

Technical paper

Energy flexibility in aerospace manufacturing: The case of low carbon intensity production

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ABSTRACT

In this paper, the prospects of energy flexibility in mitigating the environmental impact of aerospace manufacturing are explored. In collaboration with a UK-based aerospace manufacturing enterprise, demand response, in particular production time, is explored under different stochastic scenarios. This is done through a decision-support framework that consists of a stochastic discrete-event simulation model that tests different scenarios under a full factorial design of experiments framework. The simulation model tests various improvement strategies pertaining to prioritisation rules, production start-up rules, and operating hours. The model aids in scheduling energy-intensive processes, so the time of performing such processes can coincide with times of the day when the energy's carbon intensity is at its lowest. The use case constitutes a family of aluminium structural aerospace components that are characterised by high production rate. Results demonstrate promising potential of the proposed approach, with the best-case scenario resulting in a 7% reduction in CO₂e emissions. Analysis of the results demonstrate that operational decisions that do not require infrastructural changes or capital expenditures can contribute favourably to achieving net-zero targets. This research offers useful insights on leveraging operational short-term decisions to meet the aerospace manufacturing's sector decarbonisation targets.

1. Introduction

Manufacturing enterprises have been consistently exploring ways to improve their sustainability profiles. This is mainly in response to the growing concerns about environmental issues such as global warming, resource depletion, and loss of land, amongst others. Intergovernmental treaties such as the United Nations Framework Convention on Climate Change (UNFCCC), and agreements such as the Paris Agreement play an important role in setting goals and action plans for reducing greenhouse gas emissions, leading many governments to commit to achieving net-zero emissions within the next few decades. An example of this is the UK where the UK Government has committed to achieve net-zero emissions by 2050 [1]. In reaction to this near-global commitment, manufacturing enterprises are already implementing new and novel practices that span all decision-making planning horizons to realise sustainable manufacturing, and to contribute with their share to realise these net-zero commitments. Sustainable manufacturing, defined as manufacturing with reduced environmental footprint of products and

processes [2], entails changes in the way manufacturing is conventionally carried out at all planning horizons. The scope of sustainable manufacturing is, however, not confined to the environmental pillar of sustainability. Truly sustainable manufacturing is manufacturing that balances the environmental, social and economic pillars of sustainability [3].

Decision-making is conventionally classified into three planning horizons namely: strategic, tactical, and operational [4]. Implementing changes to strategic and tactical decisions (e.g., facility (re)location and supplier selection, respectively) often entails capital costs and/or disruptions. Making changes to operational decisions (i.e., short-term, day-to-day decisions [5]) to improve the performance of a manufacturing system, however, usually entails little to no capital cost with mild disruptions in many cases.

Scheduling decisions, which allocate resources to tasks [6], are important in realising sustainable manufacturing. This is especially true because changes to scheduling decisions usually require little to no additional infrastructure changes. Even as manufacturing technologies

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evolve, with the emergence of Industry 4.0, and more recently the human-centric Industry 5.0 with its focus on sustainability and resilience [7], scheduling decisions have consistently remained important in the manufacturing decision-making sphere.

Although most scheduling optimisation problems minimise energy consumption as a surrogate for cost, it is not always the case that carbon emissions will be minimised as well. The focus on electricity costs undermines the potential for production scheduling to contribute to carbon reduction goals. Recently, much research on scheduling has explored possibilities to balance the environmental pillar of sustainability with the economic one. Production scheduling can help minimise electricity consumption by consolidating idle periods by switching machines off or by batch processing to minimise the number of setups. Another common example is to incorporate the objective of minimising the electricity cost along with the minimisation of the completion time – the makespan – in scheduling problems to prevent peak electricity (which is often priced at high rates) usage times.

Energy flexibility of a system refers to its ability to adapt to changes in energy supply without significant disruptions to the system's performance [8]. In a sustainable scheduling context, energy flexibility refers to the assignment of production parameters (e.g., timing, cutting speed, or dispatching rules, amongst others), in response to the carbon intensity of energy [9]. In addition to the environmental impact, energy flexibility can also contribute favourably to reducing the cost of a manufacturing system. [10], [11]. The importance of energy flexibility has grown in parallel with the increase in energy demand, and the rapid increase in the share of renewables in electricity generation. For example, the renewable's share of the grid in the UK has increased from a mere 2.25% in 2008 [12] to around 44% in 2023 [13]. This sharp rise in renewable energy capacity has motivated both energy providers and consumers to adapt their supply/ demand patterns to maximise the share of renewable energy consumption.

In this paper, scheduling decisions will be investigated from an energy flexibility perspective with the objective of reducing CO₂e emissions under the constraint of on-time completion of all jobs. Energy flexibility will be approached from the demand-side, where different time-of-use scenarios will be investigated under stochastic conditions using discrete-event simulation (DES). In order to gain a better understanding about the proposed approach, and to reveal the main and interaction effects of key experimental factors, simulation modelling was carried out under a full-factorial design of experiments (DoE) framework. The focus of this paper will be on implementing a demand response program to reduce CO₂e emissions through different shop floor scheduling decisions. One of them will be to consider the carbon intensity (in gCO₂e/kWh) of electricity produced depending on the time of production based on the share of renewables from the grid at the time of use. This will allow energy-intensive production processes to be performed during periods of low carbon intensity, thus reducing the carbon footprint.

This research presents a decision-support framework for energy flexible scheduling with low carbon intensity. The framework was validated on a case study that was carried out in collaboration with a UK-based tier one aerospace manufacturer and systems integrator (from now on will be referred to as the Company). The Company wishes to reduce its carbon footprint in the short term while it works on establishing strategic projects that should enable it to realise its goal of net-zero emissions by 2050. This case study serves as a proof-of-concept where stochastic discrete-event simulation will be used for decision-making on a recurring basis to provide more sustainable flexible scheduling decisions under a demand response program. The case study pertains to the production of an aerospace family of aluminium structural alloys. The production processes involve several machining and treatment (both chemical and heat treatment) processes, making the chosen family of components one of the most energy-intensive ones within the Company's facility. Indeed, machining processes typically contribute a significant share of a production facility's overall energy

consumption [14], hence, even a small reduction in machining energy consumption, can have a noticeable impact on the overall energy consumption of a production facility.

