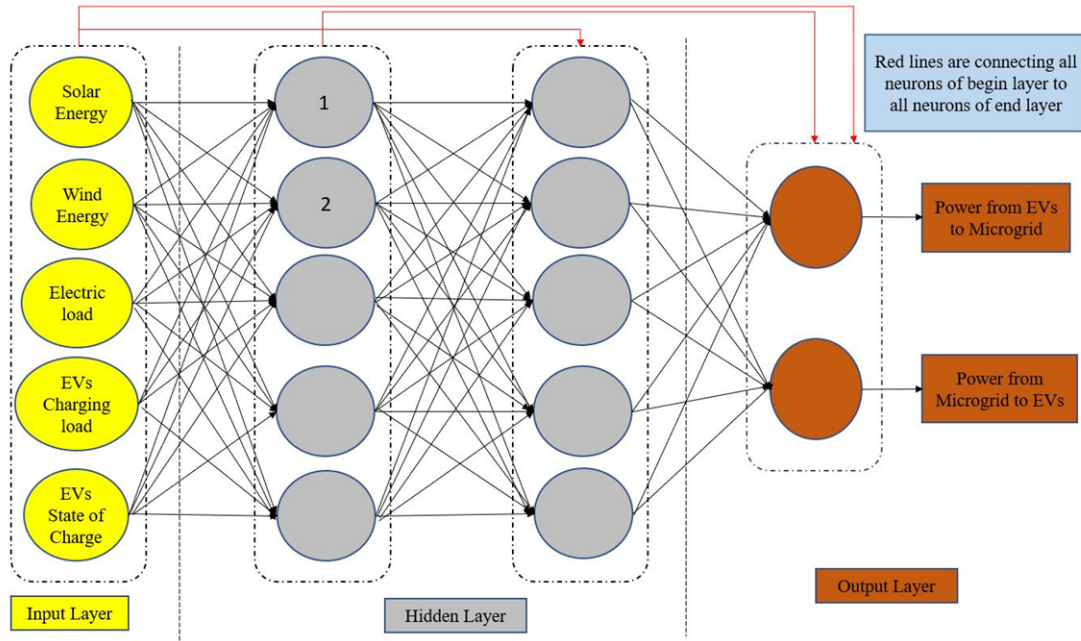


Figure 6-8: Cascade Feed-Forward Neural Network architecture in SMPC-CFFNN

$$y(t) = f(x(1), x(2), x(3), \dots, x(n)) \quad (6-18)$$

where, x denotes each element of the controller's input.

$$x^* = 2 \left(\frac{x^* - \min(x^*)}{\max(x^*) - \min(x^*)} \right) - 1 \quad (6-19)$$

$$\mathbf{X}^* = (x^*(1), x^*(2), x^*(3), \dots, x^*(n)) \quad (6-20)$$

The single hidden layer of the Feed-Forward neural network can be represented with the following mathematical expressions:

$$h_1 = f_h(w_1 \mathbf{X}^* + b_1) \quad (6-21)$$

where, $\mathbf{X}^*$ is the matrix of input vectors of the network. h_1 , b_1 and w_1 are the output vectors, bias vector, and weight matrix of the first hidden layer, respectively. While in the CFFNN, the inputs are sent additionally to each layer of the network. The equation for the CFFNN model can be written as follows:

$$y = f_o \left(w_o \mathbf{X}^* + \sum_{i=1, j=2}^{4,5} (h_i w_j + b_5) \right) \quad (6-22)$$

where, w_j and h_i represent weight matrixes of the hidden and output vectors of hidden layers, respectively while b_5 is the bias vector of the output layer. f_h and f_o are activation functions selected for the hidden layers and output layer, respectively. The zero-centred tanh function, as presented in (6-23), is proposed for all hidden layers as,

$$f_h = \frac{1-e^{-2x}}{1+e^{-2x}} \quad f_h \in (-1, 1) \quad (6-23)$$

For ANN-based binary classifier, the sigmoid function is suitable, as illustrated in (6-24) as f_o .

$$f_o = \frac{1}{1 + e^{-x}} \quad f_o \in (0,1)^n \quad (6-24)$$

The input and output data of this virtual controller are gathered as input and target of the training set for SMPC-CFFNN, respectively. To prevent underfitting or overfitting of the neural network, the distribution of the training set must be uniform.

The neural network initially assesses the control signals using recorded inputs and then compares them with the recorded control signals of virtual SMPC. The proposed neural network for SMPC-CFFNN is presented in Figure 6-9. In network architecture,

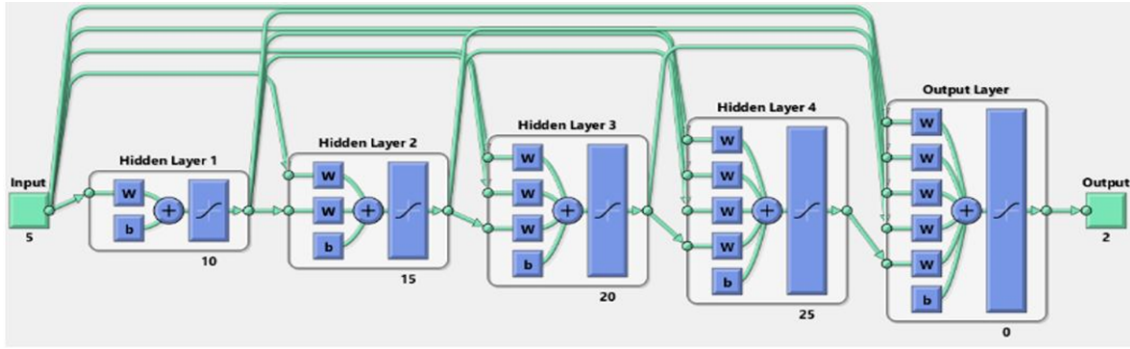


Figure 6-9 Proposed network architecture with functions.

the input layer and outputs of the cells in the hidden layers are taken as input for the next layer. Network architecture comprises five inputs and four hidden layers, with 10, 15, 20, and 25 neurons and an output layer with one neuron. In order to train, validate, and test the model, a sufficient set of simulated data was selected from the ANN simulation Matlab platform. This architecture aims to handle high-order complex mathematical models and effectively map various types of inputs and outputs. One key advantage of this method is its ability to account for nonlinear relationships between inputs and outputs without disregarding the linear relationship between them. The dataset retrieved using SMPC based simulation setup has been divided into three parts (training, testing and validation). During training, hyper parameters are randomly estimated and has been optimized during testing and validation steps.

Here, the summary of R^2 plots in the training, testing and validation stages during their training process is presented in Figure **6-10**. The overall value of R^2 is taken as 1 for the training data set. In order to design a model with the help of accurately predicted output, the neural network has been trained and validated using an available historical dataset. The input and output data set used for the training of neural network has been extracted from the simulation-based setup implemented using SMPC based optimisation. The results are deemed satisfactory because the R^2 value is close to 1. In short, it is observed that the value of R^2 at each level is close to 1 for training, testing and validation, as illustrated in Figure **6-10**.

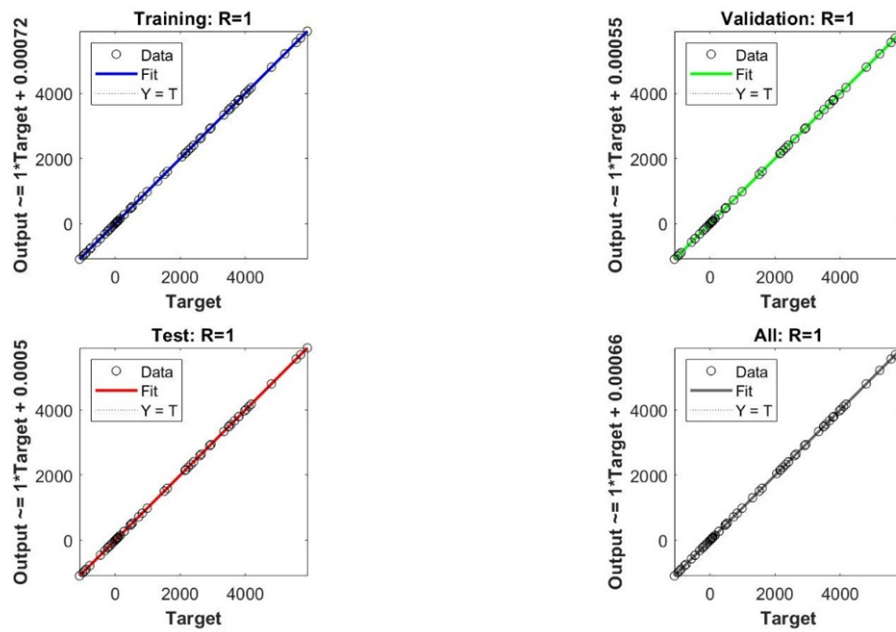


Figure 6-10: Training, testing, validation, and overall $R = 1$ obtained for training data set.

Figure **6-11** comprises a plot between Epochs and Mean Squared Error (MSE). The best validation performance was obtained with the validation plot reaching its minimum MSE value of $8.2278\text{e-}06$ at epoch 1200.A

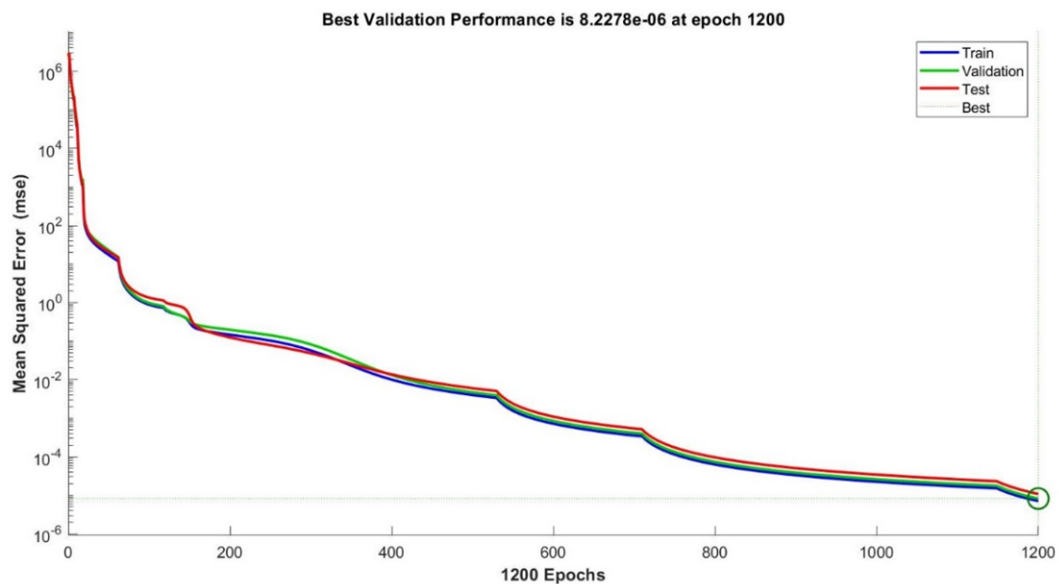


Figure 6-11: Best validation performance plot.

6.5 Results

The methodology of the SMPC-CFFNN optimisation model is discussed in section 6.4. Then, the algorithm begins to manage and control the power demand at the airport by charging and discharging the EGSVs. The main goal is to balance the electricity generation and consumption at the airport while taking into account all the previous constraints.

A comparative Matlab simulation is used to demonstrate the effectiveness and performance of the proposed method for managing airport microgrid demand during peak hours. The algorithm has been simulated on a Lenovo ThinkPad with 2.7 GHz Dual-Core Intel Core i7 and 16GB RAM. The total iteration of SMPC for a time instant optimisation takes an average of 35 seconds to complete. As a result, this method requires a long processing time for real-time applications with a shorter sampling time and can lead to the wrong actuation. While CFFNN typically takes less than 3 seconds to compute a multi-objective function for a given time instant. The simulation time taken by the trained CFFNN is significantly smaller as compared to implemented SMPC for power flow management of the proposed airport microgrid architecture. The comparative analysis between SMPC and SMPC-CFFNN for optimisation time at each instant has been presented in Figure **6-12**. The comparison shows that the suggested hybrid architecture is computationally effective. Data for wind energy is collected from the Bedford weather station, while solar energy data is collected from the KISANHUB weather station at Cranfield University [360]. In this simulation, one hour is set as the time duration, and one day (24 hours) is considered the total time. The data collected has been randomised by taking 0 mean and standard variation value of 20 to create 1200 different samples to check the robustness of the system against different weather conditions. This way, generation and load variances can be handled efficiently and effectively. Data on airport tugging load demand have also been generated from the flight schedule of London Luton Airport in the year 2021.

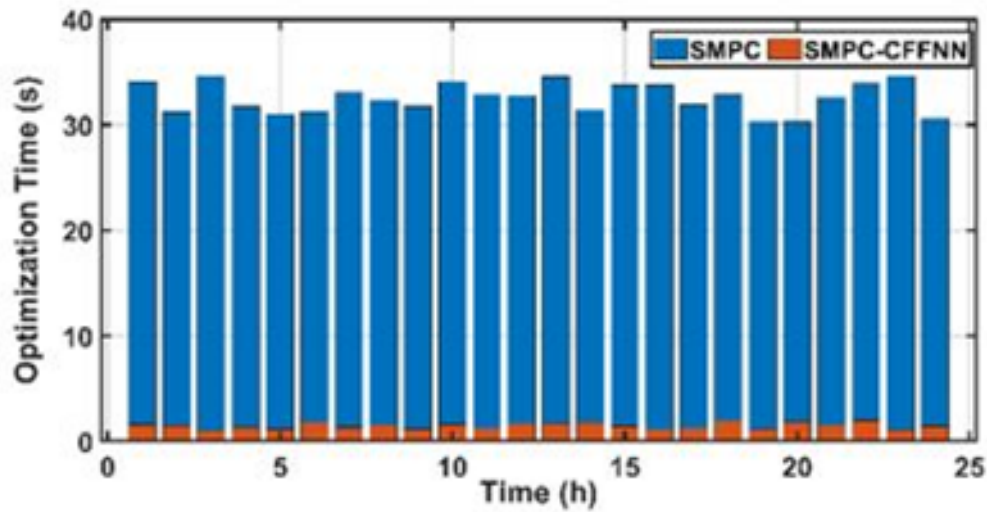


Figure 6-12: Optimisation time comparative analysis

Many European countries have strict rules for reducing aircraft noise at night, resulting in zero tugging demand after midnight hours (01:00–07:00hrs), as shown in Figure **6-13**. However, due to frequent departures and arrivals of the flights, airport tugging demand is high almost all day (07:00–18:00hrs). The model takes into account the demand for pushing and towing aeroplanes, respectively, as well as the demand for electric ground support vehicles that can transport people and cargo. It can be observed from Figure **6-13** that the tugging demand also arises at night-time (18:00–24:00hrs) for the arrival and departure of long-time flights because some of the flights leave the airport at night and reach during the daytime and vice versa.

Figure **6-14** illustrates the optimised power flow from EV batteries due to discharging and charging to meet airport electric load and transportation demand. The SMPC-CFFNN simulation results illustrate power flow, which is varied by the electric demand of the airport. Nevertheless, prior to its optimisation, the power flow from batteries simply remained positive due to the charging of batteries of electric vehicles, which overloaded the network. However, using ANN-SMPC, EGSV batteries are not just discharged for towing and pushing but also for pulling demand during peak hours from the system. This is crucial since the batteries must be fully charged to perform as intended. Discharging batteries is easily

noticed when power generation from solar energy is unavailable during night hours (01:00–07:00hrs), and overall generation from renewables is insufficient to meet the airport's electric load. The power of batteries flows in and out following their charging and discharging limits. As a result, even after being disconnected from the station, they may be employed in EVs in realistic ways to accomplish their final objectives. In this way, batteries of tugging and guest EVs can be successfully used to manage network overload.

Wind and solar sources generate power based on their inputs, such as wind speed and solar radiation. The wind turbine output power is approximately 1200 kW in the first interval, decreasing slowly between 05:00–07:00hrs. Moreover, this power decreases to such an extent that it may become zero in 07:00–08:00hrs due to different constraints such as microgrid capacity or wind speed. The PV output power increases with increasing irradiance from 06:00–12:00hrs to fulfil the load demand and export power to the utility grid. A critical situation arises in the microgrid operation due to the reduced power of PV and wind turbines simultaneously in 17:00–19:00hrs. As a result, Figure **6-15** shows that the microgrid's exported electricity is turned off during the specified time intervals.

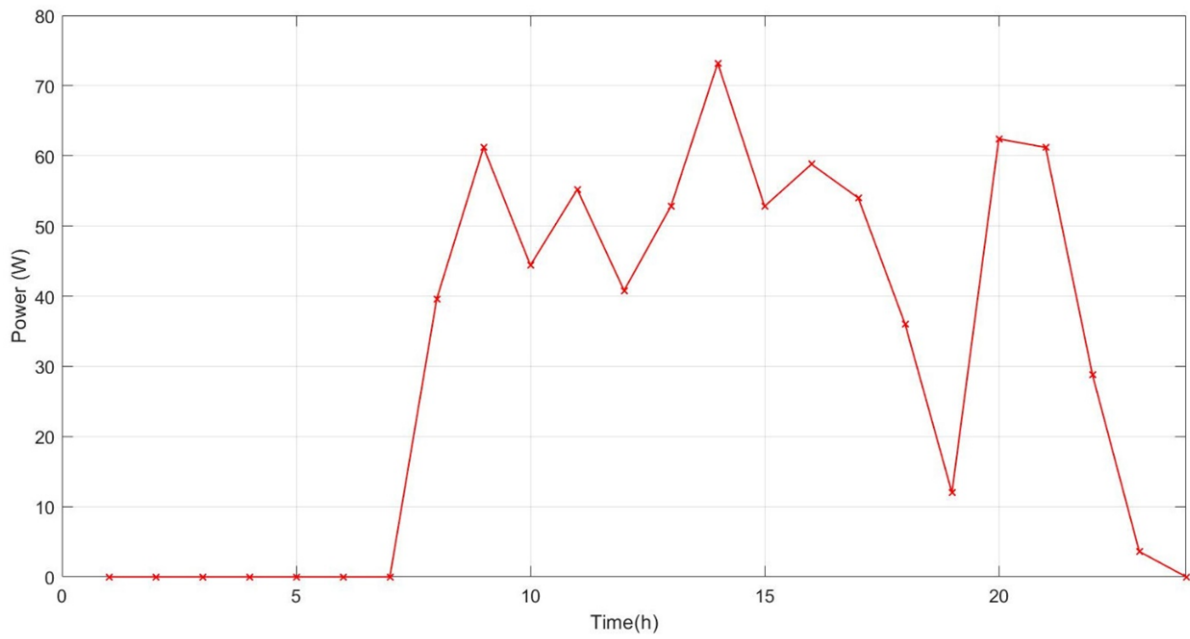


Figure 6-13 Tugging demand on a typical day

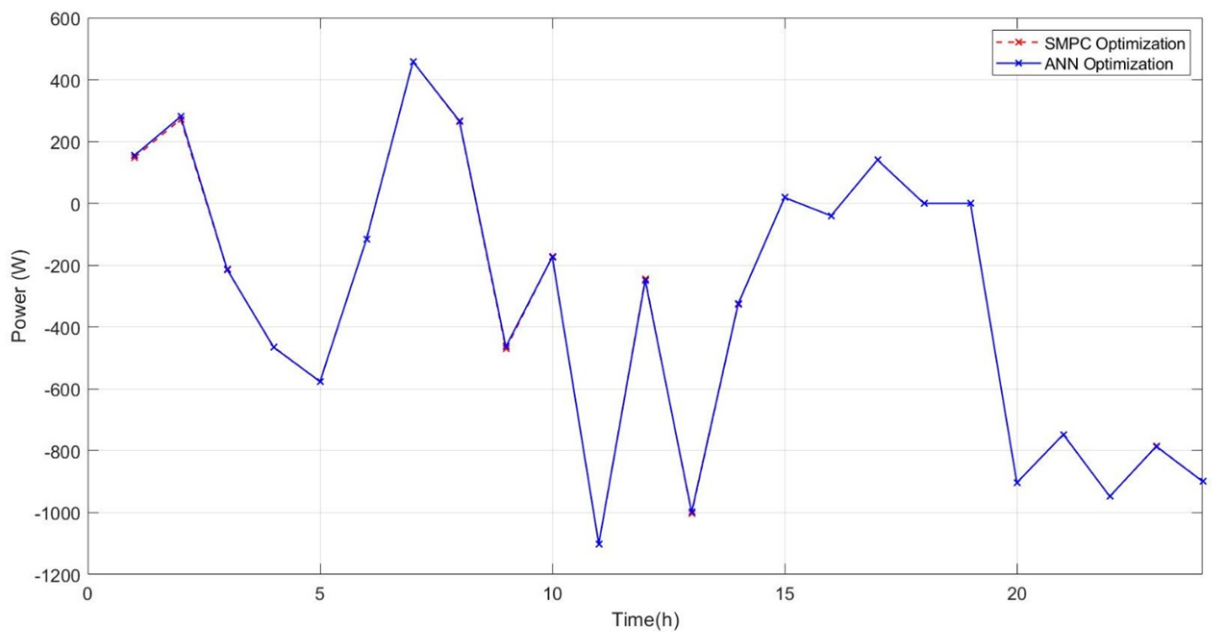


Figure 6-14 Optimized power flow from batteries of EGSVs due to discharging and charging.