The rest of the paper is organised as follows: the next section presents a critical review of the state-of-the-art in sustainable scheduling and demand response in the manufacturing sector. Next, the case study is presented and discussed. Then, the simulation model is presented and discussed. Section 5 presents the results and discussion. Finally, Section 6 presents concluding remarks and possible future research direction.

2. Related work

Researchers have long realised the prospects and impact of scheduling decisions on enabling sustainable manufacturing. Several studies have investigated sustainable (or green) scheduling and developed frameworks to enable its implementation. In [15], the authors carried out a review of sustainable scheduling models and frameworks. From their review, the authors found that energy-efficient scheduling has emerged as the prevailing field of research in sustainable scheduling. Energy efficiency is defined as the ability to perform a process and realise its intended outcome without compromising performance, with less energy [16]. In addition to energy efficiency, sustainable scheduling can be realised through variable processing times [17] and demand response [18], amongst others. In his review of demand-side management (DSM) in the industrial sector, the author in [11] classified the applicability of DSM into four main industries namely: residential, agricultural, commercial, and industrial. In the same review, the author finds that the applicability potential of DSM in the industrial sector is relatively low at around 9%, especially when compared to the residential sector. However, this does not mean that the scope to implement DSM in the industrial sector is limited as there could be yet undiscovered potential. Nevertheless, implementing DSM in industrial processes remains a complex decision due to the interdependencies and time constraints of manufacturing processes [11].

Demand response, which falls under the wider umbrella of demand-side management, and usually implemented under time-of-use tariffs or real-time pricing programs [19], entails changing electricity consumption patterns in response to changes in price or incentive payments [16]. It should be noted from the previous definition that the conventional motives to adopt demand response have conventionally been cost-saving ones. Indeed, much research on demand response in industry has focused primarily on cost minimisation. In their review on demand-side management, the authors in [10] classify demand response programs as price-based and incentive-based, both of which are motivated by cost reduction. In another study that reviews the literature on demand-side management in different energy-intensive sectors, the author in [11] reported significant power reduction in the cement and aluminium manufacturing sectors. In that same review, the author reviews modelling approaches used for decision-making with regard to the implementation of demand-side management. The author identifies optimisation and simulation modelling as decision-making approaches for demand-side management. The share of optimisation modelling was, however, unproportionally larger than that of simulation modelling with only one simulation model, employing the system dynamics paradigm, identified. Indeed, optimisation modelling (integer, mixed integer, and nonlinear mathematical programming) has been widely used in demand response, particularly for cost minimisation. In their review of the literature on green scheduling, the authors in [20] identify several optimisation modelling approaches and solution algorithms for solving green scheduling problems. The findings of the review, close to those reported in [11], lack reporting of any simulation-based solutions. In that same paper, the authors report that scheduling problems have been traditionally solved from a cost-minimisation perspective. In another paper, the authors in [21] review the literature on multi-objective hybrid flow shops. The authors reported that most research used completion-based objectives, and only 52 out of 130

studies are coupled with sustainable, primarily energy as a proxy, criteria such as total energy consumption and total energy costs. Nevertheless, the incorporation of demand-response strategies and the explicit incorporation of environmental metrics such as the minimisation of total carbon dioxide emissions are still relatively scarce for this type of scheduling problem with only 6 out of the 130 papers accounting for it.

In [9], the authors developed a nonlinear optimisation model for sustainable scheduling in machining processes in a single work centre. The model maximises monthly profit by regularly changing cutting speed in response to the share of renewables in electricity (the authors assumed two sources: the grid and a photovoltaic supply). Simulation results show a best-case scenario of around 30% energy reduction and 2.81% profit increase. The model, however, included several assumptions and simplifications, especially with regards to cost parameters estimation, stochasticity (the use of uniform distribution), limited data on the grid carbon intensity, and the limitation to machining processes. In [22], the authors develop mixed-integer linear programming (MILP) models for demand-side management to minimise cost. The authors tested and validated their approach on a use case from the metal casting industry. These models were, however, tailored to the case of metal casting, with models' parameters largely confined to the casting process, hence impeding applicability to other processes. In addition, the paper did not incorporate uncertainty into modelling, which can reveal important features of demand response. In [23], the authors propose several optimisation models for energy-aware scheduling where they minimise total energy consumption by optimising machines' idle times. In [24], the authors develop bi-objective optimisation models for scheduling, minimising makespan and energy consumption. They test their model on a use case from the glass production industry. Their model, however, approached demand-response from a primarily cost perspective based on time of use tariff. For a thorough review of optimisation modelling for scheduling under demand response programs, the interested reader can refer to [25] where the authors identify cost-saving as the primary motive for adopting time of use tariff in scheduling by end users.

As for the specific use case of this paper (i.e., aerospace manufacturing,) which is characterised by long lead times, high cost of unit production, high buy-to-fly ratio, and energy-intensive processes [26], the literature on sustainable scheduling is relatively scarce. This could be partly attributed to the relatively small environmental impact of aerospace manufacturing when compared to that of the use phase. Indeed, one study, [27], has estimated that more than 99% of the environmental impact of an Airbus 320 comes from the use phase. This unproportional distribution of an aircraft's lifecycle environmental footprint leads to most research efforts being dedicated to improving the environmental footprint of its operation (e.g., through lightweight components, aerodynamics improvements, bio-fuels etc...). Therefore, research on sustainable scheduling has mostly overlooked the case of low-volume high variety production in general, and aerospace manufacturing in particular. In one study that investigated energy-efficient scheduling decisions in an aerospace manufacturing use case, the authors in [28] integrated an optimisation model into a company's manufacturing execution system to perform real-time data and monitor the scheduling by itself. The aim was to minimise energy consumption while differentiating energy when machines are idle and during production. The use case included 10 CNC work centres in an aerospace manufacturing facility. They found that they could create an On/Off cycle that would save energy which in their case resulted in a saving of 1.2% in terms of costs. However, they quantified the gains in terms of costs and not in terms of energy or CO₂e which distorts the impact in terms of energy. In a simulation-based study, the author in [29] proposed a framework, for aerospace companies, to integrate sustainable performance indicators using a trade-off analysis to help decision-makers quantify sustainability amongst other parameters. The author employed discrete-event simulations to test different scenarios,

then evaluated key performance indicators collected from aerospace manufacturing companies by assigning a score before comparing them to the baseline by grouping them into categories.

It could be concluded from the state-of-the-art review that contemporary research in sustainable scheduling has generally prioritised electricity cost minimisation over environmental metrics, mostly using energy consumption as a proxy for cost. Nevertheless, the assumption of a direct causality between cost minimisation and the reduction of carbon emissions is not always valid. For instance, market prices are low at night, but the average CO₂e emissions can sometimes be high if there is a lack of adequate energy storage facilities. Another remark that can be made from the state-of-the-art is that the majority of sustainable scheduling decision-support studies modelled the problem as mathematical programs (i.e., optimisation models) with either cost or energy minimisation being the objective functions. Mathematical programming has been the primary vehicle for solving scheduling problems for decades [6]. Most realistically modelled scheduling scenarios are, however, NP-hard problems [23], which means that such problems cannot be solved to optimality in polynomial time. As a result, most research that employs optimisation focuses on developing solution algorithms, whether heuristics or exact algorithms, that can find the optimal, or near-optimal, solution in a reasonable amount of time. This often comes at the expense of faithful representation of the modelled scenario. In this research, however, simulation modelling has been employed to model the production system. This allows for faithful representation of the system's dynamics, complex interrelationships, and nonlinearity, amongst others. In addition, the simulation model is parameterised and does not require the user to possess significant knowledge about scheduling from a theoretical perspective.

This paper presents a model-based decision-support framework and a case study of demand response for sustainable production of an energy-intensive family of aerospace aluminium components using stochastic discrete-event simulation modelling. The choice of simulation modelling to showcase the proposed approach is to construct a dynamic, stochastic, virtual environment that faithfully captures shop floor dynamics.

3. Simulation-based decision-support framework

In this section, an abstract high-level overview of the overarching decision-support framework is presented and discussed. The decision-support framework is comprised of a stochastic discrete-event simulation model, databases, a knowledge base, and a communication protocol that links these entities with each other. The user interface is contained within the simulation model, which is fully parameterised to enable a wide range of experimentation. A top-level case-independent view of the decision-support framework is depicted in Fig. 1 below.

The decision-support framework is modelled as an expert-system [30] so that it can be used by individuals with limited knowledge of scheduling from a theoretical perspective. The decision-support framework works as follows. First, live updates of the grid's projected carbon intensity data are regularly uploaded into the system's database. In this paper, as will be discussed in detail in the next section, carbon intensity data are obtained from the United Kingdom's Carbon Intensity API (<https://carbonintensity.org.uk/>). The data upload into the system's database can be performed automatically at user-defined intervals (e.g., every hour, twice per hour, etc...) in different approaches (e.g., web scraping, API etc...). In this paper, data retrieval of the projected carbon intensity data is obtained through a Python script that is scheduled to run (via Windows' Task Scheduler) on an hourly basis to retrieve carbon intensity data, then upload these data into the system's database. These data are then passed to the simulation model's own database, the historical data database, and the knowledge base when the simulation model is triggered to run. The historical data database typically contains data from previous production processes (e.g., historical shopfloor data), carbon intensity data, demand-related data, cost data etc... The knowledge base contains input from subject matter experts with

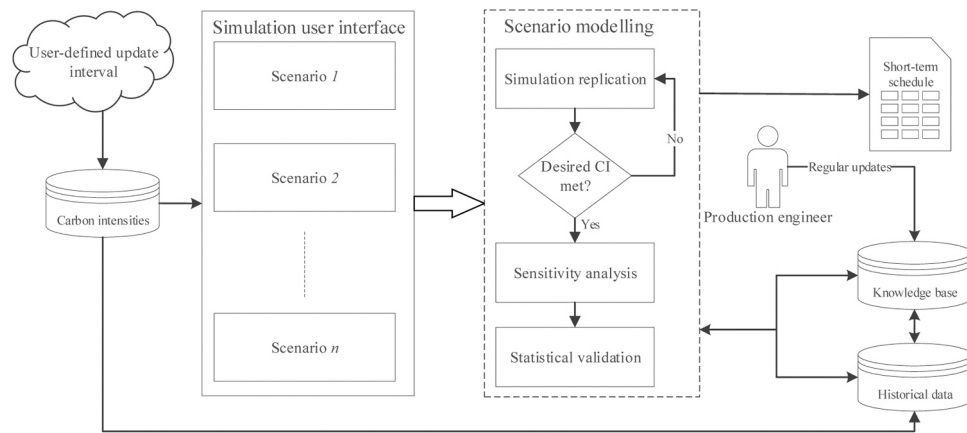


Fig. 1. Top-level view of the decision-support framework.

intimate knowledge of the modelled system. The experts' inputs are regularly updated within the knowledge base; however, expert input is not required at each simulation run. As an example, experts' input can be sought every week, month etc... as required. Information from the knowledge base will then be reflected in the simulation model on a regular basis by the decision-maker.