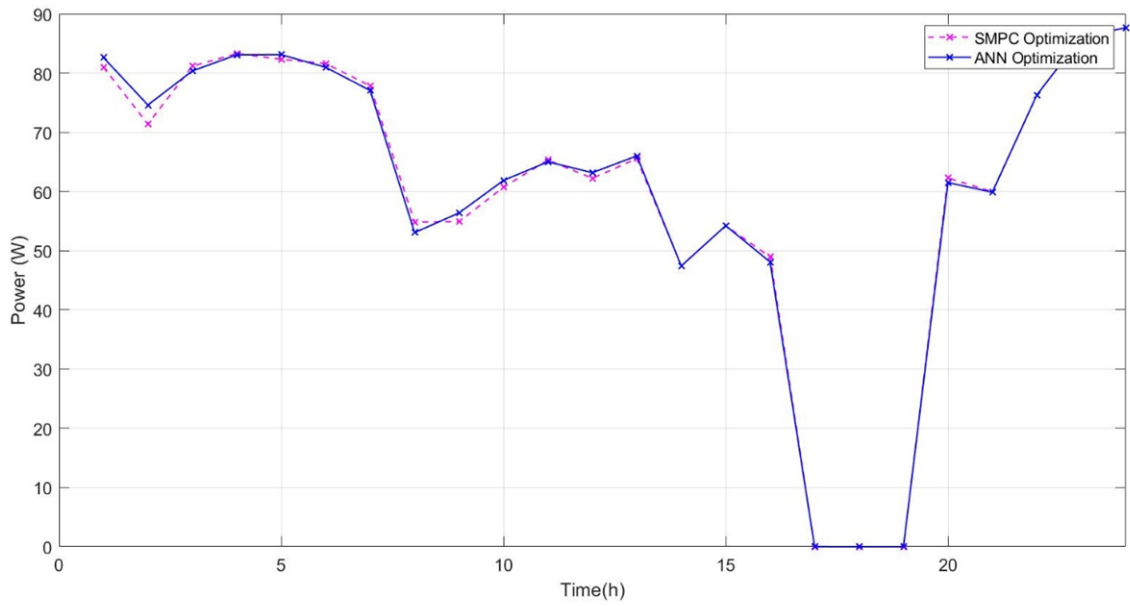


Figure 6-15: Surplus Power from the microgrid to the utility grid.

Additionally, to handle the load, the batteries of undeparted EGSVs have been charged and discharged in the past. Moreover, the BSS is recharged with an increased output power of WT for use at other times, 20:00-00:00hrs.

The energy management of microgrids based on SMPC-CFFNN has been studied in this section. The behaviour of data-driven SMPC-CFFNN closely resembles the optimisation achieved through model-based SMPC as shown in Figure 6-14 and Figure 6-15. This similarity in the optimisation plots, both with SMPC and SMPC-CFFNN, validates the performance of data-driven optimisation. In addition, it is worth noting that SMPC-CFFNN requires significantly less computational effort than SMPC, as demonstrated in Figure 6-12. As a result, the capacity of the energy storage system is optimised to store the excess energy generated by renewable sources. The parameters and constraints of the batteries are evaluated based on the maximum energy storage capacity limit. Figure 6-16 presents the results for the overall generated power P_{acc} , solar power P_s , wind power P_w , vehicle-to-grid power flow P_{V2G} , fed-surplus power to grid, P_{Sr} and optimised load demand, P_L of airport microgrid within the prescribed limit. The microgrid operation is changed due to variations in the storage capacity of batteries, as illustrated in Figure 6-16

Therefore, the batteries are discharged during 01:00–05:00hrs and then charged during 05:00–07:00hrs to reduce the microgrid deficit for the next time intervals. A critical situation arises in the microgrid operation due to the unavailability of PV power in 19:00–24:00hrs. Thus, the batteries are discharged to export power and fulfil the local loads. It will also be optimised to keep the operation economical and stable.

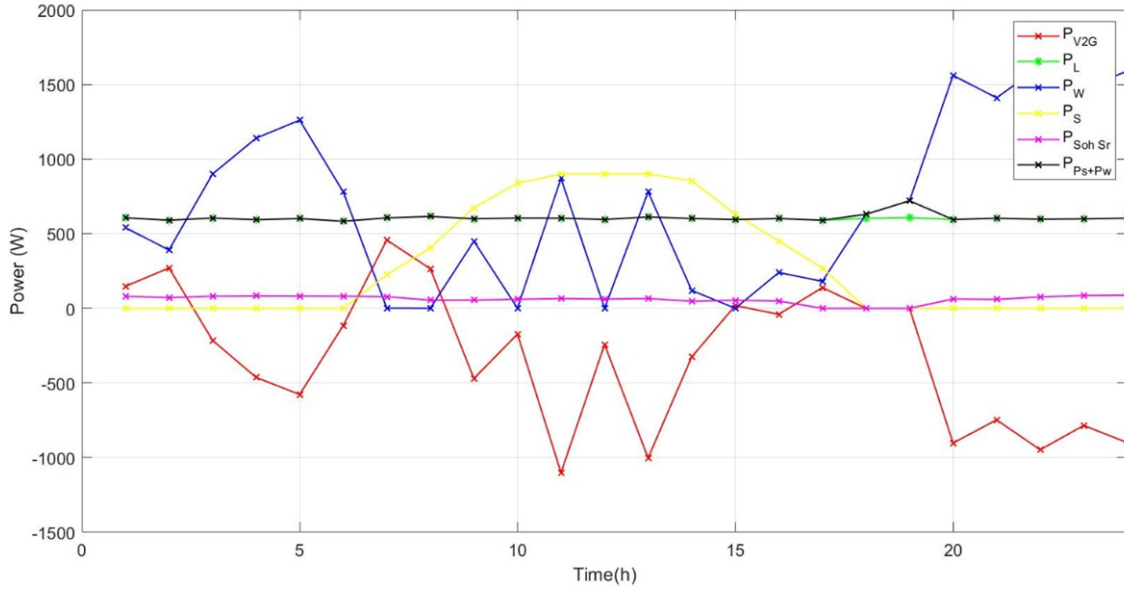


Figure 6-16 Overall power flow of the airport microgrid

6.6 Conclusion

This chapter proposes an optimum model of a wind-solar-storage integrated multi-energy system for the electrification of the green airport. First, the tugging and transportation EGSVs and A-ETR charging loads are modelled based on flight schedules. Then, using a CFFNN, a MILP problem is formulated to develop an airport microgrid optimisation algorithm. The objective of the problem is to maintain the supply-demand balance by managing the charging/ discharging cycle of EGSVBs and A-ETR, incorporating their batteries as a V2G capability to return excess power to the utility. SMPC, based on the CFFNN optimisation algorithm, shows optimal performance for the power flow management of the airport microgrid. Trained CFFNN with the SMPC controller inputs and outputs

data shows good performance both in optimisation of power flow and optimisation-time. The primary merits of using SMPC-CFFNN are preserving the SMPC control performance and using models of high-order systems with greater accuracy due to CFFNN's mathematical model.

Furthermore, the SMPC-CFFNN manages the microgrid's power flow using intelligent architecture while eliminating the iterative convergence to the optimal solution characteristic of the SMPC. In addition, the SMPC-CFFNN method showed resilience and sustainability in meeting the load demands in accordance with the FlightPath 2050 objective.

In the next chapter, two microgrid architectures were simulated on a high-fidelity model platform to investigate the best connection method to the existing airport network. In addition, the concept of the A-ETR as EaaS is incorporated to test the reliability and resilience of the proposed microgrid ecosystem by performing contingency and reliability index analysis on the model using DigSILENT power factory software.

7 Performance Analysis of E.V. Grid for Future Green Airport

7.1 Chapter Summary

This chapter studies the supportive needs for the electrical infrastructure of the green airport. Electrification of airport energy systems is one of the prospective solutions to achieve zero-emission airport operation, according to the ACARE Flightpath 2050 policy guide. However, incorporating renewable energy sources such as wind, hydrogen and solar into the airport's energy mix presents new engineering challenges. In particular, the core objective revolves around the choice of electric grid configuration required to meet the expected electrified loads, i.e., the taxiing and charging loads of hybrid /pure electric aircraft in the airport. This is investigated by comparing possible network configurations to link the proposed microgrid ecosystem with the existing airport grid. Here, two alternative architectures based on their point of common connections (PCC) are compared, one with LVAC architecture and the other with a high-rating centralised converter connection with LVDC architecture, in terms of technical and economic implications of the new loads on the existing distribution network in the airport. Then, the concept of the A-ETR as energy as service EAAS is incorporated to test the reliability and resilience of the proposed microgrid by performing contingency and reliability index analysis on the model using DigSILENT power factory software. The performance of the model in terms of power quality, short circuit fault levels, system protection requirements, voltage profile, power losses and equipment/system overloading to determine the optimal microgrid architecture is also verified and validated. The result demonstrates that the A-ETR has potentially accelerated the electrification of transportation in the

airport in addition to enabling novel emergency response systems to provide ancillary services to the grid.

Keywords— Reliability, Voltage profile, Flightpath 2050, green airport, Reactive power

7.2 Introduction

The continuous development in the air transportation industry, coupled with increased air traffic flow, has stretched most airport operational capabilities to their limits, posing serious environmental and economic concerns. Therefore, the existing airport infrastructure needs to be expanded, and its capacity has to be increased to improve its operational efficiency [10]. The aviation industry has been surrounded by critics from various environmental advocacy groups ranging from trade unions to government to local residents. The sustained criticism has been targeted against the vast amount of carbon emissions from aircraft and facilities. In response to these critics, stakeholders in the sector have begun to address the concerns and devise ways to discuss the climate challenge. One such intervention is the Flightpath 2050 guide developed by the European aviation industry and the European Commission to partially decarbonise the sector to reduce carbon footprint, environmental impact, and accidents in the aviation sector [10],[325].

Transition to MEA and AEA systems has been initiated to provide an enhanced aerospace solution in the future that satisfies the proposed regulations and has the potential to reduce GHG emissions and noise pollution considerably [361],[201],[362],[363],[102]. Airports are evolving into a new phase by incorporating sustainable energy models, such as electrifying airport ground movements, which is an important factor in achieving a zero-carbon future [170]. In addition, the electrification of transport in this sector would promote sustainable electricity generation and improve air and human health quality around the airport. Since the existing airport structure is not designed for operating EA and fully EGSV, this comes with underlying challenges [104], [364]. The impact of

integration and interaction of the EA on the power grid is envisaged to be multi-dimensioned. In particular, a modification of the current airport electric network is inevitable to adequately supply energy to the aircraft and EGSV [334]. However, there are three expected challenges to modifying the electric network to provide the extra electric power demand by the MAE, EA, and EGSV in the airport: (i) high capital investment, (ii) limitations in land and resources, and (iii) long construction period. These challenges have made the traditional expansion of the upstream power grid less practicable because such a power generation expansion scheme would increase the airport's recurrent expenditure and further increase transmission losses and the carbon footprint of the power industry [328].

Therefore, a synchronised smart infrastructure for energy, transportation, and communication is required to incorporate these new loads into the existing infrastructure in the airport [64]. Some of the existing work in this area includes [365] developed a forecast model to analyse the effect of the large deployment of e-transportation load and its influence on the local power consumption in the airports. The objective is to predict future EGSV energy demand due to different operators in the airport for ten years to minimise the effect of the charging loads on the grid. The study concludes that the impact of the electromobile load demand due to the different airport operators is negligible compared to the airport's total energy demand.

It has been projected that the current consumption of fossil fuels could reduce by one-fifth by the electrification of the whole transportation sector [366]. A roadmap and assessment methodology for the sustainable future of the airport and terminal buildings have been presented in [115]. The study compares conventional airport terminal buildings' CO₂ emission reduction prospects with green airport terminal building scenarios. The results indicate that a green airport terminal building may not balance its responsibility for CO₂ emission reduction without proper reforestation efforts and site selection. A comprehensive analysis of large airports in terms of energy consumption and generation, emissions and mitigation planning, environmental management and biodiversity is presented by [116]. The study shows that the relationship between the sustainability ranking

index and the number of passengers indicates that sustainability practice in the airport environment is multifaceted and capable of minimising its carbon footprint. [367] developed an energy management strategy to explore mobile energy storage system scheduling for an AC-DC microgrid in the airport. The proposed methodology combined a mobile energy storage system and an electricity price index to optimise the energy management of the microgrid. The study further considers replacing the aircraft auxiliary power unit of the aircraft during turnaround with a mobile energy storage system to supply the power and preconditioned air for the cabin. The result shows a reduction in the emission index and an improvement in the energy management of the airport.

This study selectively presents the smart grid-green airport paradigm and develops suitable grid architecture to enable this paradigm. The present contribution, which does not seem to have been dealt with to date, investigates the possible network configurations to link the proposed microgrid ecosystem with the existing airport grid and the A-ETR to improve resilience in the MG operation. The proposed study compares two alternative microgrid architectures based on their point of common connections (PCC), one with LVAC architecture and the other with a high-rating centralised converter connection with LVDC architecture, in terms of technical and economic implications of the new loads on the existing distribution network in the airport. Then, the concept of the A-ETR as EAAS is incorporated to provide ancillary service and test the reliability and resilience of the proposed microgrid ecosystem.

7.2.1 Airport Microgrid Implementation

The crucial role played by the airport in a country, or the economic development of a community and transportation network is disrupted whenever there is a power loss. Power outages, either for a short-time blackout or long-time utility outages due to natural disasters, impact the airport's ability to operate. Thereby causing inconveniences to the travelers such as flight delays, extended layovers, loss of income for airport concessions, or the inability of the vulnerable area to quickly receive emergency aid delivered by aircraft.

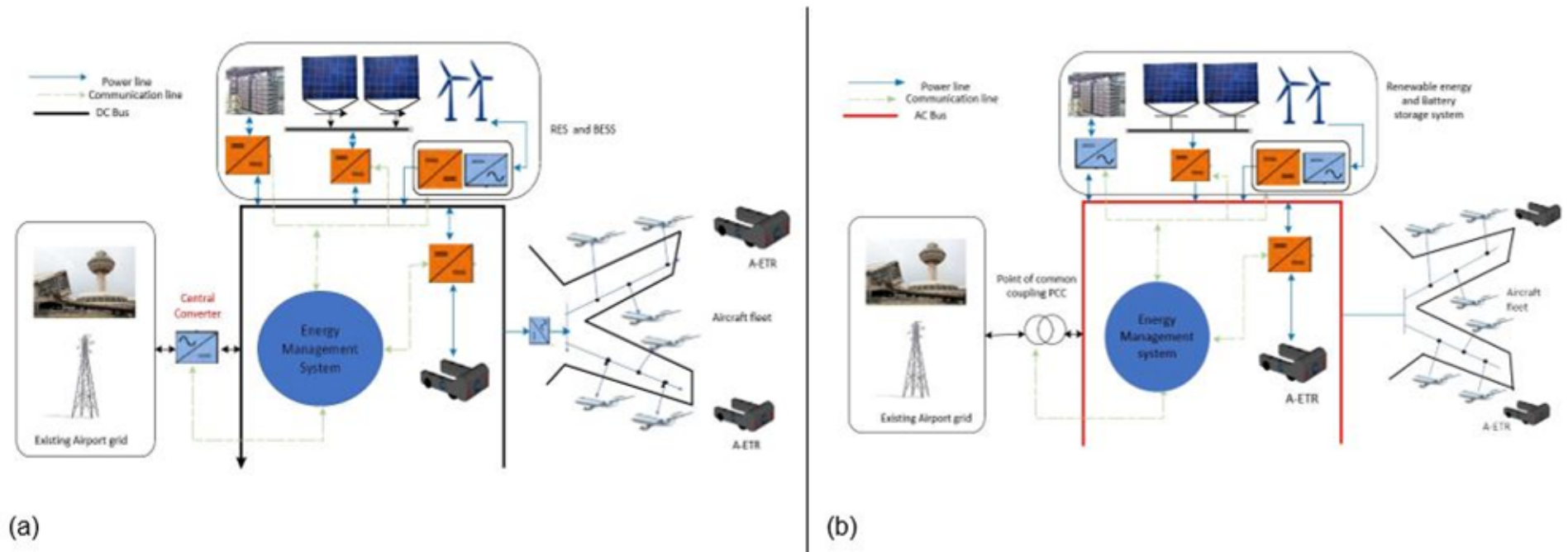


Figure 7-1 Schematics of the green airport energy supply (a) LVDC (b) LVAC microgrid architecture

A possible solution to reduce the risk and acute negative effect of power outages and GHG emissions is for airports to be self-sufficient in generating and managing their power. Subsequently, the aviation industry has redirected interest to microgrid technology as a dependable and instantaneous supplementary power source to ensure a reliable and continuous power supply for airports. Microgrids are local electrical systems built to generate their own power while operating parallel with the utility (grid-connected) or separated from the utility (island mode). They provide their load balancing to achieve stable operation. Microgrids usually incorporate many local generation resources such as cogeneration engines, wind energy, fuel cells and solar photovoltaics, as well as types of energy storage systems to meet peak loading conditions. In addition to ensuring continuity of supply and resilience of the power network, microgrids offer other benefits such as (i) providing the capability of existing in grid-connected or island mode and (ii) mitigating supply and power quality problems emanating from the local utility supply through the deployment of on-site energy storage and parking structures designed for solar panel capacity [143].

In the literature, microgrids have been defined in different ways, such as [144] defined the microgrid as a system approach which views generation and associated loads as subsystems. At the same time, [145] have referred to a microgrid as "a platform for integrating demand-side (micro-generators) and supply-side (storage) resources in a local distribution grid. [146] described a microgrid as a low-voltage network with its loads and a few small modular generation systems connected to it to provide both power and heat to the local load. According to the ABB group research, a microgrid is an electrical system that gathers, distributes, and collects data for all electrical components to optimize economy, efficiency, sustainability, and reliability. The Consortium for Electric Reliability Technology Solutions (CERTS) viewed the microgrid concept as an aggregate of micro sources and loads operating as a single system that provides both power and heat to the system [147]. Though microgrid technology is not new, it is relatively new to the aviation industry. Currently, microgrid projects are being explored in many airports across the world. These include San Diego

international airport, Denver international airport, the port authority of New York, New Jersey, Kula Lumpur Airport Malaysia, Indianapolis International Airport, John Wayne Airport, and Beijing Daxing International Airport [143],[87]. Although each stakeholder implements a microgrid for different purposes, the primary benefits are to (i) protect critical infrastructures from loss of power during grid outages,(ii) reduce vulnerability to cyber and terrorist attacks, (iii) increase operational resiliency by sustaining critical operations during prolonged utility outages, and (iv) reduce environmental impact. A model of a typical airport microgrid in Digsilent Power factory is shown in Figure **7-2**

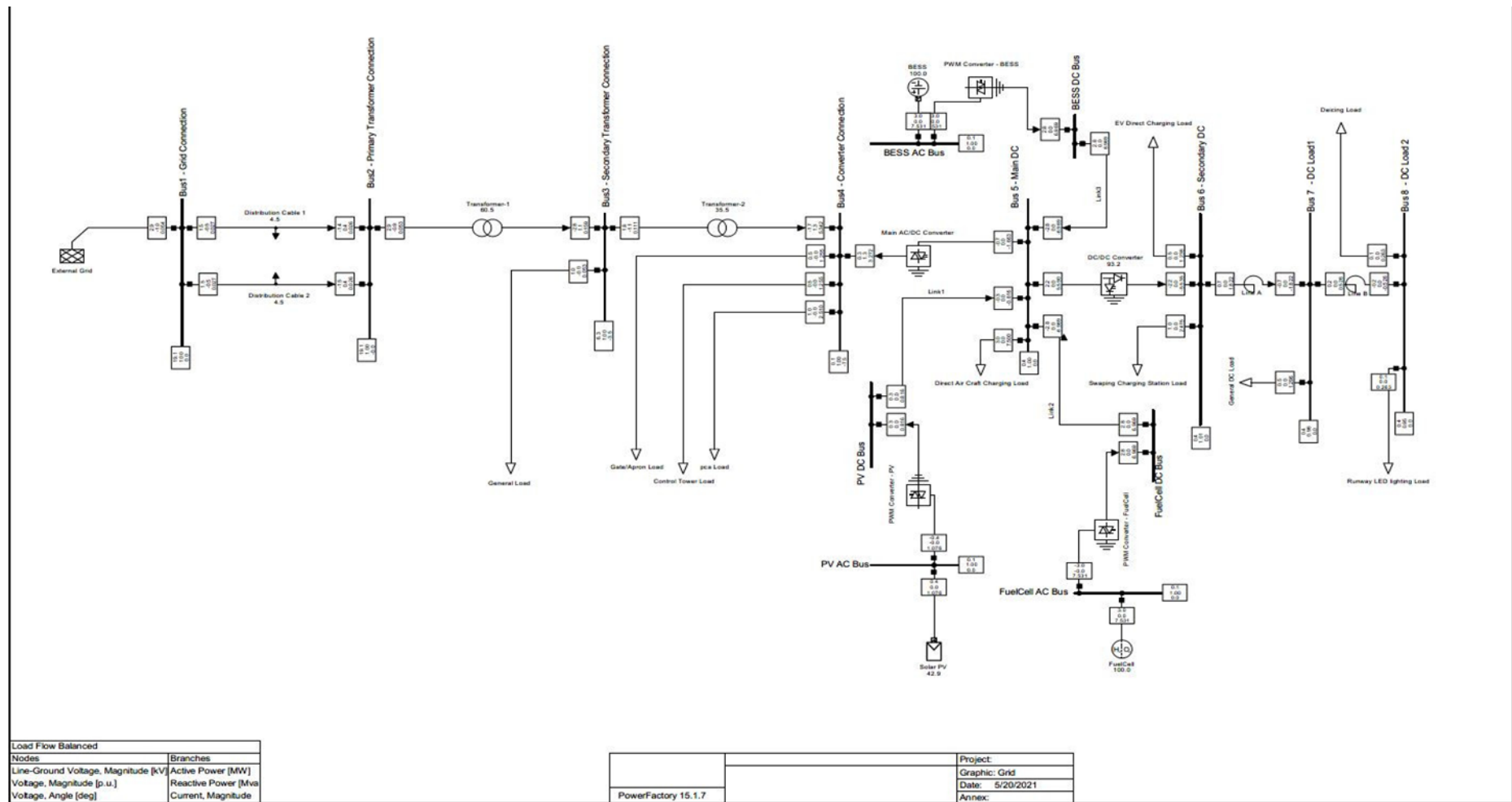


Figure 7-2 Modelling of the airport energy supply structure (LVDC) architecture in DigSiLENT power factory

7.2.2 Load flow analysis

A load flow analysis indicates the direction of real and reactive power flows, node voltage profiles, power factors, and system overloads in the network. Once accurate network parameters are entered into the model, the analysis allows engineers and system operators to investigate the system's performance under different operation conditions and confirm economic transmission power in the network.