The simulation model in Fig. 1 is presented as a blackbox to maintain the overarching framework case-independent and applicable to any industrial setting. Candidate scenarios are defined either by the decision-maker, assuming sufficient knowledge of the modelled system, or following a statistical experimental approach (e.g., factorial experimental designs as is implemented in the next section). In this paper, as will be demonstrated in the following section, a full factorial design of experiments (DoE) approach is adopted in order to uncover further information about the system (main and interaction effects), enhance knowledge acquisition, and to statistically validate the results. Full factorial, although requires a large number of runs, was preferred over other factorial design approaches (e.g., fractional factorial designs, Taguchi robust designs) as the number of experimental factors, and their associated level of interest, as will be demonstrated in Section 5 is relatively low. Full factorial was also preferred over other DoE methods, such as response surface methodology and central composite design, for its relative simplicity and because understanding the system and the effects amongst its entities was prioritised over finding the optimal experiment conditions. It is worth reiterating that, due to time and resources associated with full factorial designs, scenario definition under full factorial DoE is not always necessary as scenarios can effectively be developed by people with intimate knowledge of the modelled system.

The parameterisation of the model is realised programmatically throughout model-wide parameters and user defined functions. To explain more, the scenario-defining choices, such as production period and priority rules, amongst others, are modelled as model-wide parameters (i.e., experiment-wide parameters, which are often referred to as hyperparameters) that are passed as arguments to user-defined rule-based functions during model run. To elaborate, when an entity (i.e., part) enters a block in the model, functions that contain scenario-defining arguments (i.e., parameters) are called, and the argument values (which are manually selected by the decision-maker) are passed to these functions. These functions contain programming constructs that define the model logic based on pre-defined alternatives using conditional statements (e.g., switch and if statements). For example, part variants have different production routes, and when a part enters the model, its production route (including which machines it will be processed on, labour requirements etc...) will be determined by passing the part variant number to the respective functions in each model block. These functions will then add/ remove entities, and determine the part flow throughout the model. To better explain the internal logic of the

overall experimental framework, Fig. 2 below depicts a high-level overview of the scenario building procedure. In Fig. 2, once the simulation interface is opened by the user, the user will have to make a series of decisions, upon which, the particular instance of the what-if user-defined scenario is built. The scenario building occurs at model time zero ($t = 0$, meaning that these decisions are implemented before the simulation clock advances to the first time step). In Fig. 2, which depicts a nipper from this research's case study, once the simulation interface is opened, the user selects which part (from a predefined family of parts) will be modelled. Once the user chooses the required part, the simulation model then determined the production route (which machines the part will go through), amongst other decisions, as explained earlier. This process is then repeated until all scenario decisions have been made by the user.

Once data have been updated and scenarios built, the simulation model is then run for several independent replication repeats. Since the simulation model is stochastic, outputs from a single simulation run are unlikely to be representative of the system, therefore, the mean of several simulation replications is calculated. The number of replications is determined statistically through confidence interval method [32]. The simulation model then checks whether the desired confidence interval has been met or not (typically a confidence level of 95% is deemed sufficient). The stochasticity of the simulation model, which allows a proactive approach to uncertainty, is incorporated through stochastic parameters that are defined by either empirical or theoretical probability distribution. In addition to the proactive approach to uncertainty, sensitivity analysis is also carried out to uncover the impact of uncertainty of key parameters. The parameters to be changed are, however, context-dependent and are usually identified by the decision-maker.

To the best of the authors' knowledge, this is the first study that integrates live carbon intensity API data as a decision factor in manufacturing scheduling decisions in dynamic modelling. To explain more, most studies in this regard model the problem from a mathematical programming perspective, hence resorting to many assumptions and simplifications required to control the computational complexity of the often NP-hard mathematical models. These assumptions and simplifications subsequently adversely impact and limit the flexibility, applicability, and accuracy of the modelled system. In this paper, in order to account for the dynamic nature, stochasticity, and complex interrelationships of production scheduling, simulation modelling has been employed.

4. The case study

The proposed approach determines the production times for the case study's components based on the carbon intensity of energy. Production periods and start times will be adjusted based on electricity carbon

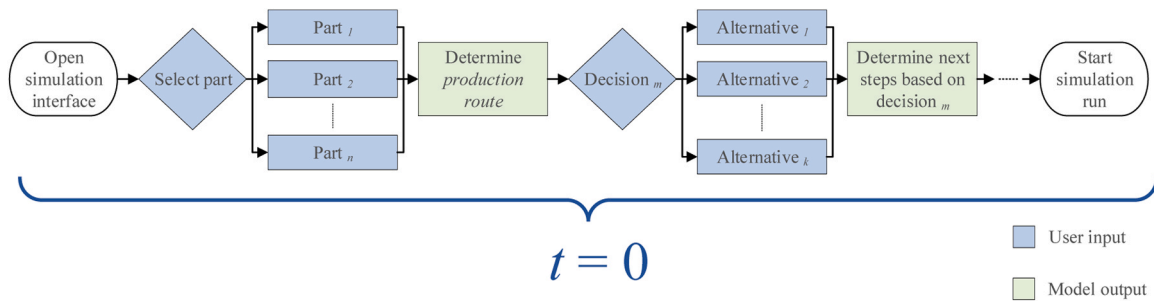


Fig. 2. High-level overview of the experimental-level scenario building procedure.

intensity, facilitated by a carbon intensity forecast developed by National Grid ESO, Environmental Defence Fund Europe, University of Oxford, and World Wildlife Fund: <https://carbonintensity.org.uk/>, integrated into the simulation for real-time CO₂e evaluation. This is the first carbon intensity forecast with a regional breakdown which provides a trend of 96 h ahead of real-time and carbon intensity in 30-minute segments.

The case study is conducted in collaboration with a UK-based tier 1 aerospace manufacturer and systems integrator with over 40 factories around the world. The production site where the case study was carried out operates three 8-hour shifts each day, has a workforce of around 1300 people, produces around 800 different stock-keeping units (SKUs), and has a turnover of over £ 300 million per year. The case study investigates the production of a family (six variants) of high-demand aerospace aluminium structural components for the A320/A321 aircraft family and is manufactured daily at one of the company's manufacturing sites in the UK. Due to confidentiality reasons, the properties and the names of the production processes of the component cannot be disclosed. Fig. 3 below, however, demonstrates a high-level flowchart of the production processes of the family of components from a sequential perspective. The two machining 1 stages refer to two distinct CNC group of machines. The choice of each group to select, depends on the part variant being processes. For confidentiality reasons, some processes were emitted from Fig. 3 below but were included in the simulation model. In response to the high demand and fluctuating orders, the planning team has implemented the Heijunka [31] method. This method levels the production, ensuring a consistent weekly target is met.