The purpose of a load flow analysis is as follows:

- Determine the voltage magnitude and phase angles at each feeder node.
- To determine the power flow in each line section.
- Calculate the power loss.
- To determine the Kilo Watt (kW) and VAr inputs to the feeder
- Determine the active and reactive power of the load based on the load model.

7.3 A-ETR for resilience enhancement

Several authors have investigated the use of mobile energy resources for service restoration and resilience improvement in power systems. Methods for service restoration include network reconfiguration, multiple microgrid coordination, distributed energy generation integration and demand response strategy [66], [77]–[79], [368], [369].

The deployment of the A-ETR in the form of mobile energy storage (MESS) enhances the reliability of distribution systems by reducing the likelihood of outage occurrences due to severe weather events or natural disasters. Consequently, the number of affected customers during an outage will be reduced, and outage time will be shortened. MESS is capable of delivering services to isolated locations and also provide backup power during natural disasters [66]. MESS can be used to support microgrids to reduce load loss during an outage when the necessary connection infrastructure is available. A

community experiencing an outage can become more resilient and adaptable with the help of MESSs, which can react swiftly to changing demands, unlike stationary technologies [370]. In the event of a brief blackout, the MESS can support microgrids and supply electricity from an easily accessible energy source.

The MESS is able to depart the damaged region, refuel, and then come back to power the microgrid. An available resource could be a generation resource that has been left stranded by fallen cables or damaged utility infrastructure. Utility-scale wind farms and solar systems are examples of such resources.

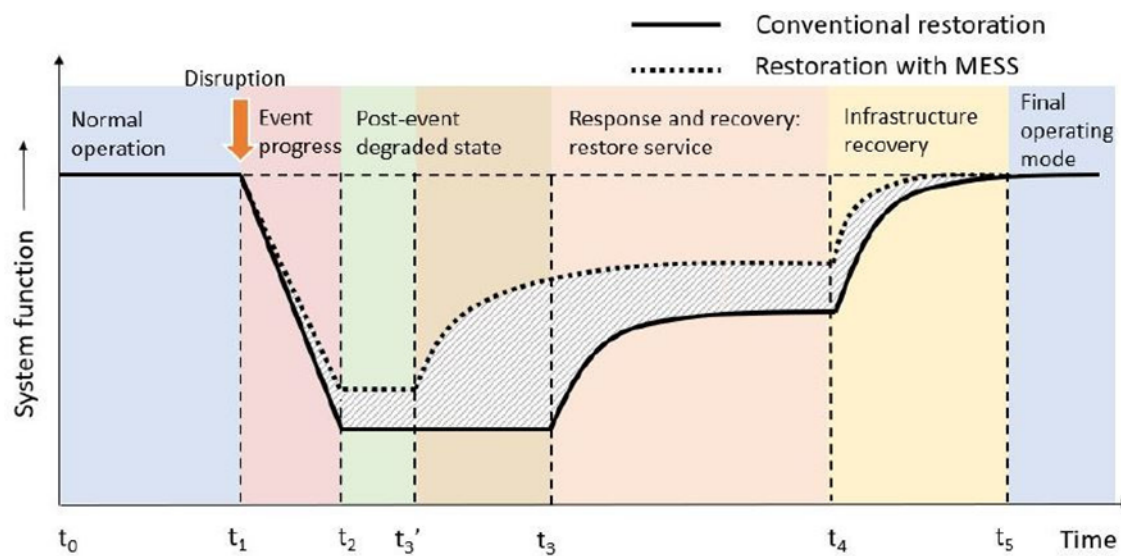


Figure 7-3 Conceptual contrast between restoring a distribution system after a disruptive event with and without MESSs.[66]

Figure 7-3 illustrates how MESSs could increase the resilience of the distribution system during crises. Taking reference from the works of [371], [372], and [67]. A demonstration of the system's performance when MESSs are used or not used is conducted during fault. The works reflect that the load capacity of a distribution system determines its performance, and its efficiency is a reflection of total customer satisfaction. As a result of the weighting of loads, critical infrastructure may be given priority in the event of an outage. In the associated time frame, there are a variety of events stages, such as the normal operation [t_0 , t_1], disruption time and aftermath of the disruption. The amount of available time

before a disaster will determine the level of preparedness for support such as charging and prepositioning MESSs. After a disruption at time 1, the event continues at t_1 and t_2 , during which the distribution system is damaged, causing load shedding. The system deteriorates after the occurrence and peaks at time t_2 after all damages have been done and no loads have been restored. Service restoration could begin following time t_1 even before all damages have been done, ensuring the system's performance remains stable. MESSs prepositioned at areas likely to experience service outages during and after events will improve the system's performance. Following a degraded condition, there is a response and recovery period during which the service is restored. Despite damage to utility infrastructure, service restoration can start with the assistance of MESSs. The infrastructure recovery process begins at t_4 damaged infrastructures are repaired. At time t_5 , the system is fully recovered and operational. Based on

Figure 7-3, the dotted line illustrates the benefits of MESSs over conventional restoration since these systems can re-energise loads that would otherwise be out of service. Also, the ultimate operating mode (expressed by t^1_3) is reached earlier, and the service restoration period (expressed by t_3) begins earlier. As can be seen, by the difference between the solid and dotted lines, the resilience of the system is enhanced by the reduction in lost load. MESSs, therefore, result in shorter and milder outages than those without them. As shown in

Figure 7-3, MESSs have the potential to recover the cost of investment during typical operations and provide additional benefits to resilience [71], [76], [79].

A stochastic framework is proposed by [373] to plan MESSs and establish several microgrids to restore service following an incident. Using a time-space network, they analyse the MESS scheduling problem and optimise service restoration plans to reduce expenses. These costs include disruptions to customers and the operational cost of the microgrid. The scheduling of MESSs charging and operation within the microgrid and those experiencing outages are expressed in [12]. As a means of reducing the cost of investment and anticipated sanctions during outages, an algorithm for stochastic planning of mobile energy generators

has been proposed in [375]. [71] propose a plan to compare MESSs' economic benefits during emergencies with their costs when they are operated normally. Both scenarios are optimised using progressive hedging algorithms, and it is determined that MESSs offer enough value to warrant their use in emergencies.

[369] provide an organised random operational plan for MESS operation within a combined heat network to reduce operational expenses and enhance load restoration during power interruptions. The dispatch of MESS must be coordinated with the dispatch of other energy resources in the distribution system since it is an energy resource. A model for the combined operation of MESSs, renewable power sources and operators was implemented by [376]. [377] developed a strategy to integrate renewable energy sources, dynamic network reconfiguration, and MESS fleets while considering their deficiencies. The model maximises both the overall value of the load given and the financial benefit of using renewable energy. [368] use a two-stage approach to determine the minimum rating of MESS that can perform service restoration while working on a power network.

7.4 Methodology

The main purpose of the study is to conduct a comparative technical analysis of energy management of the proposed microgrid system with two different interconnection architectures. The feasibility of integrating the proposed A-ETR to improve microgrid resiliency is also discussed. In order to establish the best microgrid architecture for future green airport electrification, the proposed airport electrical network has been modelled and simulated as a low-voltage AC and DC microgrid in a DigSILENT power factory. DigSILENT PowerFactory is a powerful software that enables users to perform a wide range of power system analysis tasks, including steady-state and dynamic analysis, power flow, and short-circuit analysis. It offers advanced modelling capabilities, allowing users to model complex power system components using extensive libraries of pre-built models that can be customized as required. Additionally, PowerFactory is capable of integrating with other software packages, enabling users to import and export

data between different software platforms [378]. Two case scenarios have been considered:

- Case 1: Also known as (the base scenario), where the proposed microgrid is modelled as an LVDC and connected to the existing airport grid via a high-power centralised converter architecture through a DC bus.
- Case 2: A modified case where the proposed microgrid is modelled as an LVAC and connected to the existing airport grid via the point of common coupling (PCC) through an AC bus.

The following six-step methodology has been followed to perform a comparative technical analysis of the proposed cases to ascertain their suitability for future green airport electric grids.

Step 1: Modelling and simulation of the base case LVDC microgrid architecture while performing load, real and reactive power flow analysis.

Step 2: Determining the optimum rating /size/capacity of each piece of equipment as per load demand and load flow analysis.

Step 3: Modelling the varying load as per the airport's typical day flight schedule. It is important to mention here that the aircraft taxiing and charging load is the only variable load that varies with the flight schedule.

Step 4: Modelling the economic dispatch from the fuel cells, grid supply, BESS and A-ETR as per assumed per-unit.

Step 5: Performing the protection studies (fault level) determination by replacing the central AC/DC converter, installing individual converters with all DC loads, and performing load flow and protection studies (fault level) on the modified case.

Step 6: performing Quasi-dynamic, contingency, and reliability index analysis on the microgrid with and without integrating A-ETR to support grid operation.

Based on the comparison of the aforementioned technical analysis, a conclusion can be drawn about the suitability of the two architectures mentioned above.

Secondly, the benefit of the A-ETR application as an EaaS concept is technically demonstrated.

7.5 System Modeling

7.5.1 Low voltage DC (LVDC) architecture

The proposed green airport energy supply structure has been modelled in the power factory DigSILENT as shown in Figure 7-2. The external grid connection is modelled using Slack Bus with a set-point of voltage 1.0 p.u. and an angle of 0 degrees [64].

The PV, fuel cell and BESS systems have been modelled as static generators and connected to the 0.4kV LV DC bus five via PWM converters and other buses with nominal voltages are modelled as shown in Appendix E

7.5.2 Bus-bars modelling

The following buses are modelled with nominal voltages as shown in Table 7-1

Table 7-1 Buses with nominal voltages

No.	Bus Name	Voltage (kV)
1	Bus1 - Grid Connection	19.05(L-G)/33(L-L)
2	Bus2 - Primary Transformer Connection	19.05(L-G)/33(L-L)
3	Bus3 - Secondary Transformer Connection	6.35(L-G)/11(L-L)
4	Bus4 - Converter Connection	0.132(L-G)/0.23(L-L)
5	Bus 5 - Main DC	0.4
6	Bus 6 - Secondary DC	0.4
7	Bus 7 - DC Load1	0.4
8	Bus 8 - DC Load 2	0.4

7.5.3 Lines /Cables modelling

The line data is shown in Table 7-2

Table 7-2: Lines/cables parameters

No.	Line Name	Voltage (kV)
1	Distribution Cable 1	19.05(L-G)/33(L-L)
2	Distribution Cable 2	19.05(L-G)/33(L-L)
3	Link 1	6.35(L-G)/11(L-L)
4	Link 2	0.132(L-G)/0.23(L-L)
5	Link 3	0.4
6	Line A	0.4
7	Line B	0.4

Links 1, 2 and 3 are zero impedance lines. The basic parameters of cables 1 and 2 are shown in Appendix E

7.5.4 Load modelling

For analysis, all loads are fixed except the aircraft and EGSV electric load.

Table 7-3 Load parameters

No.	Loads	Maximum value (MW)	Minimum value (MW)
1	General load	1	1
2	Gate/Apron load	0.5	0.5
3	Control tower load	0.5	0
4	PCA load	1	1
5	Direct aircraft taxiing load	8.4	0.5
6	Swapping charging station load	1	1
7	EGSV direct charging load	0.5	0.5
8	General DC load	0.5	0.5
9	Deicing load	0.1	0.1
10	Runway LED lighting load	0.1	0.1
	Total	13.6	5.2
*All loads are fixed except direct aircraft and EGSV charging load			

According to the Table 7-3, the maximum and minimum value of other loads in the airport are fixed to allow the simulation account for only the electric aircraft and EGSV charging loads.

Similarly, the basic parameters for lines A and B are as follows:

- Rated Voltage: 0.4 kV (L-L)
- Rated Power: 1 MVA
- System Type: DC
- Inductance L: 0.01 mH
- Resistance R: 0.01 Ohm
- Max. Loading: 100%

7.5.5 Converter modelling

The parameters of the main AC/DC converter and the PWM converters for the (BESS, solar PV, and fuel cell) are shown in Appendix E. The parameters for the PWM converters and the DC/DC Converter, the following parameters are:

- Rated Current: 6000 A
- Alpha U2/U1: 1.01

7.5.6 Aircraft electric load modelling

There are sets of EGSVs for passengers and goods transportation on the airside. But in this analysis, only the hourly electric load profile of the aircraft and EGSV model according to [201] is made to vary with respect to the flight schedule, while other loads are fixed to account for the taxiing and charging load demand in the airport. Aircraft electric load for a terminal in the airport shown in Table 7-4 varies according to the flight schedule [243].

Table 7-4 Aircraft hourly electric load profile at the contact.

Time (hrs.)	Electric aircraft load (MW)	Time (hrs.)	Electric aircraft load (MW)
00:00	0.9	12:00	1.6
01:00	0.4	13:00	2.2

Time (hrs.)	Electric aircraft load (MW)	Time (hrs.)	Electric aircraft load (MW)
02:00	0.4	14:00	2.6
03:00	0.4	15:00	1.8
04:00	0.4	16:00	1.2
05:00	0.6	17:00	1.0
06:00	1.2	18:00	2.0
07:00	3.0	19:00	0.9
08:00	2.5	20:00	1.8
09:00	0.9	21:00	2.4
10:00	0.9	22:00	3.0
11:00	0.9	23:00	2.0

This load has been modelled in DigSILENT power factory for direct aircraft taxiing load and EV charging load, as shown in Figure 7-4.

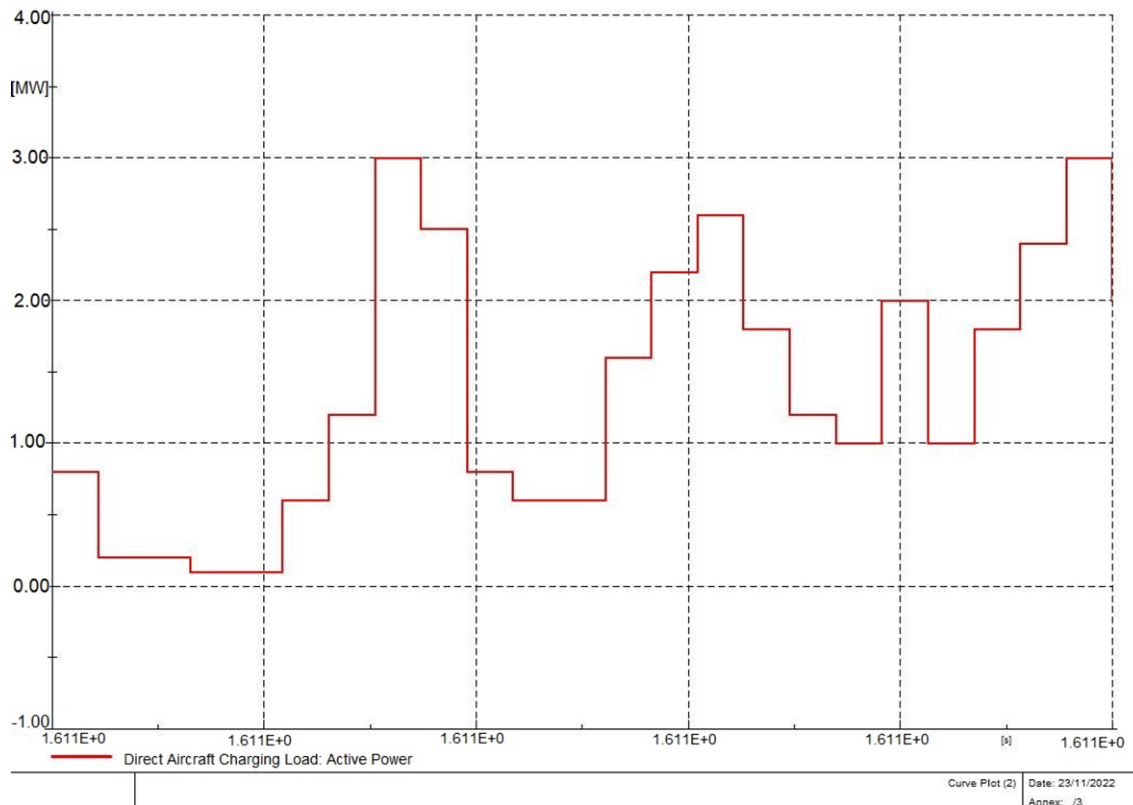


Figure 7-4 Taxiing/E.V charging load variation on a typical day

7.5.7 Generator modelling

7.5.7.1 Solar PV Modelling:

The availability of a large and sufficient land area in most airports supports the implementation of the ASPV worldwide. Depending on the airport's layout, PV power plants may be constructed on rooftop systems, photovoltaic carports, and open spaces, capable of generating clean and self-sufficient airport energy supply [31],[379],[87],[86].

Real-time data recorded every half-hour between June 2018 to May 2019 at Cranfield University (Cranfield, UK) has been used to obtain the temperature and solar irradiance (G) values. Other parameters are considered constants, as provided in the manufacturer data table. Therefore, the power output from the inverters of the PV power plant can be calculated as follows [212]:

$$P_{inv} = \frac{G}{G_{ref}} * P_{mp,ref} * [1 + \gamma(T - T_{ref})] * N * \eta_{inv} \quad (7-1)$$

The cell temperature T_c can be calculated as:

$$T_c = T_a + \frac{NOCT - 20}{800} * G \quad (7-2)$$

And the output power at the grid side is given by:

$$P_o = P_{inv} * \eta_{cables} \quad (7-3)$$

Other constant parameters are mentioned in Table 7-5.

Table 7-5 Cranfield airport Solar PV parameters

Parameter	symbol	Value
Reference irradiance at STC	G_{ref}	1000 kWh/m ²
Annual generating capacity		1,000 MWh
Maximum power of the PV module at STC	$P_{mp,ref}$	285 W
Temperature coefficient of V_{oc} = -0.3 %/°C	γ	-0.144V/K

Parameter	symbol	Value
Temperature coefficient of Power = -0.3 %/°C		-0.4%K
Reference ambient temperature at STC	T_{ref}	25 °C
Number of PV modules N	N	3508
Inverter Efficiency	η_{inv}	0.985
Number of inverters (Fronius Eco/Symo)	Ta	35
Nominal Operating Cell Temperature	NOCT	45 °C
Cables Efficiency	η_{cables}	0.99
Maximum Power Voltage	V_{mp}	31.99 V
Maximum Power Current	I_{mp}	8.91 A
Open-Circuit Voltage	V_{oc}	39.22 V
Short-Circuit Current	I_{sc}	9.46 A
Cell Efficiency	η	17.6%
Series Fuse Rating		20A

The modelled output profile from solar PV for a typical day is shown in Figure 7-5

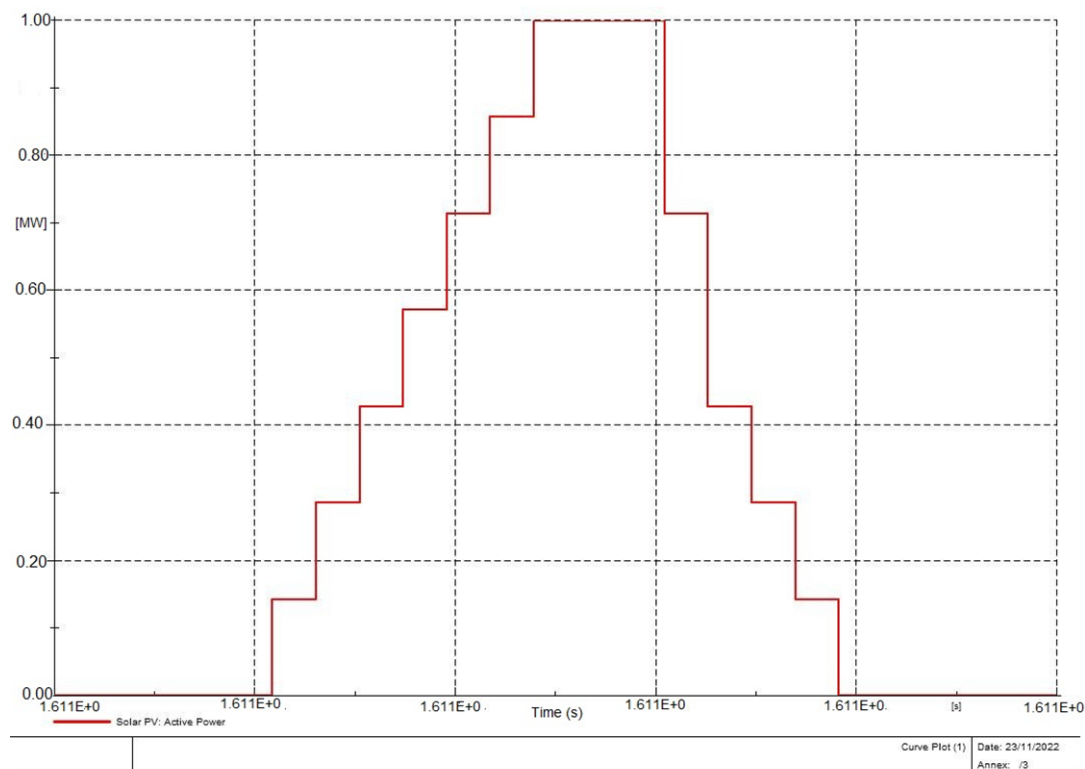
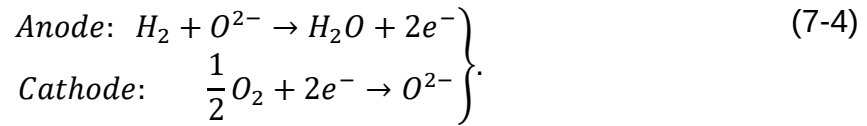


Figure 7-5 PV power output from the DigSiLENT Powerfactory simulation

7.5.7.2 Fuel cell Modelling

Fuel cells (FCs) are electrochemical devices that convert the chemical energy of fuel into electrical energy. Different types of FCs are available, such as polymer electrolyte membrane FC, solid oxide FC (SOFC), alkaline FC, etc. In this study, the SOFC has been used due to its exceptional efficiency and thermal stability in high-power stand-alone power applications. The SOFC stack's energy-conversion efficiency can reach up to 65%, and its overall efficiency, when utilized in combined heat and power (CHP) applications, can exceed 70% [380].

The chemical reaction taking place at the electrodes is written as [381]:



The Nernst equation can be used to express the voltage generated in a cell (V_{cell}) based on the chemical reactions occurring at the cathode and anode. [380]

$$V_{cell} = E_{cell} - V_{act,cell} - V_{ohm,cell} - V_{conc,cell} \quad (7-5)$$

With

$$E_{cell} = E_{0,cell} - kE(T_{fc} - 298) + \frac{RT_{fc}}{2F} \ln \left\{ \frac{p_{H_2} \sqrt{p_{O_2}}}{p_{H_2O}} \right\} \quad (7-6)$$

$$V_{fc} = N_{cell} V_{cell}, \quad P_{fc} = V_{fc} I_{fc} \quad (7-7)$$

Where E_{cell} is the Nernst's potential, $V_{act,cell}$ is cell-activation potential $V_{conc,cell}$ is concentration potential, $V_{ohm,cell}$ is ohmic potential drop, $E_{0,cell}$ is the Gibbs potential, kE is Boltzmann constant, P_{fc} is power from FC, N_{cell} is the number of cell in the stack, and T_{fc} is the operating temperature.

7.5.8 Mobile storage allocation for resilience

7.5.8.1 Objective function

The optimal switch position and location of the A-ETR in the microgrid is considered an optimisation objective function to minimise power system losses. The objective function can be defined as:

$$\text{Min}(F) = \text{Min}(P_{\text{loss}}) \quad (7-8)$$

The microgrid power distribution losses can be calculated as

$$P_{\text{loss}} = \sum_{n=1}^{N_c} P_L^d \times \beta \times t_N \quad (7-9)$$

Where N_c is the number of state resulting from uncertainties in the energy generation from renewable resources such as wind and solar PV [382]. P_L^d is the daily losses on the system, β is the probability of zero autonomous state and t_N is the time interval of the autonomous state.

The balance of power equation in the microgrid is calculated as [77]:

$$P_T = \sum_{n=1}^{24} (P_{gt} + P_{slt}) \quad (7-10)$$

$$- \sum_{n=1}^{24} \left(\sum_{j=1}^{NDG} P_{DGt} + \sum_{n=1}^{24} \sum_{m=1}^{N_{A-ETR}} \eta P_{A-ETR} - \sum_{n=1}^{24} \sum_{m=1}^{N_{A-ETR}} \frac{P_{A-ETR}}{\eta} \right)$$

Where P_{gt} is the total generation power in the system at time t , P_{slt} is the total system losses at time t , P_{DG} is the power generated by the j^{th} -based DG at time t , NDG is the total number of DGs, P_{A-ETR} is the real power of the A-ETR in kW, N_{A-ETR} is the number of A-ETR within the microgrid in the power distribution system, and η is the efficiency of the mobile storage system battery.

The amount of renewable energy penetration offered by the A-ETR system on the grid can be calculated as follows:

$$\%RES = \frac{\text{Total RE Power Plant Generation}}{\text{Total Power Generated}} \times 100\% \quad (7-11)$$

7.5.8.2 Constraints

- Real and reactive power flow should satisfy the following equation.

$$P_{A-ETR} + \sum P_{DGt} \quad (7-12)$$

$$- \sum P_{Load(t)} = \sum_{k=1}^{nbus} V_{t,k} \times V_{t,j} \times Y_{k,j} \\ \times \cos(\theta_{k,j} + \delta_{k,j} - \delta_{t,k})$$

$$Q_{A-ETR} + \sum Q_{DGt} \quad (7-13)$$

$$- \sum Q_{Load(t)} = \sum_{k=1}^{nbus} V_{t,k} \times V_{t,j} \times Y_{k,j} \\ \times \sin(\theta_{k,j} + \delta_{k,j} - \delta_{t,k})$$

- Feeder capacity limit

$$P_{loss} = \sum_{n=1}^{N_c} P_L^d \times \beta \times t_N \quad (7-14)$$

- Power limit for P_{A-ETR}

$$P_{SA-ETR(min)} \leq P_{SA-ETR(t,k)} \leq P_{SA-ETR(max)} \quad (7-15)$$

- Bus voltage and power line current limit

$$V_{(min)} \leq V_{(t,k)} \leq V_{(max)} \quad (7-16)$$

$$I_{(k)} \leq I_{(max,k)} \quad (7-17)$$

7.5.9 Economic dispatch

The economic dispatch problem has been presented as an optimisation problem to minimise the total fuel cost of all committed plants while still fulfilling demand and losses. There are many variants of the problem, each modelling the objective and constraints differently. Nevertheless, the fundamental economic dispatch problem can be described mathematically as minimising the total fuel cost of all committed plants subject to constraints.

$$\text{Minimize} \sum_{i=1}^n F_i(P_i) \quad (7-18)$$

$(F_i(P_i))$ is the fuel cost equation of the i^{th} generator. It is the variation of fuel cost (£) with generated power (MW). It is usually expressed as a continuous quadratic equation.

$$F_{ij}(P_i) = a_1 P_i^2 + b_i P_i + C_i, \quad (7-19)$$

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

The total generation (P_i) should meet the total demand (D) and transmission losses (P_l).

The joint optimisation objective function can be expressed as

$$\text{Min}(F) = \text{Minimise} \sum_{n=1}^{N_c} P_L^d \times \beta \times t_N + \sum_{i=1}^n F_i(P_i) \quad (7-20)$$

7.5.10 Load distribution between sources and loss coefficient

Because of the transmission losses caused by the plant with the lower incremental fuel cost, the economy may require lowering the load at that plant while boosting it at the plant with the higher incremental fuel cost. Therefore, the overall transmission loss of the system must be expressed as a function of the plant loadings to account for transmission line losses in estimating the economic loading of plants. Figure 7-6 shows a simple transmission loss diagram for two DGs and one load, illustrating simple transmission losses.

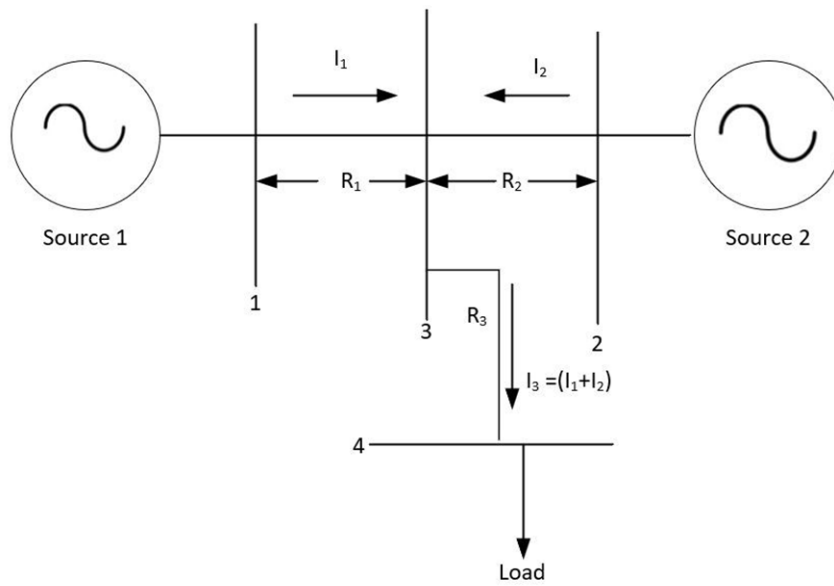


Figure 7-6 A simple system for connecting two generators to one load

Let R_1 , R_2 and R_3 be the resistance of lines 1,2 and 3, respectively. Then the total power loss of the three-phase transmission system is given by

$$P_L = 3|I_1|^2 R_1 + 3|I_2|^2 R_2 + 3|I_3|^2 R_3 \quad (7-21)$$

I_1 and I_2 , are assumed to be in phase so that,

$$I_3 = |I_1 + I_2| = |I_1| + |I_2| \quad (7-22)$$

$$(I_1 + I_2)^2 = (I_1 + I_2)(I_1 + I_2) = I_1^2 + 2I_1 I_2 + I_2^2 \quad (7-23)$$

Substituting (7-22) in (7-21)

$$P_L = 3|I_1|^2 R_1 + 3|I_2|^2 R_2 + 3[I_1^2 + 2I_1 I_2 + I_2^2] R_3 \quad (7-24)$$

$$P_L = 3|I_1|^2 [R_1 + R_3] + 3|I_2|^2 [R_2 + R_3] + 6[I_1 I_2] R_3 \quad (7-25)$$

P_1 and P_2 are the output power at DG₁ and DG₂ respectively with bus voltages V_1 and V_2 at power factor $\cos\theta_1$ and $\cos\theta_2$, so that

$$|I_1| = \frac{P_1}{\sqrt[3]{V_1 \cos\theta_1}} \quad \text{and} \quad |I_2| = \frac{P_2}{\sqrt[3]{V_2 \cos\theta_2}} \quad (7-26)$$

Substituting (7-26) in (7-25) gives

$$|P_L| = \frac{P_1^2 (R_1 + R_3)}{|V_1|^2 (\cos\theta_1)^2} + \frac{2P_1 P_2 (R_3)}{|V_1| |V_2| (\cos\theta_1) (\cos\theta_2)} + \frac{P_2^2 (R_2 + R_3)}{|V_2|^2 (\cos\theta_2)^2} \quad (7-27)$$

$$P_L = P_1^2 B_{11} + 2P_1 P_2 B_{12} + P_2^2 B_{22} \quad (7-28)$$

Where

$$B_{11} = \frac{(R_1 + R_3)}{|V_1|^2 (\cos\theta_1)^2}, \quad B_{12} = \frac{(R_3)}{|V_1| |V_2| (\cos\theta_1) (\cos\theta_2)}, \quad B_{22} = \frac{(R_2 + R_3)}{|V_2|^2 (\cos\theta_2)^2} \quad (7-29)$$

B_{11} , B_{12} and B_{22} are referred to as the loss coefficients or the B – coefficients which remain constant with the variation of P_1 and P_2 if the bus voltage and power factor at the DGs remain constant. (7-28) represents the bus coefficient approach used to account for transmission loss in the economically balanced load distribution between the sources. Its unit is (MW⁻¹).

The loss equation for jth number of sources can be represented with the general form

$$P_L = \sum_i^n \sum_j^n B_{ij} P_i P_j \quad (7-30)$$

Where $\sum_i$ and $\sum_j$ represent the summation of the sources in the microgrid.

The transmission loss matrix equation is $P_L = B_{ij} P^T$

$$P = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_j \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1j} \\ B_{21} & B_{22} & \cdots & B_{2j} \\ B_{31} & B_{32} & \cdots & B_{3j} \\ \vdots & \vdots & \ddots & \vdots \\ B_{j1} & B_{j2} & \cdots & B_{jj} \end{bmatrix} \quad (7-31)$$

The distribution loss can be determined from the B_{mn} coefficients as:

$$\sum_{i=1}^n P_i = D + P_L \quad (7-32)$$

where B_{ij} are the elements of matrix B representing loss coefficients. This program solves the economic dispatch problem with the particle swarm optimisation (PSO) toolbox developed by Brian Birge [383],[384]. The constrained optimisation problem is converted to an unconstrained problem using the penalty function method defined in (7-33).

$$\sum_{i=1}^n F_i(P_i) + 1000 * abs\left(\sum_{i=1}^n P_i - D - \sum_{i=1}^n \sum_{j=1}^n B_{ij} P_i P_j\right) \quad (7-33)$$

The data matrix for the dispatching cost coefficients and plant limits is described in Table 7-6

Table 7-6: Allocation schedule and plant limits.

	C (£/MW ²)	B (£/MW)	Fixed cost (£/hr.)	Min Dispatch (MW)	Max Dispatch (MW)
Slack	0.0048	1.21	1.61	0	15
BESS1	0	0	2.98	0	1.5
BESS2	0	0	2.98	0	1.5
Fuel Cell1	0	0	3.14	0	1.5
Fuel Cell2	0	0	3.22	0	1.5
PV	0	0	2.01	0	1

7.6 Solution algorithm

The heuristic particle swarm optimisation (PSO) is used for the optimisation as an evolutionary optimisation technique inspired by nature. Unlike other evolutionary-type methods, PSO does not use filtering operations (such as crossovers and mutations) and maintains the entire population throughout the search procedure [385]. PSO is developed by simulating bird flocking or fish schooling in two-dimensional space. In this case, the positions of each agent are expressed as X-Y axes positions, and their velocity is expressed as V (velocity of X-axis and Y-axis). Information about the agent's position and velocity is used to adjust the agent's position. Every agent knows its best value (Pbest) and its X-Y coordinate position. Also, each agent knows the best value in the group (Gbest) from the list of Pbests. Agents adjust their positions based on the following information:

- Distance between currently occupied position and “Pbest
- Distance between the current position and “Gbest
- The concept of velocity can be used to represent this modification.

PSO algorithms are composed of a number of randomly generated particles. Each particle has its own position and velocity, which is given as:

$$P_i = (P_{i1}, P_{i2} \dots \dots \dots P_{in}) \quad (7-34)$$

$$V_i = (V_{i1}, V_{i2} \dots \dots \dots V_{in}) \quad (7-35)$$

Particles remember their best position (P_{best}), and (G_{best}) is the best position achieved by any particle in the population. The value of the P_{best} and G_{best} update at every iteration to get the optimal configuration. The following equation will update the particle velocity:

$$V_i^{k+1} = V_i^k \times W + C_1 r_1 (P_{best\ i} - P_i^k) + C_2 r_2 (g_{best\ i}^k - P_i^k) \quad (7-36)$$

where V_i^{k+1} is the velocity of the i^{th} particle at $(k+1)^{th}$ iteration, V_i^k is the velocity of the i^{th} particle at k^{th} iteration, r_1 and r_2 are random numbers between [0,1], C_1

and C_2 are numbered between 1.5 to 2.5, *and* W is the inertial weight expressed as in (7-37) [386]:

$$W = W_{max} - \frac{W_{max} - W_{min}}{I_{trmax}} \times I_{tr} \quad (7-37)$$

where

W_{max} , is the final inertial weight, W_{min} is initial inertial weight, I_{trmax} is the maximum iteration number, I_{tr} is the current iteration. Each particle position is then updated again by equation (7-38) following the velocity update:

$$p_i^{k+1} = p_i^k + v_i^{k+1} \quad (7-38)$$

Where, p_i^{k+1} represent the i^{th} particle position in $(k+1)^{th}$ iteration, p_i^k represent the i^{th} particle position in k^{th} iteration.

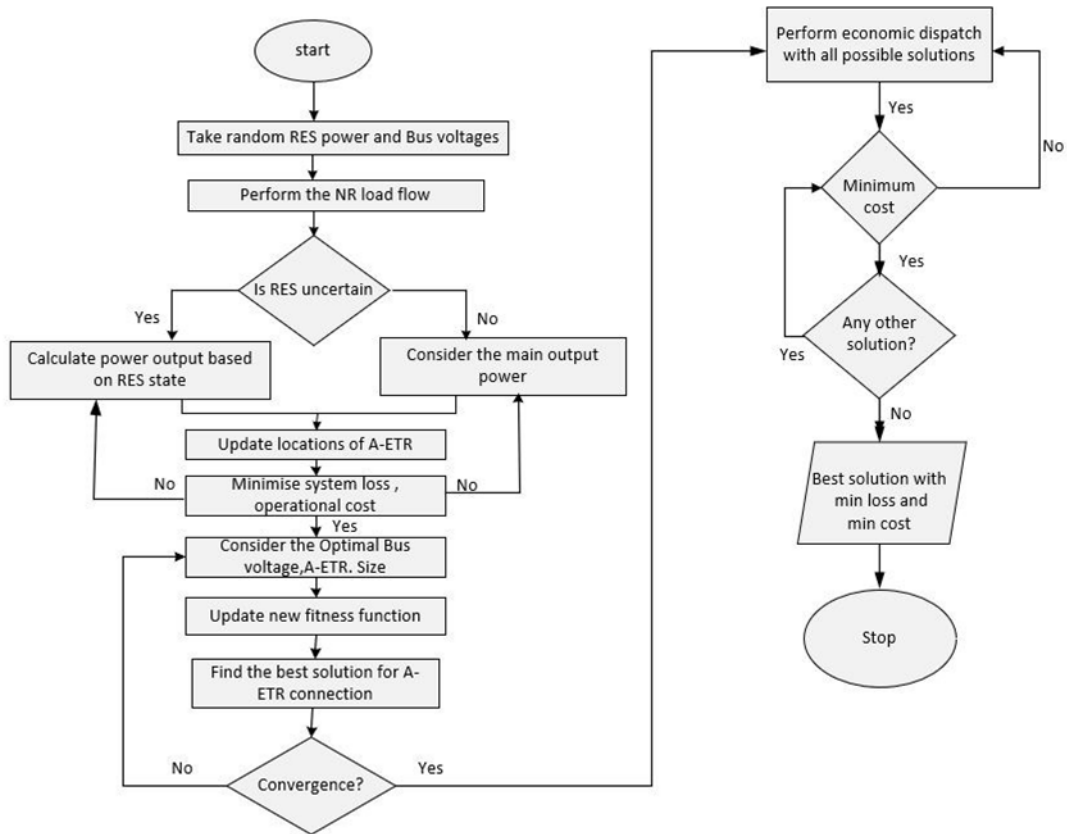


Figure 7-7 Algorithm Flowchart

The output from DigSILENT Power Factory is used to define the fitness function for the PSO algorithm. The fitness function is based on the total cost of power generation, the RES output generation, the line losses, and the bus voltages. The PSO algorithm uses this fitness function to evaluate the performance of each particle and adjust the position of the particles in the solution space to optimize the fitness function. By iteratively evaluating and adjusting the particles, the PSO algorithm converges to a set of optimal solutions for dispatching costs and A-ETR allocation schedules. The output from the PSO algorithm is then used to determine the optimal dispatching and allocation schedule for the A-ETR in the microgrid system.

The PSO algorithm interface with Digsilent Power Factory is well-suited for solving economic dispatch and scheduling problems in microgrids because it allows users to define the objective function, decision variables, and constraints of the optimisation problem in a user-friendly interface. This makes it easier to set up and solve microgrid optimisation problems using Power Factory than others. In addition, PSO is more suitable for optimisation problems with complex search spaces and non-linear objective functions [387], while GA is better suited for optimisation problems with discrete decision variables [273]. In addition, PSO is faster and requires fewer computational resources than GA. PSO is also more suitable for solving multi-objective optimisation problems compared to simulated annealing SA, which is suitable for optimisation problems with a large number of local optima, but it can be slow and may require more computational resources [388]. PSO is also more suitable than the ant colony optimisation ACO which is suitable for optimisation problems with discrete decision variables and can be slower and more computationally expensive [389]. The computational efficiency of the PSO makes it suitable for solving large-scale optimisation problems in real-time. This is important in power systems where optimal operating conditions must be determined quickly to avoid system instability and ensure a reliable power supply [390].

7.7 Result and discussion

As stated earlier in Table 7-3, the minimum and maximum load demand for our study are 5.2 and 13.6 MW, respectively. Based on the minimum and maximum load demand, four cases are simulated in the PSO algorithm by feeding load demands at 10%,15%, 20% and 30% penetration of electric taxiing charging load, i.e., 4, 5.6, 7.5, and 13.6 MW, respectively. The results of the respective economic dispatches from the microgrid in the different cases are given in Table 7-7.

Table 7-7 Economic load dispatch

	Case 1	Case 2	Case 3	Case 4
Load	13.6	5.6	4	7.5
Dispatch (MW)	(30%) penetration	(15%)	(10%)	(20%)
Slack	6.6039	0.0000	0.0000	0.5016
BESS1	1.5000	1.5000	1.4999	1.5000
BESS2	1.5000	1.0451	0.6961	1.5000
Fuel Cell1	1.5000	0.9600	0.6660	1.5000
Fuel Cell2	1.5000	0.7000	0.1382	1.5000
PV	1.0000	1.0000	0.9999	1.0000

We have considered (BESS1+BESS2) and (Fuel cell1 +Fuel cell 2) for simplicity in the DigSILENT simulation.

7.7.1 Load flow simulation

The results of load flow simulation using the Newton-Raphson, three-phase balanced method are shown in Table 7-8 for the LVDC and LVAC microgrid.

7.7.2 Short circuit analysis (LVDC) and (LVAC)

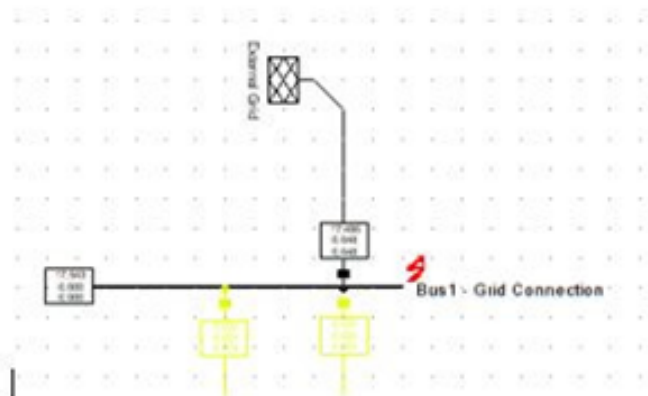
Protection study/short circuit analysis has been performed on the LVDC and LVAC microgrid to determine the fault level at various buses in the modelled system, and a maximum short circuit fault level of 92.4kA under LVDC and 38.3

kA under LVAC architecture are obtained. Hence, the equipment with a standard short circuit rating of 95 kA will be installed for the LVDC and 40 kA for the LVAC architecture, respectively, as shown in Table 7-8. Hence, since the LVAC microgrid architecture has a lower short circuit fault level, it will require lower-rating protective equipment with reduced cost.