To highlight the electricity-consuming stages, Fig. 4 below provides a

high-level schematic of the production processes, with electricity-consuming processes highlighted where there is an opportunity for improvement in terms of carbon emissions. On-site visits to the shop-floor, observations and discussions with the Company's engineers helped in the identification of queues, and in a better understanding of stage-specific details, including size-dependent variations. The Company also pinpointed the bottleneck stage that needs to be dealt with separately and the stages shared with other products. Resources were dedicated solely to the case study's family of components until the outsourced stage, where they became shared resources. The outsourced stage is a surface treatment process that is carried out by a specialised supplier in another facility in the UK.

Once processes have been mapped, the DES model built and uncertainties analysed (through historical data and empirical distribution fitting), several replications of each factor/level combination are run in order to provide statistically significant results. The simulation experiments under a full factorial design of experiments (DoE) framework [32]. It should be noted here that the simulation model receives regular (e.g., daily) updates on carbon intensity projection. The specific number of replications is statistically determined by the confidence interval method [33] with a significance level $\alpha = 5\%$. After the required number of simulation replications has been run, sensitivity analysis for key parameters is then conducted. Conducting sensitivity analysis will naturally then entail further simulation runs, with each change in parameter value going through several simulation replications as determined by the confidence interval method. Once more information was revealed from the sensitivity analysis, results can be examined from a system's approach (e.g., using system dynamics simulation) as will be discussed later. Finally, due to the assumptions and simplifications in

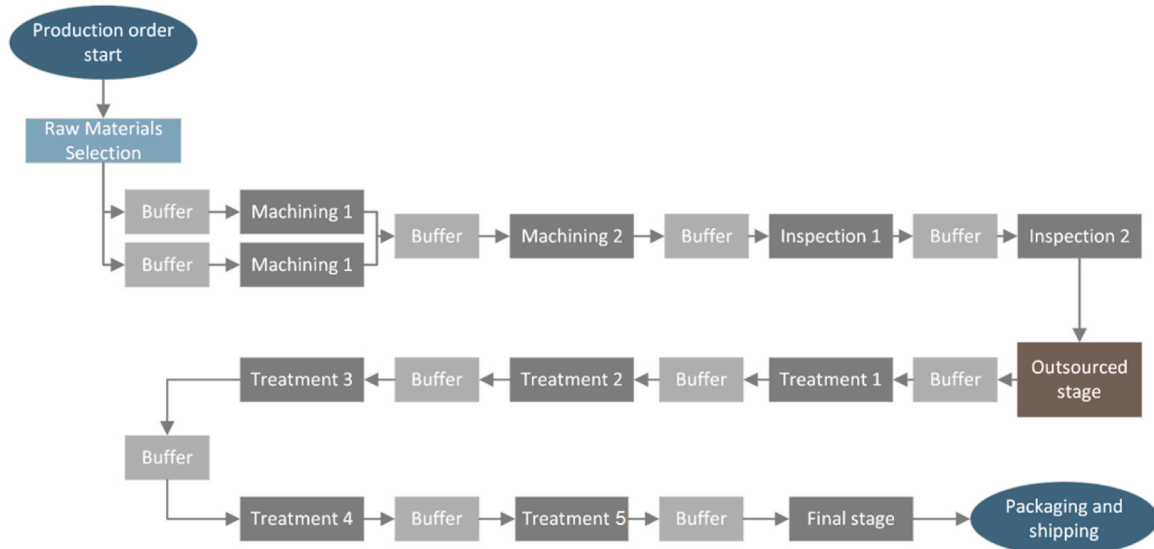


Fig. 3. High-level schematic of the production flow.

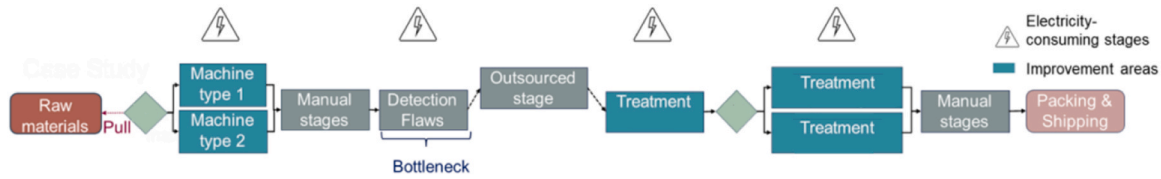


Fig. 4. Processes where carbon emissions can be reduced.

simulation modelling, it is important to validate the results by subject matter experts with intimate knowledge of the system being modelled.

5. The simulation model

The simulation model was developed using a discrete-event simulation (DES) paradigm through Lanner WITNESS 23 Horizon® software. The DES model incorporates uncertainty through stochastic parameters that were carefully assigned empirical probability distribution parameters after analysing historical data of inputs deemed by the company as having relatively high uncertainty. Key stochastic parameters include demand rate for the family of components, processing times and mean time between failures. Unfortunately, due to confidentiality reasons, the values of none of these parameters can be revealed.

To validate the as-is model, a comparison with historical data was used. Indeed, this method of validation is amongst the most reliable and widely used methods of simulation models validation [34]. The model was run for a period of six months where the throughput of parts and the occupancy of buffers were displayed in real-time as shown in Fig. 5. In addition, Fig. 6 below shows where buffers are occupied, and where they were not. The results plotted in Fig. 5 and Fig. 6 were reviewed with the Company's production engineers that were involved in this study in order to compare the model behaviour with that of the real system. These results presented in Fig. 5 and Fig. 6 where the outcome of several iterations of review and model calibration in collaboration with the Company's production engineers. After several iterations, the Company's production engineers were satisfied that the results reported in Fig. 5 and Fig. 6 bear sufficient resemblance to the behaviour of the real system within the intended domain of the study. Therefore, Fig. 5 and Fig. 6 serve to demonstrate the primary validation process adopted in

this research (i.e., comparison with the real system).