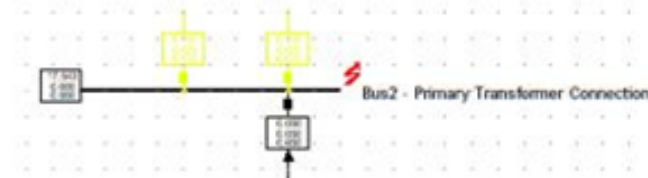
Table 7-8 Load flow and short-circuit analysis.

	Load flow analysis			Short-circuit analysis		
	Average transformer loading (%)	Max transformer loading (%)	Lowest voltage bus	Average line loading (%)	Max short circuit fault current (kA)	Max fault current
LVDC	48	60.5	Bus 8	4.5	92.4	Bus 4
LVAC	67.1	69.5		67.3	38.3	

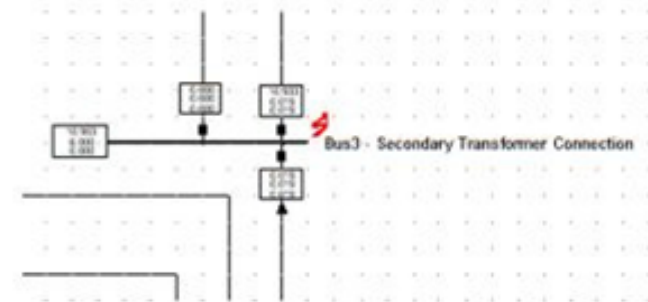
Bus 1 – Grid Connection:



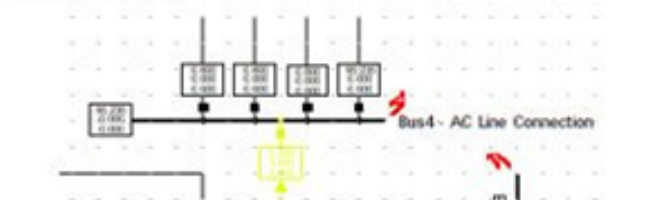
Bus 2 – Primary Transformer Connection:



Bus 3 – Secondary Transformer Connection:



Bus 4 – AC Line Connection:



Bus 5 – Generators Connection:

Figure 7-8 Single-phase short circuit analysis of LVAC architecture using the IEC 60909 method.

Table 7-9 Short circuit data

Component	Initial Current I_k'' (kA)	Peak Current I_p (kA)
Bus 1	17.54	43.32
Bus 2	17.54	43.32
Bus 3	10.95	23.98
Bus 4	95.23	208.78
Bus 5	95.23	208.77
Bus 6	95.23	208.76
Bus 7	95.22	208.76
Bus 8	95.22	208.75

7.7.3 Power losses

The quasi-dynamic simulation performed on the microgrid for 24 hours and their comparison in terms of power losses are shown in Figure 7-9. Figure 7-10 below shows that the average power losses in the LVDC are around 0.9 MW, which is higher than 0.31MW in LVAC architecture under the same loading condition. Hence, this would pay off significantly during the actual operation years and reduce the overall energy cost for the microgrid operation. The microgrid experience the highest voltage deep during the fault at bus eight and the highest fault current at bus four. These two buses will be prioritised for A-ETR integration for grid support.

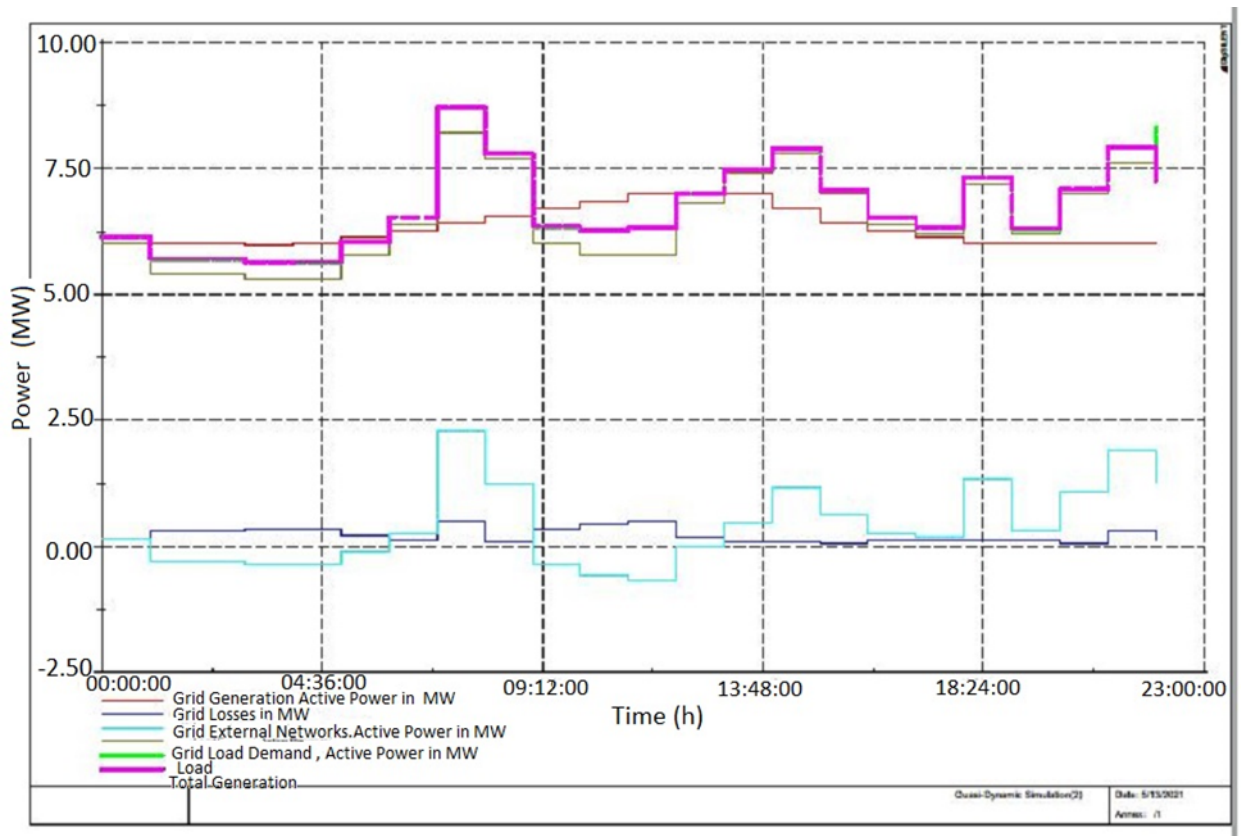


Figure 7-9 Losses (LVAC) architecture

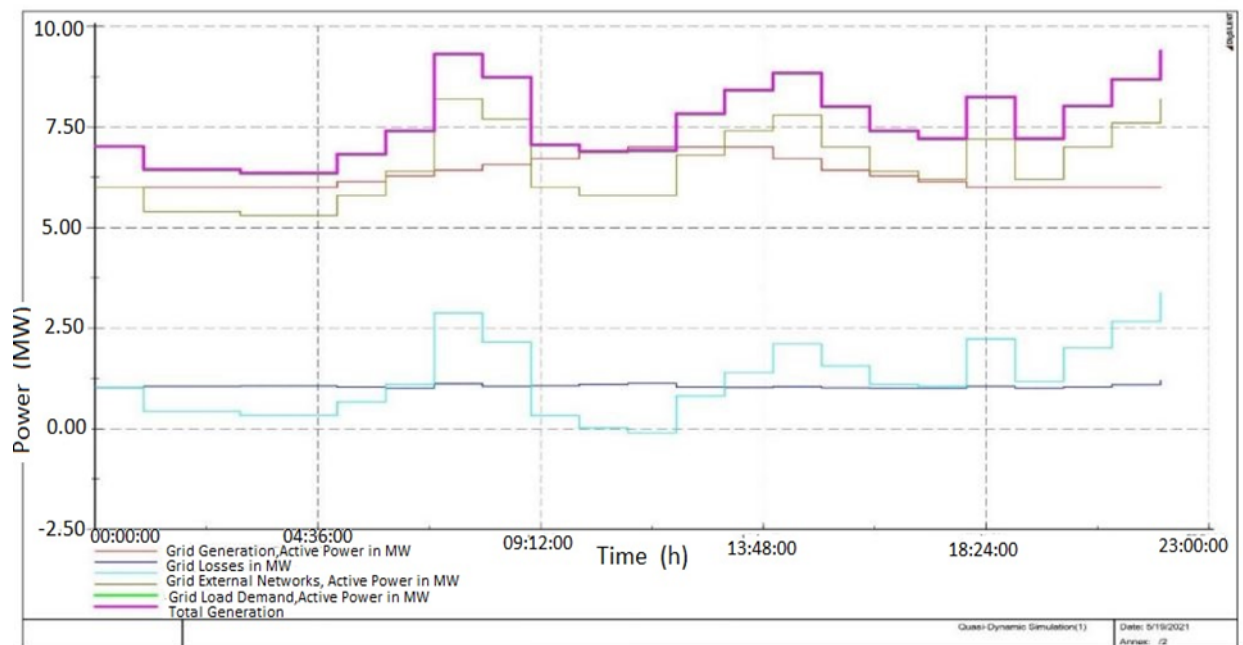


Figure 7-10 Losses (LVDC) architecture

7.7.4 Voltage profile

From Figure 7-11 and Figure 7-12, it can be seen that the LVDC architecture minimum voltage profile improved from 0.70 p.u in the LVAC architecture to 0.95 p.u in the LVDC architecture. As shown in Figure 7-11, the voltage was steady for all the buses and within the statutory voltage range between 0.94 p.u (-6%) to 1.10 p.u (+10%) for the low-voltage network [391]. The voltage profile in the LVAC in Figure 7-12 fluctuates and is sometimes outside the statutory voltage range. At peak load demand at 07:00 and 22:00, there are potential violations of the statutory voltage range resulting in significant voltage drops in the LVAC to the values of 0.70 and 0.75 p. u, respectively, on a typical day under simulation. This result permits future studies for optimal compensation in the network.

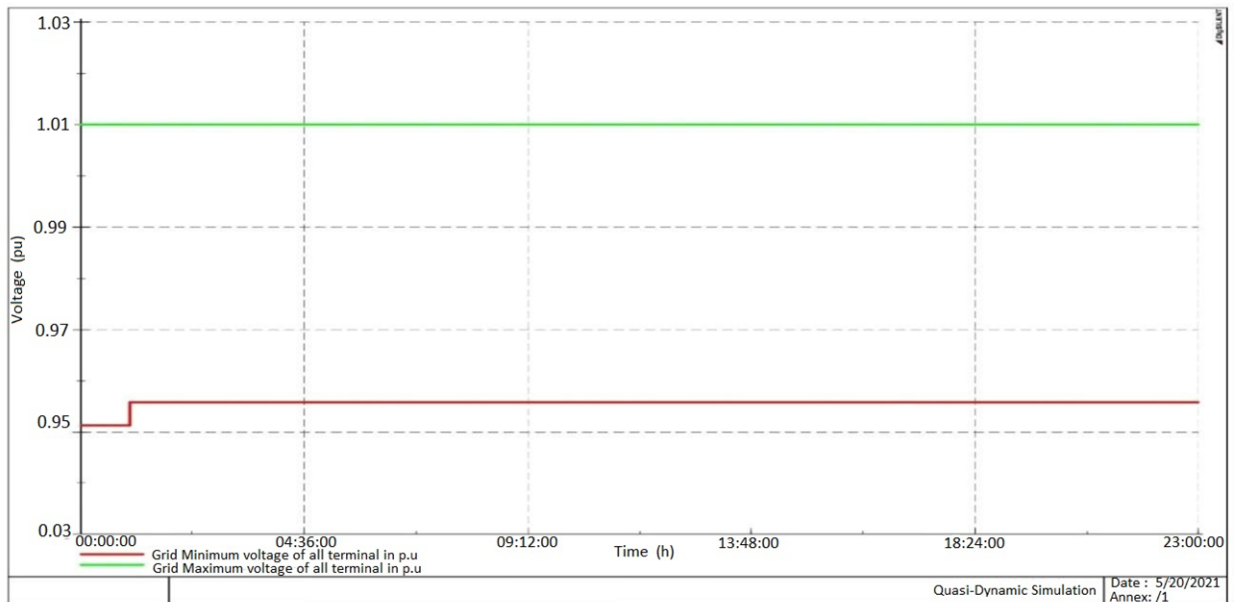


Figure 7-11: Voltage profile (LVDC) architecture

Figure 7-11 and Figure 7-12 show indicators that measure the quality of the voltage profile in the network.

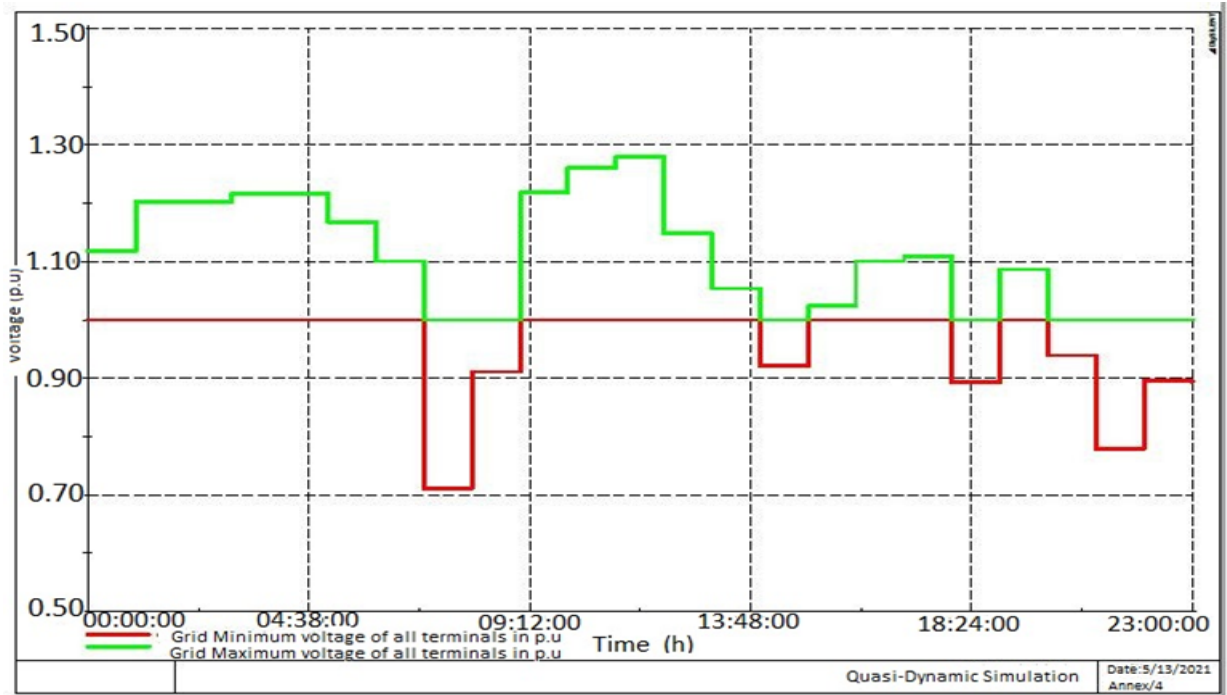


Figure 7-12 Voltage Profile (LVAC) architecture

7.7.5 Percentage loading

From the load demand and the optimal generation, the maximum percentage loadings on the line and equipment in the microgrid are steady and remain at 100% in the LVDC architecture. In contrast, there are potential violations in the maximum percentage loading in the microgrid in the LVAC architecture. The maximum percentage loading rises to 149% and 129% at peak load demand at 07:00 and 22:00, respectively, as shown in Figure 7-13.

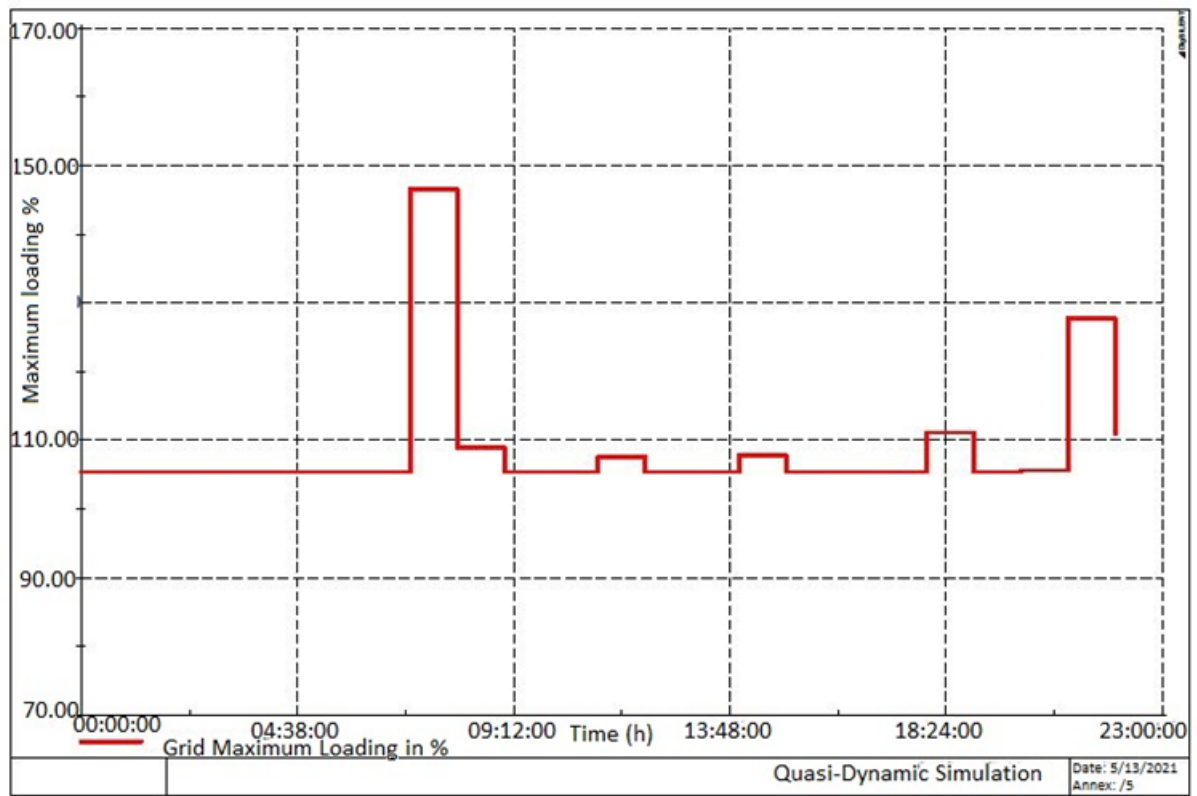
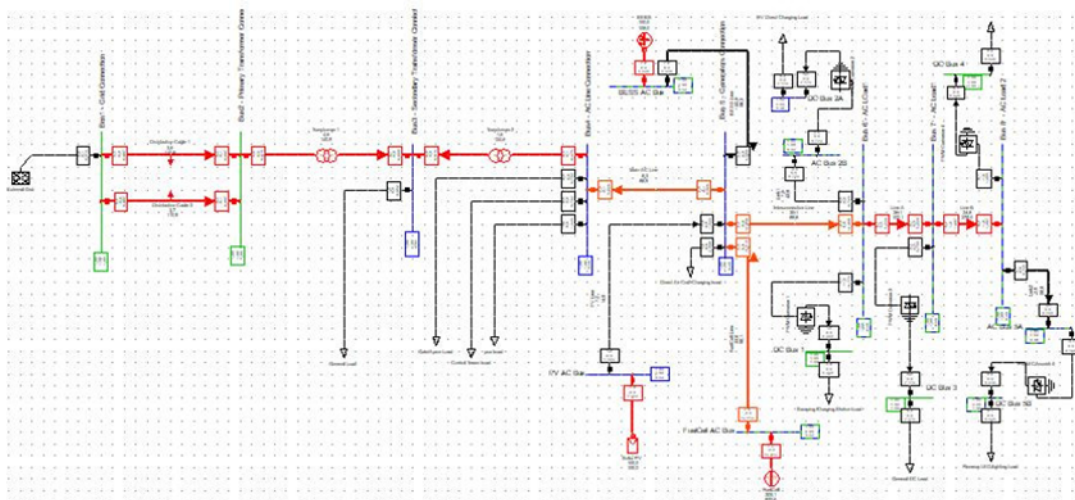


Figure 7-13 Percentage Loading LVAC architecture

7.8 Microgrid system resilience improvement analysis with and without A-ETR



Minimum Voltages:

	Component	Branch, Substation or Site	Voltage Min. [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name	Base Case and Post Voltage [0.854 p.u. - 1.000 p.u.]
1	AC Bus 2B		0.854	-0.146	1.000	2	FuelCell	
2	AC Bus 5A		0.854	-0.146	1.000	2	FuelCell	
3	BESS AC Bus		0.854	-0.146	1.000	2	FuelCell	
4	Bus 5 - Generators Connec		0.854	-0.146	1.000	2	FuelCell	
5	Bus 6 - AC Load 1		0.854	-0.146	1.000	2	FuelCell	
6	Bus 7 - AC Load 2		0.854	-0.146	1.000	2	FuelCell	
7	Bus 8 - AC Load 3		0.854	-0.146	1.000	2	FuelCell	
8	Bus4 - AC Line Connector		0.854	-0.146	1.000	2	FuelCell	
9	FuelCell AC Bus		0.854	-0.146	1.000	2	FuelCell	
10	PV AC Bus		0.854	-0.146	1.000	2	FuelCell	

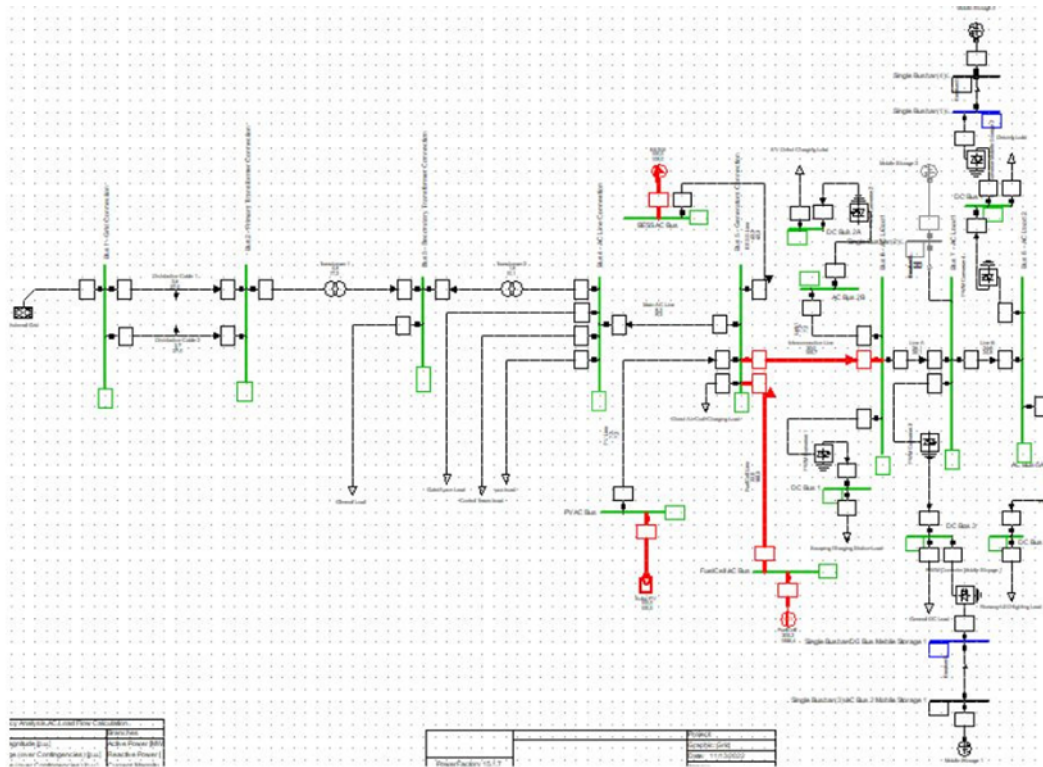
Maximum Voltages:

	Component	Branch, Substation or Site	Voltage Max. [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name	Base Case and Post Voltage [1.000 p.u. - 2.410 p.u.]
1	DC Bus 2A		2.410	1.410	1.000	12	Main AC Line	

Maximum Loading :

	Component	Branch, Substation or Site	Loading Continuous [%]	Loading Short-Term [%]	Loading Base Case [%]	Contingency Number	Contingency Name	Base Case and Continuous Loading [0 % - 298 %]
1	Line B		298.4	298.4	12.4	107	Link 1-Main AC Line	
2	FuelCell Line		184.7	184.7	71.7	170	Main AC Line	
3	Interconnection Line		181.9	181.9	68.7	170	Main AC Line	
4	Transformer-1		132.3	132.3	4.6	21	FuelCell-BESS	
5	Transformer-2		116.9	116.9	1.6	21	FuelCell-BESS	
6	Distribution Cable 2		104.2	104.2	3.7	21	FuelCell-BESS	
7	Distribution Cable 1		104.1	104.1	3.6	21	FuelCell-BESS	
8	Line A		100.7	100.7	14.9	107	Link 1-Main AC Line	

Figure 7-14 Contingency analysis result without A-ETR



Minimum Voltages:

Min. Voltage		<div><div>0.940</div><div></div></div>	[p.u.]	Min. Voltage Limit:		<div><div>0.94</div><div></div></div>	[p.u.]
	Component	Branch, Substation or Site	Voltage Min. [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name

Maximum Voltages:

Max. Voltage		1.100	[p.u.]	Max. Voltage Limit:		1.100	[p.u.]
Component	Branch, Substation or Site	Voltage Max. [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name	

Maximum Loading:

Loading Limit:		<div><div>100.0</div><div></div></div>	<div><div></div><div>[%]</div></div>	Overloading Limit:		<div><div>100</div><div></div></div>	<div><div></div><div>[%]</div></div>
	Component	Branch, Substation or Site	Loading Continuous [%]	Loading Short-Term [%]	Loading Base Case [%]	Contingency Number	Contingency Name

Figure 7-15 Contingency analysis result with A-ETR

This figure demonstrates that the grid is capable of sustaining itself in contingency conditions, as indicated by the majority of its components being highlighted in green, which signifies that they are in good condition. Comparison of the microgrid improvement analysis results without A-ETR support Figure 7-14 and with A-ETR connected at buses 7 and 8 Figure 7-15 are discussed in the following sections:

7.8.1 Load flow comparison

From the load flow simulation result in Figure 7-16, we observe that integrating the A-ETR to the grid under normal operating conditions makes more clean electric power generation available to the microgrid. Thus, reducing the in-feed from the external grid which is mostly from fossil fuel-based power plants. The renewable energy penetration provided by the A-ETR on the grid from the load flow analysis report, according to (7-11), is 88.78% before and 89.24% after integrating A-ETR. The renewable energy percentage contribution is higher in the latter than former. However, a critical point from the load flow result is the issue of losses in the grid; if the system demand is lower than the renewable energy generation, there is no need for the integration of additional energy sources to minimise losses as a result of additional reactive power injection into the microgrid. This point is one of the significant advantages of mobile battery energy grid support over the stationary battery storage system. Mobile storage is also an excellent idea for tackling load-shedding issues.

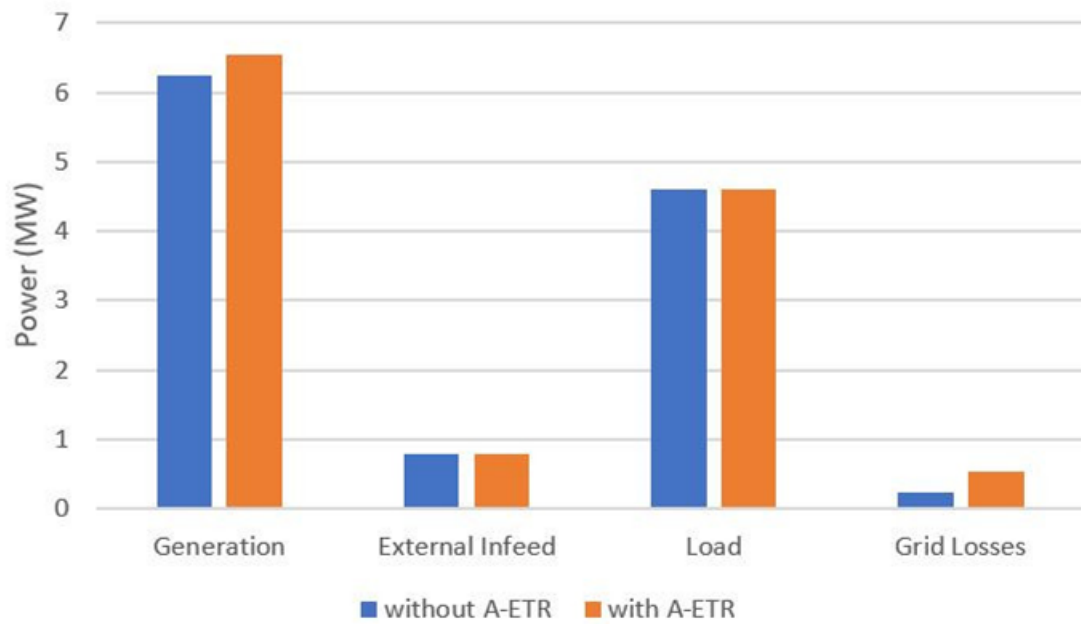


Figure 7-16 Comparison of load flow result with and without A-ETR

7.8.2 Quasi dynamic simulation

7.8.2.1 Grid stability

In the Quasi dynamic simulation, we apply the worst scenario that can happen. The grid stability and voltage profile analysis results show that without the A-ETR, the microgrid can only sustain operation for 9 hours under the worst condition when there is a short circuit near all the generators. But after integrating the AETR, the microgrid can sustain operation for 14+ hours under the same conditions. These results show the resiliency of the microgrid increases with the integration of the A-ETR. Furthermore, the voltage in both cases are close to 1p.u, which indicates that all bus voltages are stable.

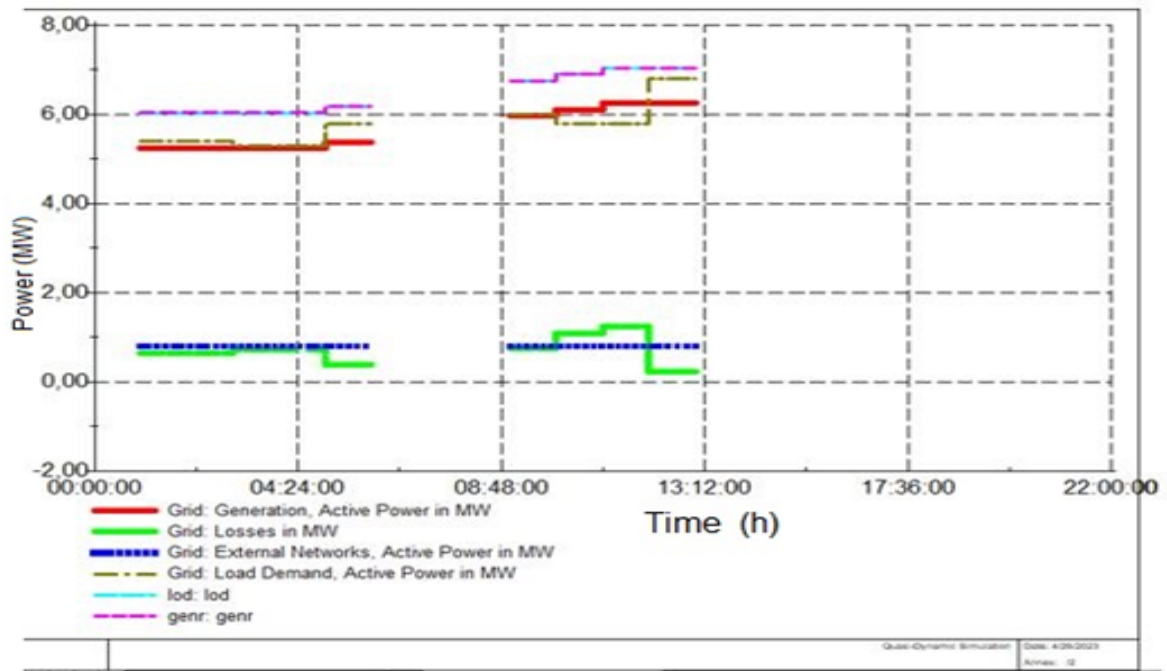


Figure 7-17 Grid stability duration without A-ETR

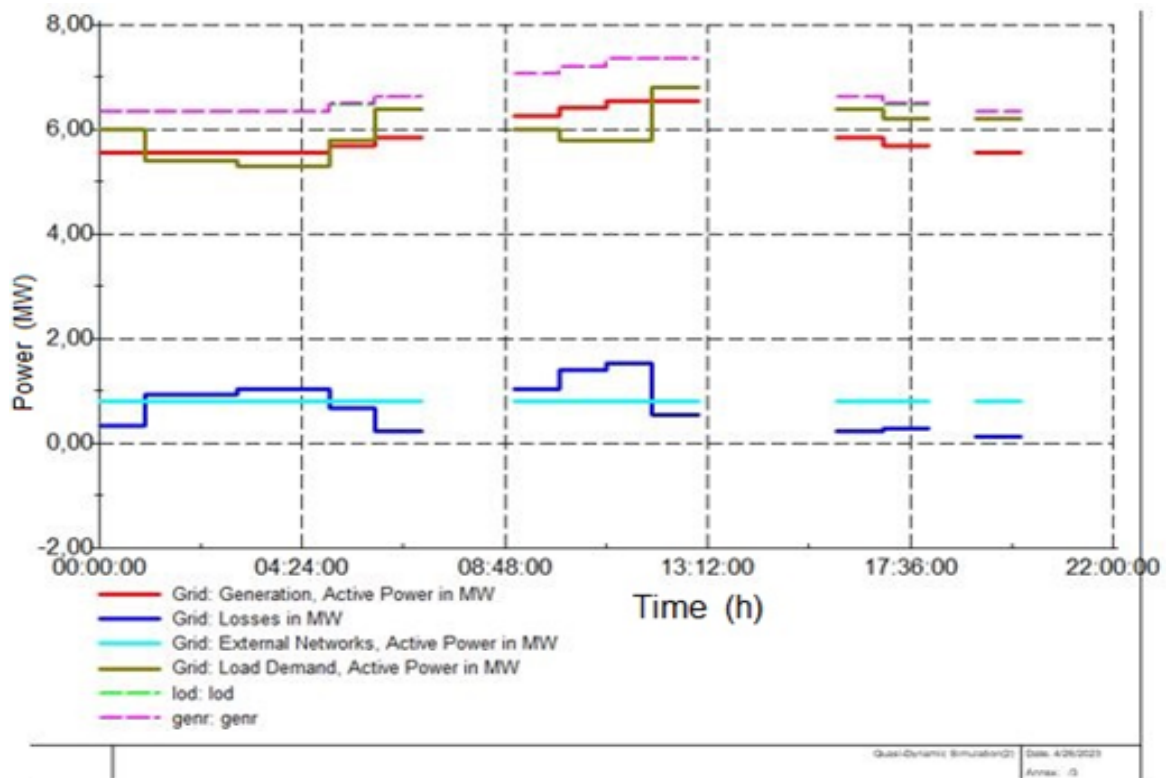


Figure 7-18 Grid stability duration with A-ETR

7.8.2.2 Voltage profile

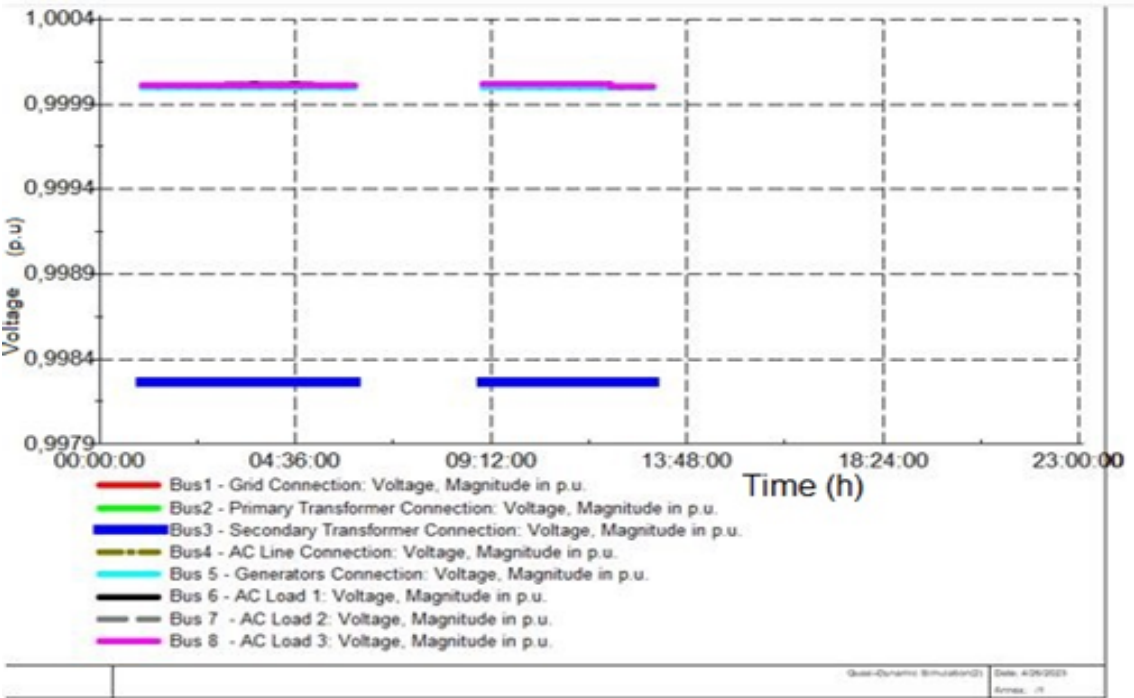


Figure 7-19 Voltage profile without A-ETR

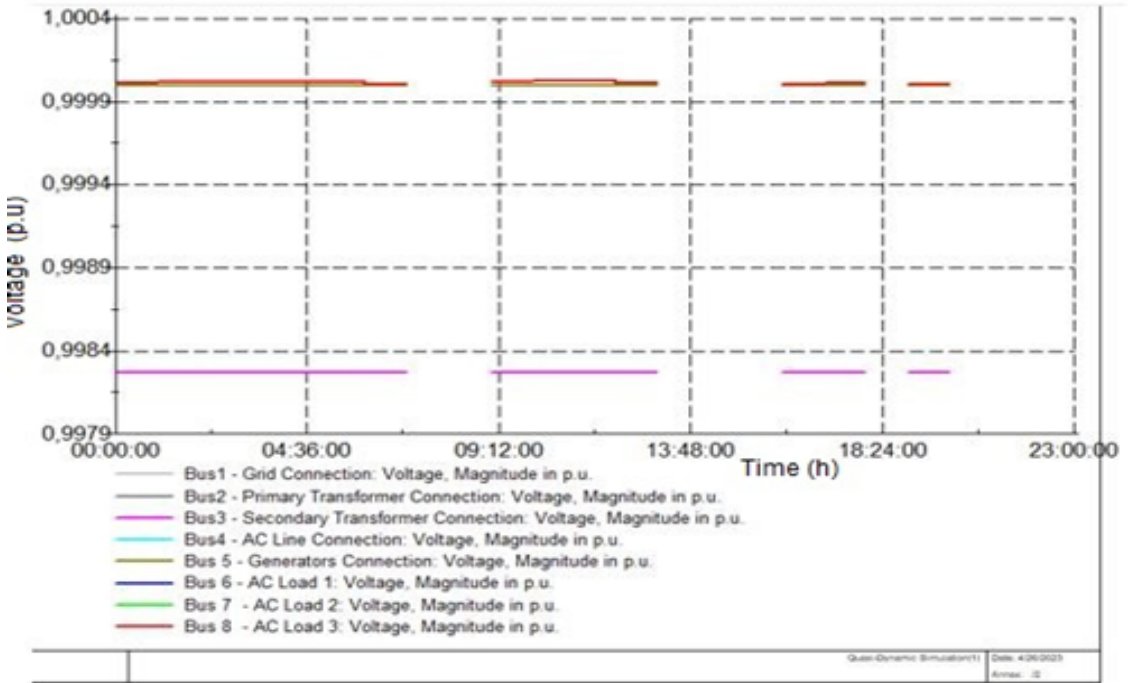


Figure 7-20 Voltage profile with A-ETR support

7.8.3 Contingency analysis

As a result of the contingency analysis result in Figure 7-14, it is found that without the A-ETR, the lowest busbar voltage reaches below 0.854 p.u volt (-14.6%), which is lower than the minimum standard which is 0.94 p.u (-6%). However, whenever the voltage reaches that level, the busbar is forced to produce more current, which can cause a fatal injury to consumers. Meanwhile, after integrating the A-ETR, the lowest busbar voltage of the microgrid was 0.95 p.u (-5%), which is higher than the minimum standard of 0.94 p.u (-6%), in Figure 7-15 which means the busbar can still transmit power under that circumstance. The maximum voltage in the system without A-ETR is about 2.41 p.u in Figure 7-14 which is above the maximum voltage standard of 1.1 p.u (+10%). However, the integration of the A-ETR reduces the maximum voltage in the system to 1.1 p.u (+10%) in Figure 7-15, which means mobile storage can reduce the maximum voltage of the busbar when the contingency (n-1) occurs in the system.

In this scenario, the maximum voltage and line loading are higher with the A-ETR because the microgrid generates more active and reactive power.

7.8.3.1 Maximum and minimum voltage in contingency

The integration of A-ETR to the microgrid increase the minimum available bus voltage under fault condition by (0.86-0.94) p.u and reduces the maximum voltage from (2.48-1.10) p.u, as shown in Figure 7-21

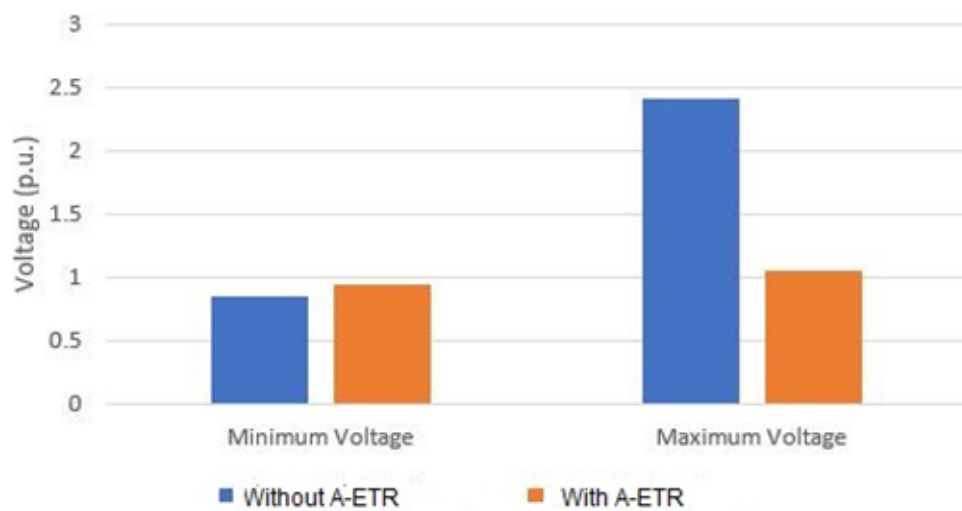


Figure 7-21 Maximum and minimum voltage in contingency

7.8.3.2 Maximum Loading in contingency

The maximum loading percentage of the microgrid under fault conditions increases from (100 to 80), 20% when supported by A-ETR. Thereby extending the availability of power in the microgrid.