Following the validation of the simulation model with historical data and subject matter experts, the experimental factors were chosen based on areas for improvement in the flow, with the reduction in CO₂e emissions as the main goal of the study. In the baseline (as-is) model, various decisions were made, including the adoption of a first-come-first-served dispatching rule, the assumption that machines remain busy throughout the entire working time, and the definition of several runs for certain stages.

These features broadly resemble reality but in a more conservative manner. The first-come, first-served system, along with the assumption of a random production order, prolongs product shipment wait times. Specifically, during the packaging phase, one component variant of each size is required, yet the current priority rules overlook this requirement, resulting in pre-packaging queues. From these three base scenario features, certain improvements were derived to reduce the KPIs that are of interest to the Company; cycle time and CO₂e emissions. Cycle time in this paper refers to the time it takes to make one unit. It is calculated as the time that elapses from a part entering the model up until it leaves the system. This is calculated by the built-in features of WITNESS software. As for the CO₂e emissions per unit, it is calculated by multiplying the energy consumption throughout each production run by the emission factor for that same period provided by the carbon intensity KPI as follows where:

$$\text{CO}_2\text{e emissions per unit} = \sum_{m \in M} \sum_{p \in P} \sum_{s \in S} \sum_{t \in T} E_{mps} \times EF_t$$

the set M refers to the set of production machines, P refers to the set of parts variants, S refers to the set of the production machines' status (i. e., idle, setup, and production), and T refers to the set of time periods. Each instance, t , of the set T is obtained from the model's carbon

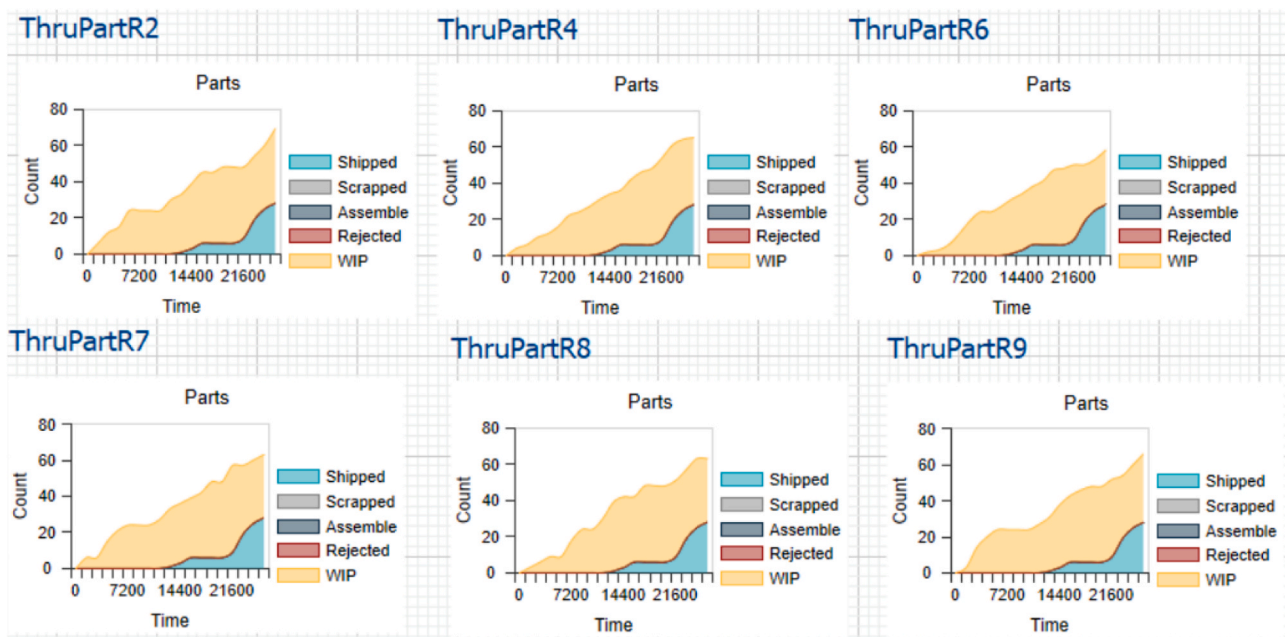


Fig. 5. Throughput charts per each of the component's family variants.