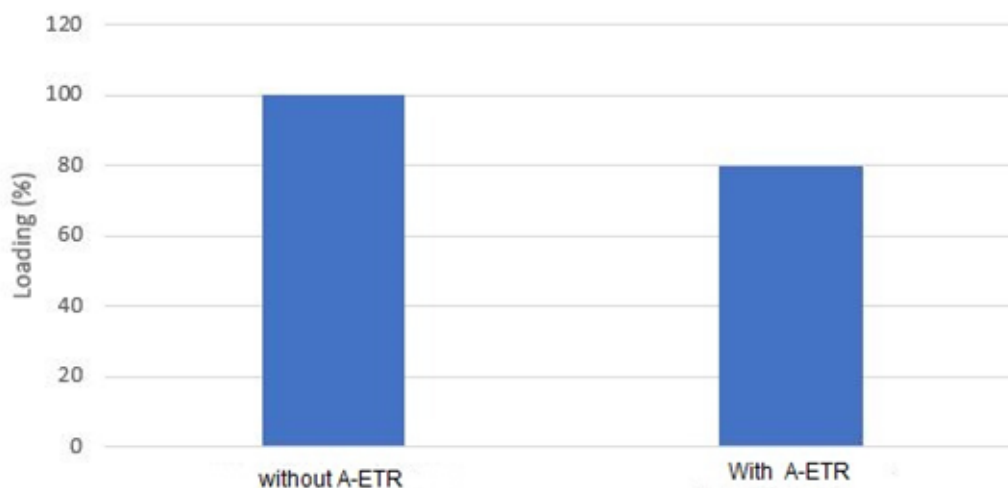


Figure 7-22 Maximum grid loading in contingency.

7.8.4 Reliability assessment

7.8.4.1 System Average Interruption Frequency Index (SAIFI).

The reliability assessment result showed that the SAIFI index with A-ETR is lower than the SAIFI index without A-ETR. That means the airport will experience fewer interruptions when the A-ETR is deployed to support the microgrid. SAIFI can be calculated as [392]:

$$SAIFI = \frac{\sum \lambda_i N_i}{N_T} \quad (7-39)$$

Where λ_i is the number of failures in the i th feeder, N_i is the number of loads in the i th feeder, N_T is the total number of loads served in all feeders in the system. From the simulation result in DigSILENT, we obtain SAIFI data that is represented in Figure 7-23

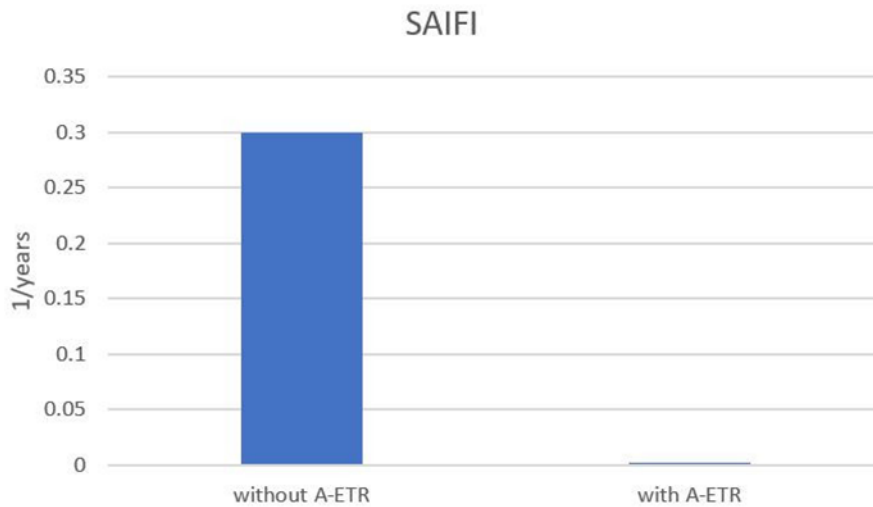


Figure 7-23 System Average Interruption Frequency Index (SAIFI).

7.8.4.2 System Average Interruption Duration Index (SAIDI).

The reliability assessment result showed that the SAIDI index reduced from 1.2 hours per year to 0.2 hours per year with A-ETR is lower than the SAIDI index without A-ETR. That means the airport will experience a shorter blackout duration

while the A-ETR provide ancillary service to the microgrid. SAIDI can be calculated as [392]:

$$SAIDI = \frac{\sum U_i N_i}{N_T} \quad (7-40)$$

Where U_i is the duration of failure in the i th feeder N_i is the number of loads in the feeder, N_T is the total number of loads served in all i th feeders in the system. From the simulation result, the SAIDI data obtained is represented in Figure 7-24

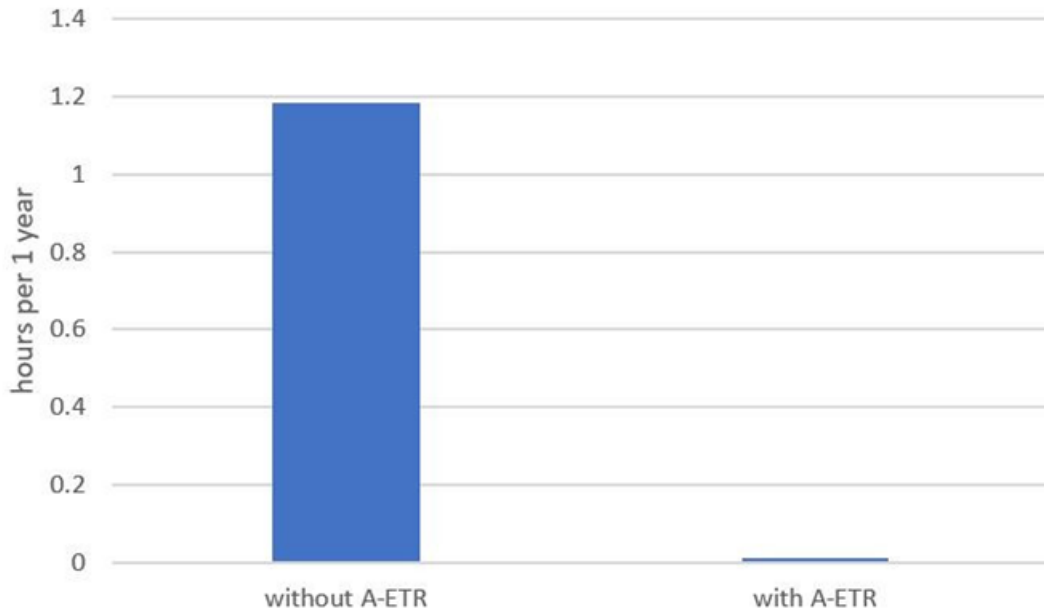


Figure 7-24 System average interruption duration index

7.8.4.3 Energy not serve (ENS).

The reliability assessment result showed that the ENS reduced from 5.8MWh/year without A-ETR to 0.1MWh/year with A-ETR. That means the A-ETR as mobile storage minimises the amount of energy not delivered during grid failure. This result is an indication of improved sustainability in the microgrid. The ENS can be calculated as [393]:

$$ENS = SAIDI \times P_i \quad (7-41)$$

Where P_i is the total expected power loss of load in the i th feeder. From the simulation result in DigSILENT, the ENS data obtained is represented in Figure 7-25

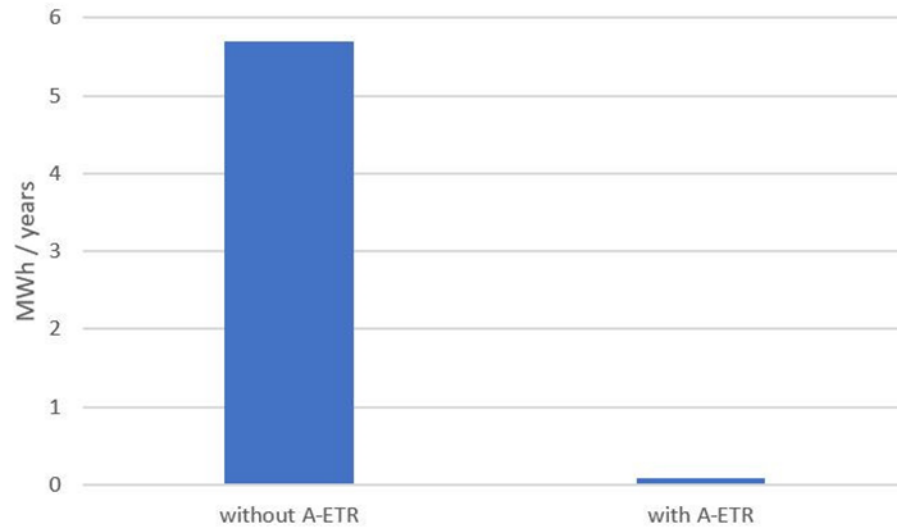


Figure 7-25 Energy not used (ENS).

7.8.4.4 Average service availability index (ASAI)

The reliability assessment result showed that the ASAI with A-ETR is higher than without AETR. That means electricity will be more available when the A-ETR is deployed to provide ancillary services in the microgrid. ASAI can be calculated as [394]:

$$ASAI = 1 - SAIFI \quad (7-42)$$

From the simulation result in DigSILENT, the obtained ASAI data is represented in Figure 7-26

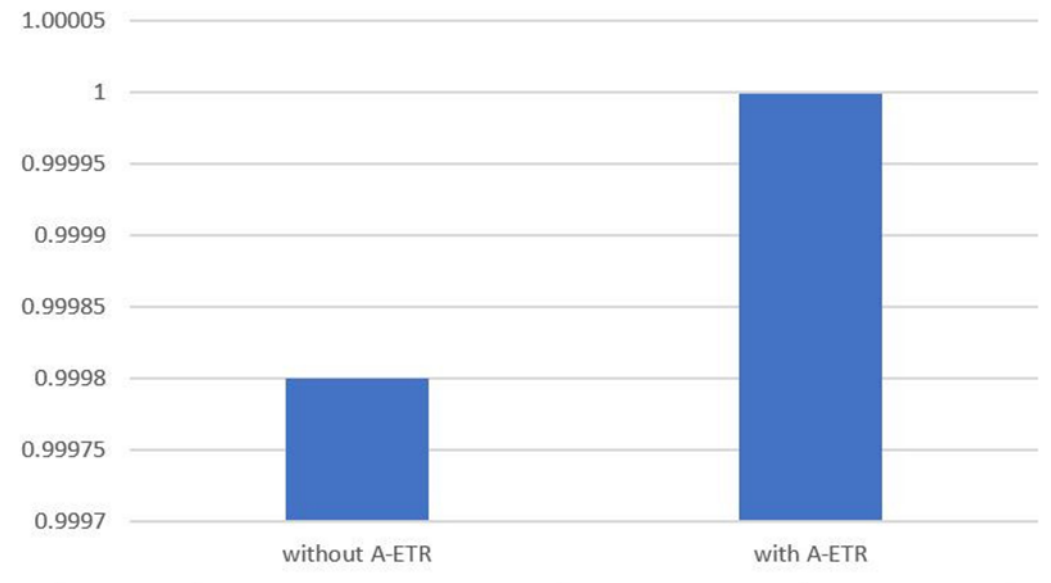


Figure 7-26 Average service availability index

From all the reliability assessment results using complex numerical operations in Digsilent, we can conclude that the novel microgrid infrastructure integrating A-ETR to deliver energy as a service (EaaS) in the form of mobile storage improves the resilience and reliability of the microgrid and energy supply in the airport.

7.8.4.5 Critical fault clearing time.

The critical fault clearance time ((CCT) refers to the maximum time to clear a fault from the line beyond which the synchronous generator will lose its stability. The results of the CCT for a three-phase short circuit fault initiated at 50% of the distribution lines and cables are shown in Table 7-10 and illustrated in Figure 7-27. Figure 7-27 shows that the distribution cable is more sustained than any other component in the microgrid. From the CCT simulation result, we can conclude that the integration of the A-ETR extends the maximum fault clearance time in the microgrid. This extension provides improved resilience and additional advantage for the operation and maintenance engineers with more time for clearing the fault.

Table 7-10 Critical Fault Clearing Time Simulation Result

No	Line Name	CCT without A-ETR (s)	CCT with A-ETR (s)
1	Distribution Cable 1	0.97	4.81
2	Distribution Cable 2	0.97	4.81
3	BESS Line	0.00	0.00
4	Fuel cell Line	0.00	0.00
5	Interconnection Line	0.00	0.00
6	Line A	0.00	1.37
7	Line B	0.00	1.70
8	Link 1	0.00	0.00
9	Link 2	0.00	0.00
10	Main AC Line	0.00	0.00
11	PV Line	0.00	0.00

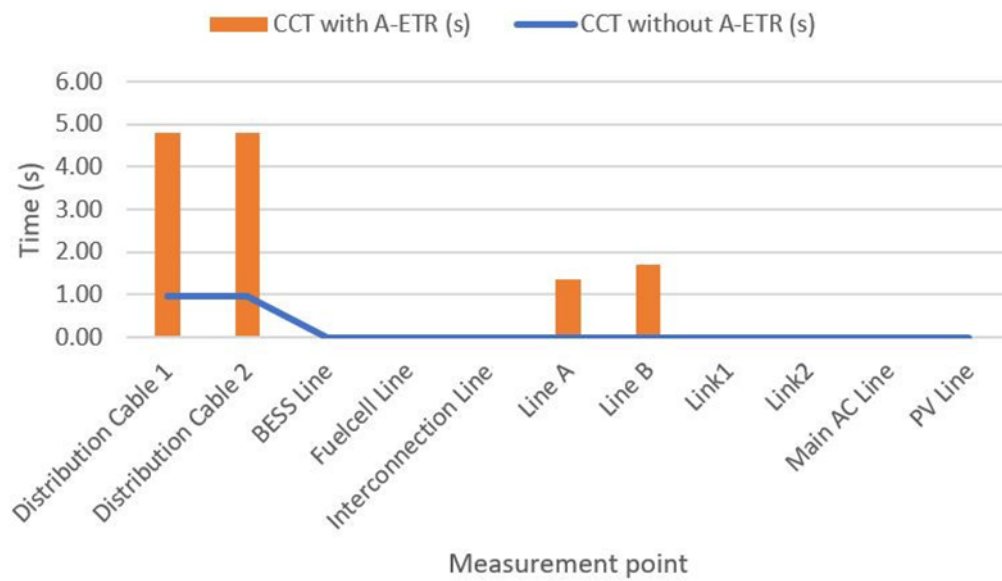


Figure 7-27 Critical Fault Clearing Time Simulation Result

7.9 Conclusion

From the various comparison factors discussed in this chapter, the LVDC gives better results than the LVAC architecture from the perspective of voltage profile and percentage loading because it is not affected by reactive power change. However, the advantages of having lesser power, energy losses and infrastructure costs (lower short circuit ratings) for LVAC outweigh the considerable benefits of the LVDC. The analyses in Dig SILENT power factory have shown that for short-length distribution networks such as the case study in airports, the LVAC architecture of the microgrid gives better performance than the LVDC architecture for the future electrical grid for the green airport, and the revision in the topology/design is justified and feasible. That is, the AC bus with smaller-size converters connected to DC loads LVAC is preferable when connecting the proposed EV grid to existing airport infrastructure to a DC bus with a high-rating central converter connecting DC loads LVDC.

Finally, our proposed A-ETR promotes the concept of energy as a service (EaaS) which has potentially accelerated the electrification of transportation in the airport and enables novel emergency response systems to provide ancillary services to the grid. This work aimed at reducing the AC and DC grid to the minimum necessary and replacing it with a more flexible grid that will eliminate the current rigid physical overhead lines with their antecedent challenges in the form of mobile microgrid controllable by a software application.

8 Conclusions and Recommendations

8.1 Chapter Summary

A summary of the research is presented in this chapter. In addition, the main contributions and directions for future research are also discussed.

First, the thesis examines the concept of the green airport, which is designed, operated, and managed to minimise environmental impacts and increase its sustainability. The need for air travel is anticipated to increase along with the rapid growth of the world's population, particularly in the BRIC 16 nations (Britain, Russia, India, and China). Also, increasing air transport, population growth, pollution levels, and climate change may result in a very low tolerance for pollution by 2050.

This thesis provides a grid solution to the challenges of the future green airport to meet the increasing load demand due to the electrification of transportation in the airport. The novel A-ETR has been used to realise the flexible power line linking airport ground operation and the grid. The efficiency of this powerline depends on the microgrid energy management system to coordinate existing resources in terms of spatial and temporal information of the A-ETR.

The concept of MaaS (taxiing of aircraft using the A-ETR) has been exploited and developed into EAAS (providing ancillary services to support the grid) through the A-ETR. The FlightPath 2050 policy guide provides the context and enabling platform to exhibit this novel microgrid ecosystem. The A-ETR has potentially accelerated the electrification of transportation in the airport and enabled novel emergency response systems to provide ancillary services to the grid, as shown from the contingency and reliability assessment analysis of the system in chapter seven. Furthermore, the concept can potentially reduce the existing AC-DC microgrid and replace it with a more flexible grid controllable by the software application.

The proposed mobile microgrid concept has revolutionised the shortcomings of the existing grid systems, as shown in the models, as much as possible by replacing them with a more flexible grid that will eliminate the current rigid physical overhead lines with their antecedent challenges in the form of mobile microgrid controllable by a software application. This is a critical requirement for the decarbonisation of airports, as the future airport will need a new grid structure to supply the electrical energy to meet the increasing demand due to ground operation electrification in the airport. Other contributions from this study based on the investigation findings are:

- **Taxiing Robot Model** - A contribution was made by proposing the optimisation of a novel electric taxiing robot and employing it in the mobility as a service (MaaS) concept in the form of an electric taxiing system and applying it as a mobile interface between aircraft ground movement and airport-based renewable energy resources. The central element of the planning optimisation is the development of the traction load profile generation program, as described in chapter 3, to determine the kinematic parameters of the A-ETR.
- **Battery Size Optimisation** - The model was then expanded to cater for the intermittency in the solar PV power output in respect to meeting the charging load of the A-ETR by integrating machine learning-based forecasting models to forecast the PV output. An operational optimisation model was developed to match PV power, A-ETR battery's charging and discharging cycle and electricity price based on real-world data of Cranfield and Luton airport ground movement load profiles to cover both private and commercial airport operation as described in Chapter 4. The operational cost of the proposed microgrid was optimised to determine the optimal size of battery energy storage that can support the microgrid operation under both private and commercial airport ground operation load profile-based simulation scenarios based on previously developed system architecture.

- **Energy Prediction Model** - Also, a novel machine learning-based data-driven energy prediction model was developed to cater for the mismatch between increased load demand of the commercial airport ground operation and PV power output to ensure continuity and resilient operation in the airport, as described in Chapter 5. The entire model was based on the Facebook prophet algorithm, which is particularly suitable for regular time series data, such as flight schedule time series. Furthermore, it was built on a decomposable time series model that integrates trends, seasonality, and holidays. This optimisation aids airport operators in making more efficient planning and offers an accurate prediction for ground operation energy demand and clean energy production in the airport.
- **Multi-Energy System Model** - A key contribution was made by developing a novel stochastic model predictive control-based cascade feedforward neural network (SMPC-CFFN) optimisation model for the microgrid as described in Chapter 6 to explore more data that is available in the green airport and incorporating additional RES and engaging the batteries of the A-ETR and GSEV in the form of a multi-energy system following the shortcomings of PV output in chapter 4. The motivation for this development is the intermittency complications of solar PV. The model optimises the flow of power between the microgrid RES sources and controls electricity output based on charging and discharging the A-ETR and GSEVBs in the V2G capability and supplying excess power to the utility grid. The microgrid was made to only export surplus electricity to the grid without buying from it, thus indicating complete zero emission-based microgrid operation in the airport.

Finally, a key part of the microgrid ecosystem is the reliability and resiliency of the system. This is investigated by comparing possible network configurations to link the proposed microgrid ecosystem with the existing airport grid. The proposed study compares two alternative architectures based on the PCC, with LVAC architecture with smaller-size converters and a high-rating centralised

converter connection, with LVDC architecture in terms of technical and economic implications of the new loads on the existing distribution network in the airport.

- **Energy as a Service Model** - Further, the concept of the A-ETR as EaaS is incorporated to test the reliability and resilience of the proposed microgrid ecosystem by performing contingency and reliability index analysis on the model using DigSILENT power factory software. The performance of the model in terms of power quality, short circuit fault levels, system protection requirements, voltage profile, power losses and equipment/system overloading to determine the optimal architecture is also verified and validated. The result demonstrates that the A-ETR has potentially accelerated the electrification of transportation in the airport in addition to enabling novel emergency response systems to provide ancillary services to the grid, as described in Chapter 7. This solution will help to revolutionise the whole grid concept without the need for building transmission lines which are fixated, ageing, and no longer fit for the future distributed renewable energy world.

The comprehensive simulation results from the multidisciplinary system-level optimisation approach adopted not only validate the novelty of the proposed study but also serve to provide compelling evidence for the potential to solve common problems in the future green airport by creating a microgrid ecosystem between the airport ground movement operation and on-site renewable energy generating source.

8.2 Recommendations for future work

This research has opened up new research avenues addressing the future grid for green airports and unveiled potential routes and strategies for its accomplishment. In addition, future research has been suggested for the possible extension of this study, given the technological state of the art:

- Investigate the possibility of generating alternative energy from harnessing the vast kinetic energy stored in landing aircraft and the wake vortex of

departing aircraft. Since this energy source is not weather-related, it is unaffected by bad weather, which is one of the drawbacks of completely renewable energy-based microgrids in the airport. As a result, the airport will produce more green energy, helping it to achieve its goal of zero emissions ground operations.