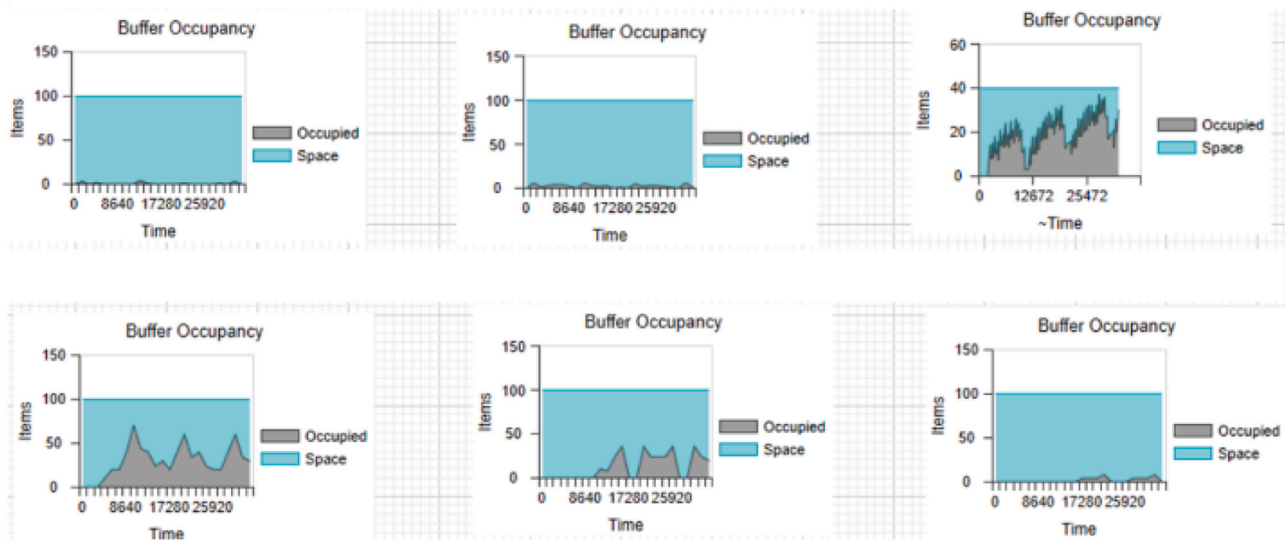


Fig. 6. Occupation of buffers charts for each of the processes.

intensity database, which is updated on regular intervals. As for the values of the set S , they are defined as ratios of each machine's maximum energy consumption value. So, the formula above reads as the product of the energy consumption (E_{mps} in kWh) throughout the production of a product variant multiplied by the emission factors (EF_i in gCO₂e/kWh) for the period that covers the production period. As for energy consumption data, for machines that have power monitoring devices fitted, historical data from these were collected, and their mean values for each machine state were used. For machines that do not have power monitoring devices, assumptions were made about their energy consumption based on each machine's manufacturer specifications.

The experimental factors chosen were priority rules, production start-up rules and production time, each with two distinct states (i.e., levels) as outlined in Table 1. In the DoE method, coded values were assigned to these states and the changes made in the simulation are explained in Table 2.

The experimentation framework will therefore follow a three-factor two-level experimental design with $2^3 = 8$ experimental runs.

Table 1
details of the DoE factors.

Experimental factor	State	Details	Coded value
A. Priority rules	First come/First served	The first product in the queue is the first to be manufactured	-1
	Depending on shipping requirements	The shipping requires one variant of each size, so machines choose the next product to be manufactured to prevent waiting for a variant size at the end	+1
B. Production start-up rules	Number of runs per day per machine	For the treatment and painting lines, the machines are running a certain number of times without considering if the machine is full	-1
	If the machine's load is full	The treatment and painting lines are running only if the capacity is full	+1
C. Production period	Full-time production during shifts	The machines are running according to the shifts	-1
	During off-peak CO ₂ e emissions periods	The machines are not running during off-peak CO ₂ e to reduce the emissions	+1

Table 2

Implications of the new states for the simulation.

Experimental factor	State	Implications for simulation
A. Priority rules	+ 1: Depending on shipping requirement	Parts are entering the model with a certain sequence and the electrical machines are also machining according to an optimised sequence
B. Production start-up rules	+ 1: If the machine's load is full	The input of the machines is not an interval of parts but a precise number. For the semi-automatic paint line, the machine is running only if there are 12 parts in the buffer as it is a conveyor that takes the parts to 5 different stages
C. Production period (i.e., peak vs off-peak hours)	+ 1: During off-peak CO ₂ e emissions periods	Preliminary analysis of carbon intensities over the simulation period and introduction in the simulation of new shifts with idle hours corresponding to CO ₂ e peak hour for all electrical machines except the bottleneck.

6. Results and discussion

All carbon intensity data were taken from the website <https://carb.onintensity.org.uk/> during the simulation period mentioned above. A linearised approach of half-hour intervals was employed to incorporate these data. In addition to simplifying data integration, this allows temporal consistency and aids interpretation. The simulation period was also chosen according to the seasonality of the carbon footprint. A study about how the carbon intensity varied between October 2021 and May 2022 was carried out as demonstrated in Fig. 7 below. Overall, average carbon intensity remained in a 95% confidence interval during the simulation period. This can be explained by the heating requirements during this time. This result improved the credibility of the simplification chosen for linearising the results on a half-hourly basis as shown in Fig. 8, despite the loss of granularity.

According to the data recorded in Fig. 8, the highest amount of carbon intensity occurs at peak times where demand at electricity is usually at its highest. This is equivalent to 3.5 h of peak time: from 4 p.m. to 7:30 p.m. In all scenarios in Table 1 with the +1 state of the experiment factor 'Production Time', all the machines were idle during this time.

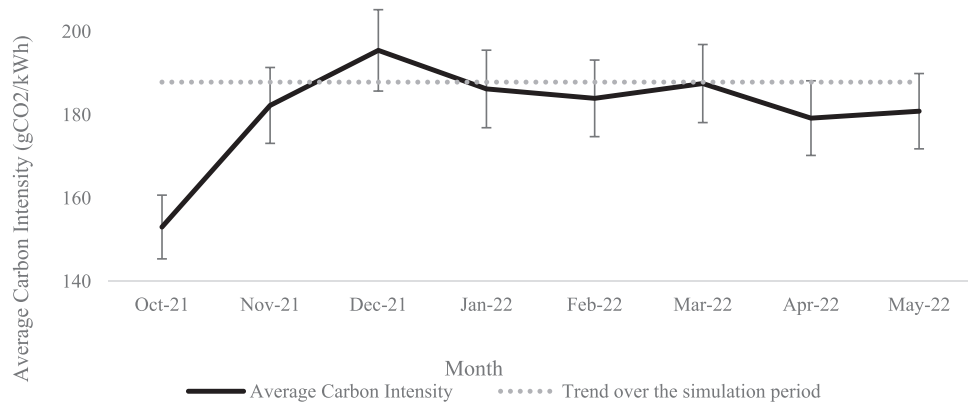


Fig. 7. Carbon Intensities from October 2021 to May 2022.