- Develop reliable scheduling and routing algorithms for the grid's A-ETR functioning. These algorithms will improve its performance as an EAAS in an off-grid environment.
- The incorporation of a predictive maintenance control system to improve model performance should be investigated in further studies. As A-ETR can be prepositioned to vulnerable nodes prior to fault incidence to maximise critical fault clearance time and improve resilience.
- The energy demand in the terminal building is related to the flight data of the airport, despite the fact that the energy prediction model developed considered ground operations as the initial step to green airport electrification. Future work should therefore expand the investigation to include landside operations in the airport.
- The proposed energy prediction model utilising the Facebook Prophet algorithm can be further investigated and implemented. The main advantage of the technique is that it breaks down forecasts into time components, making it easy to interpret with very high forecasting accuracy. Furthermore, methods using autoregressive models can be a suitable research direction to compare their performance.
- The microgrid resilience assessment and improvement under various disasters should be investigated in future work.

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Appendix A : The seasonality of ASPV at Cranfield Airport

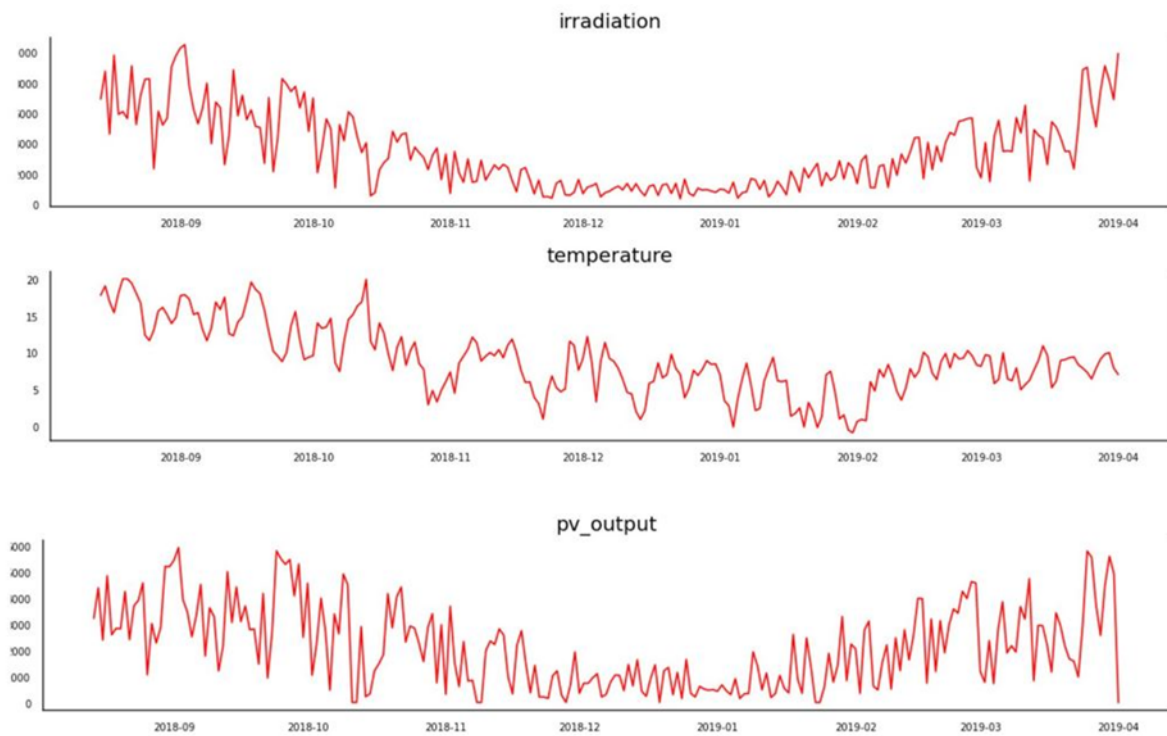


Figure A-1 Seasonality trend for irradiation, temperature and PV output at Cranfield ASPV

Appendix B : Flight schedule data

Table B 1 Section of daily hourly flight schedule analysis Cranfield Airport

	0	1	2	3	4	5	6	7	8	9	.	15	16	17	18	19	20	21	22	23	Flight total	
Date																						
02-01-11	0	0	0	0	0	0	0	0	0	1		1	0	0	0	0	0	0	0	0	0	4
04-01-11	0	0	0	0	0	0	0	1	0	16		24	17	2	0	0	0	0	0	0	0	146
05-01-11	0	0	0	0	0	0	0	0	0	3		2	1	1	0	0	0	0	0	0	0	37
06-01-11	0	0	0	0	0	0	0	0	1	6		35	7	2	0	0	0	0	0	0	0	115
07-01-11	0	0	0	0	0	0	0	0	0	1		0	0	1	0	0	0	0	0	0	0	20
.....	.	.	.	..	..	..	..	..	...	..	.	..	..	..	..	..	..	..	..	..	..	..
26-06-21	0	0	0	0	0	0	0	0	0	3		13	9	0	0	0	0	0	0	0	0	111
27-06-21	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	5
28-06-21	0	0	0	0	0	0	0	0	1	0		1	0	0	0	0	0	0	0	0	0	3
29-06-21	0	0	0	0	0	0	0	0	1	7		17	5	0	0	0	0	0	0	0	0	99
30-06-21	0	0	0	0	0	0	0	0	0	15		49	6	4	0	0	0	0	0	0	0	176
3515 rows * 25 columns																						

Appendix C : Load flow and contingency analysis

Load Flow Calculation				Total System Summary			
AC Load Flow, balanced, positive sequence				Automatic Model Adaptation for Convergence	Yes		
Automatic tap adjustment of transformers	No			Max. Acceptable Load Flow Error			
Consider reactive power limits	No			Bus Equations(HV)	10.00 kVA		
				Model Equations	0.10 %		
Total System Summary				Study Case: Study Case	Annex:	/ 1	
No. of Substations	0	No. of Busbars	14	No. of Terminals	0	No. of Lines	2
No. of 2-w Trfs.	2	No. of 3-w Trfs.	0	No. of syn. Machines	0	No. of asyn.Machines	0
No. of Loads	10	No. of Shunts/Filters	0	No. of SVS	0		
Generation	=	6.00 MW	0.00 Mvar	6.00 MVA			
External Infeed	=	0.46 MW	0.04 Mvar	0.46 MVA			
Load P(U)	=	3.01 MW	0.00 Mvar	3.01 MVA			
Load P(Un)	=	3.01 MW	0.00 Mvar	3.01 MVA			
Load P(Un-U)	=	0.00 MW	0.00 Mvar				
Motor Load	=	0.00 MW	0.00 Mvar	0.00 MVA			
Grid Losses	=	1.05 MW	0.05 Mvar				
Line Charging	=		-0.17 Mvar				
Compensation ind.	=		0.00 Mvar				
Compensation cap.	=		0.00 Mvar				
Installed Capacity	=	7.00 MW					
Spinning Reserve	=	0.00 MW					
Total Power Factor:							
Generation	=	1.00 [-]					
Load/Motor	=	1.00 / 0.00 [-]					

Figure C- 1 Load flow simulation result for LVDC architecture

		DigSILENT		Project:	
		PowerFactory			
		15.1.7		Date: 11/13/2022	
Reliability Assessment					
Method		Connectivity analysis			
Network		Transmission			
Calculation time period		2022			
Consider Maintenance		Yes			
Fault Clearance Breakers		Use all circuit breakers			
Switching procedures		Concurrently			
Time to open remote controlled switches		1,00 min.			
Automatic Contingency Definition					
Selection		Whole System			
Busbars / terminals		Yes	Common mode		Yes
Lines / cables		Yes	Independent second failures		Yes
Transformers		Yes	Double earth faults		Yes
			Protection/switching failures		Yes
Study Case: Study Case				Annex:	
				/ 1	
System Summary					
System Average Interruption Frequency Index : SAIFI = 0,087041 1/Ca					
Customer Average Interruption Frequency Index : CAIFI = 0,087041 1/Ca					
System Average Interruption Duration Index : SAIDI = 0,348 h/Ca					
Customer Average Interruption Duration Index : CAIDI = 3,998 h					
Average Service Availability Index : ASAI = 0,9999602798					
Average Service Unavailability Index : ASUI = 0,0000397202					
Energy Not Supplied : ENS = 1,631 MWh/a					
Average Energy Not Supplied : AENS = 0,326 MWh/Ca					
Average Customer Curtailment Index : ACCI = 0,317 MWh/Ca					
Expected Interruption Cost : EIC = 0,000 M\$/a					
Interrupted Energy Assessment Rate : IEAR = 0,000 \$/kWh					
System energy shed : SES = 0,000 MWh/a					
Average System Interruption Frequency Index : ASIFI = 0,088690 1/a					
Average System Interruption Duration Index : ASIDI = 0,354545 h/a					
Momentary Average Interruption Frequency Index : MAIFI = 0,000000 1/Ca					

Figure C- 2 Reliability assessment report for LVAC microgrid

Minimum Voltages :

	Component	Branch, Substation or Site	Voltage Min [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name	Base Case and Post Voltage [0.384 p.u. - 1.000 p.u.]
1	DC Bus 2A		0.384	-0.616	1.000	50	BESS-Main AC Line	
2	AC Bus 2B		0.487	-0.513	1.000	33	FuelCell-BESS	
3	AC Bus 5A		0.487	-0.513	1.000	33	FuelCell-BESS	
4	BESS AC Bus		0.487	-0.513	1.000	33	FuelCell-BESS	
5	Bus 5 - Generators Connection		0.487	-0.513	1.000	33	FuelCell-BESS	
6	Bus 6 - AC Load1		0.487	-0.513	1.000	33	FuelCell-BESS	
7	Bus 7 - AC Load1		0.487	-0.513	1.000	33	FuelCell-BESS	
8	Bus 8 - AC Load 2		0.487	-0.513	1.000	33	FuelCell-BESS	
9	Bus4 - AC Line Connector		0.487	-0.513	1.000	33	FuelCell-BESS	
10	FuelCell AC Bus		0.487	-0.513	1.000	33	FuelCell-BESS	
11	PV AC Bus		0.487	-0.513	1.000	33	FuelCell-BESS	
12	Bus3 - Secondary Transformer		0.860	-0.138	0.998	33	FuelCell-BESS	

Maximum Voltages :

	Component	Branch, Substation or Site	Voltage Max [p.u.]	Voltage Step [p.u.]	Voltage Base [p.u.]	Contingency Number	Contingency Name	Base Case and Post Voltage [1.000 p.u. - 4.498 p.u.]
1	DC Bus 5B		4.498	3.498	1.000	8	Link1-Main AC Line	
2	DC Bus 2A		2.453	1.453	1.000	23	Link2-Main AC Line	

Maximum Loading :

	Component	Branch, Substation or Site	Loading Continuous [%]	Loading Short-Term [%]	Loading Base Case [%]	Contingency Number	Contingency Name	Base Case and Continuous Loading [0 % - 278 %]
1	Line B		278.0	278.0	24.8	8	Link1-Main AC Line	
2	Transformer-1		140.9	140.9	4.6	33	FuelCell-BESS	
3	Transformer-2		124.6	124.6	1.6	33	FuelCell-BESS	
4	Distribution Cable 2		110.9	110.9	3.7	33	FuelCell-BESS	
5	Distribution Cable 1		110.9	110.9	3.6	33	FuelCell-BESS	
6	Line A		102.1	102.1	26.1	8	Link1-Main AC Line	

Figure C- 3 Maximum and minimum voltage in contingency

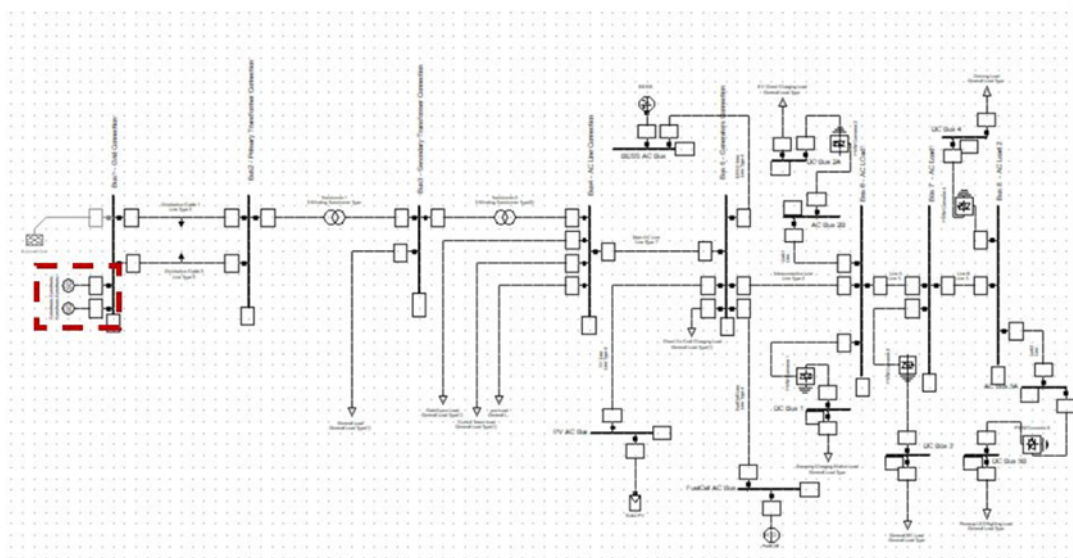


Figure C- 4 Critical fault clearing time simulation.

Appendix D : Battery size optimisation algorithm results

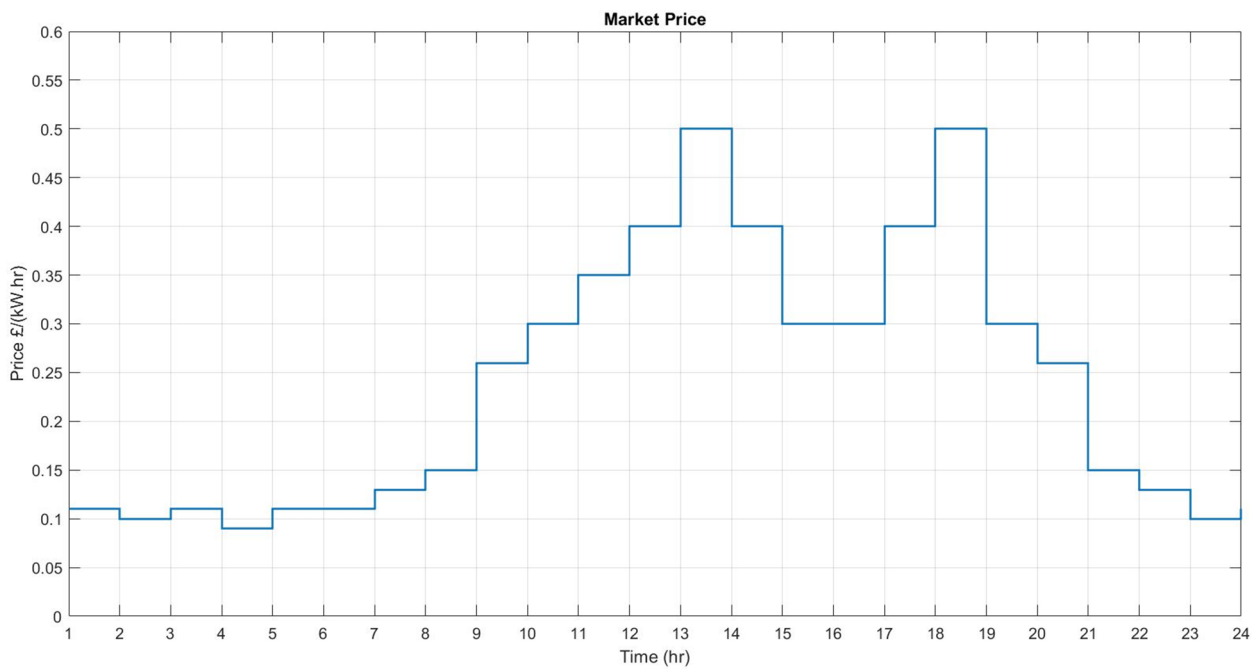


Figure D- 1 TOU market price

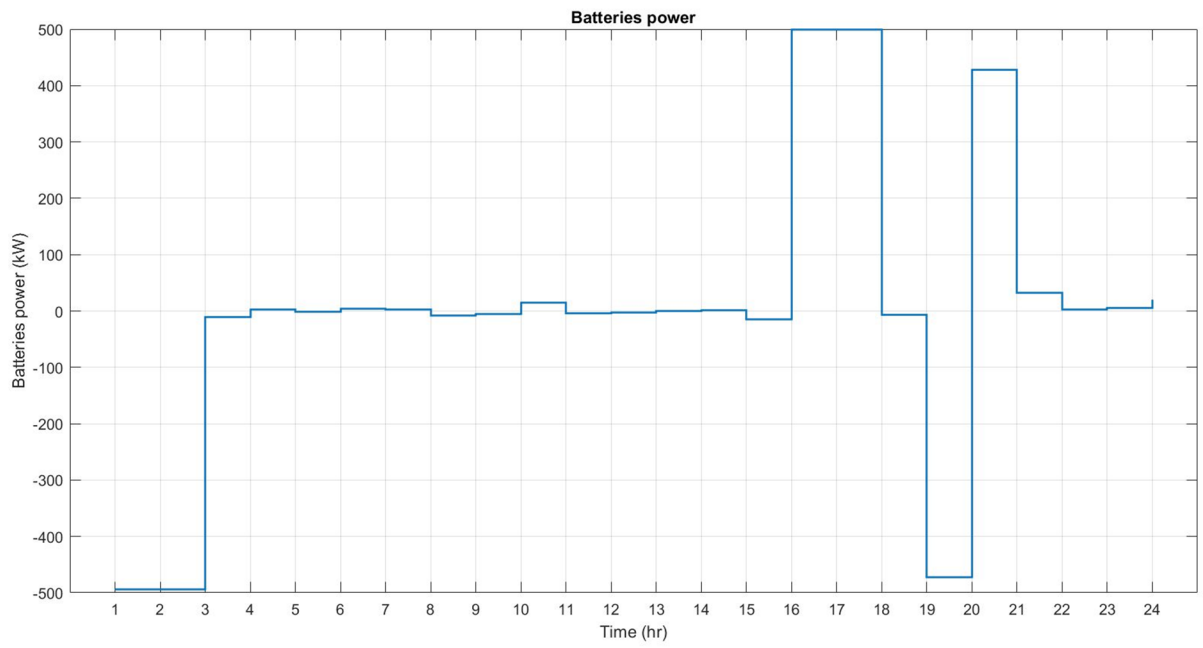


Figure D- 2 Battery power exchange

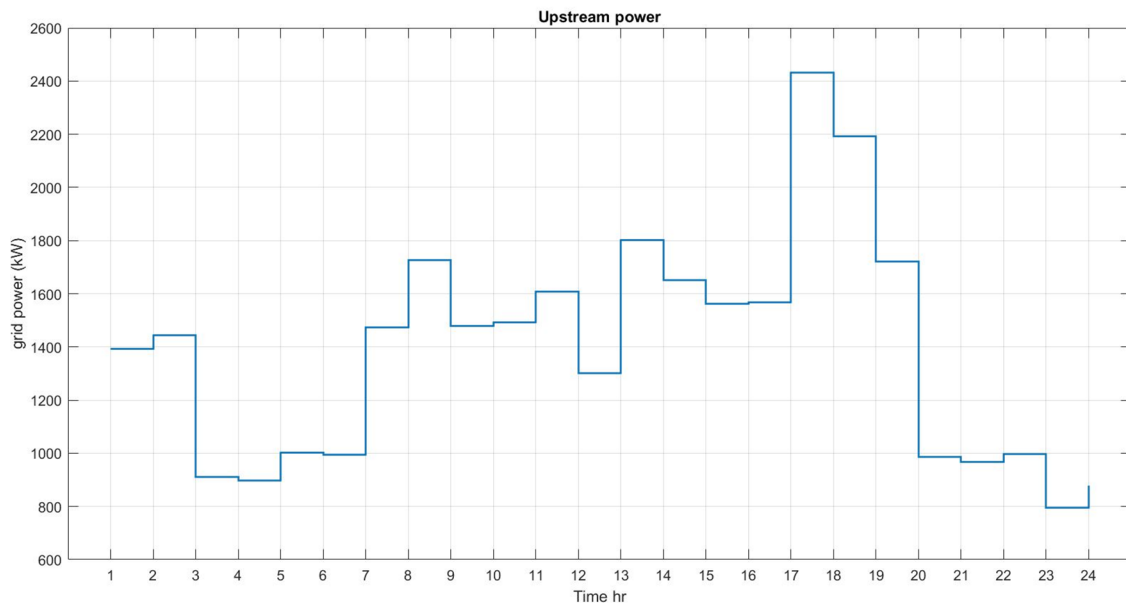


Figure D- 3 Power exchange with the upstream grid

Appendix E : System parameter modelling in Power factory platform.

Name

Main AC/DC Converter

Terminal AC

▼

Grid\Bus4 - Converter Connection\Cub_5

Terminal DC

▼

Grid\Bus 5 - Main DC\Cub_3

Zone

Terminal AC

▼

→ ...

Area

Terminal AC

▼

→ ...

☐ Out of Service

Number of parallel Converters

1

Ratings

Rated AC-Voltage

0.23

kV

Rated DC-Voltage (DC)

0.4

kV

Rated Power

7500.

kVA

Series Reactor

Short Circuit Impedance

10.

%

Copper Losses

750.

kW

Modulation

☒ Sinusoidal PWM

☐ Rectangular PWM

☐ No Modulation

No-Load Losses

350.

kW

Bus4 - Converter C

Bus 5 - Main DC

Figure E- 1 Main AC-DC converter parameters

Name

PWM Converter - BESS

Terminal AC

▼

Grid\BESS AC Bus\Cub_2

Terminal DC

▼

Grid\BESS DC Bus\Cub_2

Zone

Terminal AC

▼

→ ...

Area

Terminal AC

▼

→ ...

☐ Out of Service

Number of parallel Converters

1

Ratings

Rated AC-Voltage

0.23

kV

Rated DC-Voltage (DC)

0.4

kV

Rated Power

4000.

kVA

Series Reactor

Short Circuit Impedance

5.

%

Copper Losses

200.

kW

Modulation

☒ Sinusoidal PWM

☐ Rectangular PWM

☐ No Modulation

No-Load Losses

100.

kW

BESS AC Bus

BESS DC Bus

Figure E- 2 PWM converter parameters