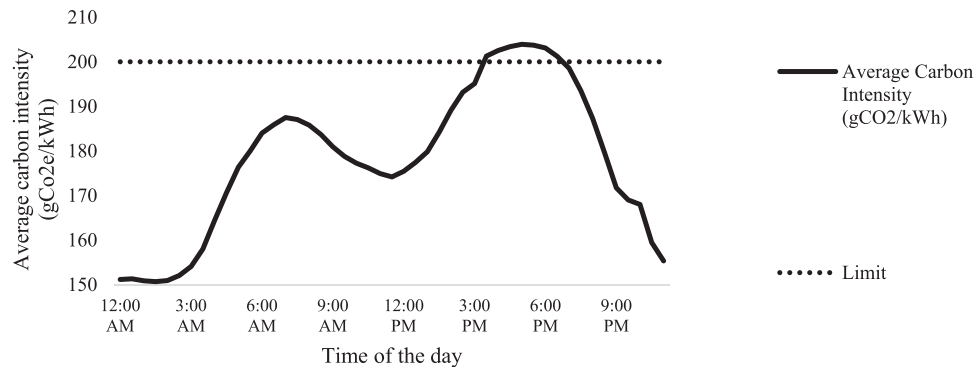


Fig. 8. Half-hourly linearisation of carbon intensity during the simulation.

Since the model is stochastic, with each run's stochastic parameters determined by a random seed according to given distribution parameters, the results of a single simulation run are hardly representative. Therefore, several simulation replications have to be run in order to produce statistically significant results that are representative of real-life scenarios. In order to determine the number of simulation replications required to produce reliable results, the confidence interval method, with a significance level ($\alpha = 5\%$), was employed. A total of 10 simulation replications were run, and, due to the small variation with regards to the total amount of carbon footprint, it was determined that 3 simulation replications would be sufficient where a significant level of 1.43% was achieved. As for the other objective of interest (i.e., cycle time), the significance level was 2.97% by the third iteration.

6.1. Design of experiments framework

In this section, the outcomes of the simulation runs, under the DoE framework, are reported and discussed. Each DoE factor/level combination constitutes a distinct scenario; therefore, 8 scenarios were investigated as shown in Table 3 below. The results of the cycle time have been normalised for confidentiality reasons as they were deemed commerciality-sensitive data by the Company. For the normalisation of the cycle time, the outcome of the factor/level DoE combination that resulted in the highest cycle time was assigned a value of 1, while the rest were scaled proportionally.

It can be noticed from Table 3 that the as-is (baseline) scenario resulted in the highest cycle time and CO₂e emissions when compared with the other scenarios. At first, this might seem counterintuitive as scheduling decisions in shop floors address cycle time either in the objective function, or as a constraint [21]. This, however, has a twofold explanation: first, the FIFO dispatching rule currently in place, especially when implemented on multiple product variants, can result in

Table 3
Outputs of modelled scenarios.

Scenario	Factor A: priority rules	Factor B: production start-up rules	Factor C: production period	Mean cycle time response (normalised)	Mean CO ₂ e emissions response (gCO ₂ e)
1	-1	-1	-1	1	81,602
2	+1	-1	-1	0.94	78,512
3	-1	+1	-1	0.99	80,103
4	+1	+1	-1	0.93	78,375
5	-1	-1	+1	0.99	78,715
6	+1	-1	+1	0.95	76,625
7	-1	+1	+1	0.99	77,434
8	+1	+1	+1	0.88	75,655

large quantities of WIP [35]. The other dispatching (i.e., +1 level for factor A) is an optimised one where the variant to be processed is selected to complete the processing of a batch that contains a whole shipset. Indeed, this behaviour has been reported in the literature before where the authors in [35] found that even the most simplistic dispatching rules can have a much greater impact on cycle time than FIFO. In addition, scheduling at the Company with regards to the case study's family of components, within the timeframe of the collected data, is in many instances determined by the experience of the production engineers, rather than by specialised scheduling algorithms. This is, in many cases, due to the expedited orders that they receive for these components, or for varying other reasons where they have to prioritise the production of a certain part within the family of components over others.

The DoE approach allows for uncovering the interaction effect of factors where the isolated effect of one factor might be minimal, while

when examining the impact when other factors are changed simultaneously, the impact might be much more significant [32]. In order to examine the statistical significance of the simulation results with regard to the cycle time response, an analysis of variance (ANOVA) of the results was carried out as reported in Table 4. This table presents the statistical results related to the factors (A, B, C) and their interactions (AB, AC, BC, ABC). The p-value measures the statistical significance, and the effects are negative if it indicates a reduction.

The significance level used to conduct the ANOVA was 5% which means that if the p-value < 0.05, the association between the response and the term in the model is statistically significant. Table 4 shows that the interaction AC is not statistically significant with regard to the cycle time response. As with the factors' effect on the CO₂e response, the interaction effect BC is also statistically insignificant. That means that there is not enough evidence to conclude that there is a relationship between these interactions.

This has also been confirmed by the Pareto charts of the standardised effects displayed in Fig. 9 and apparent in the parallel lines on the interaction plots presented in Fig. 10.

As for the standardised factors effects, factor A (i.e., priority rule) has the most significant effect with respect to the cycle time as the main effects graph displayed in Fig. 10 shows with the steepest downward slope. As for the CO₂e response, factor C (i.e., production period) has the highest impact on CO₂e emissions, while the interaction effects have a mild impact, which can be noticed from the interaction effects plot in Fig. 10 below. Therefore, A (i.e., priority rules) is the factor that has the greatest impact on minimising cycle time, i.e. the difference between the state + 1 and - 1 has the best positive impact in reducing cycle time, but the combination of ABC with each factor at the state + 1 is the optimal one to minimise the lead time. Similarly, the production period (Factor C) has the largest effect on lowering CO₂e emissions.

From the given results, Scenario 8 resulted in an overall improvement of 7% in CO₂e emissions and 12% in lead time. Although these numbers might seem modest, these improvements constitute important advancements in aerospace manufacturing settings, particularly since no capital investment was required to achieve these improvements. Indeed, such modest improvements in environmental performance are important steps on the road to net-zero manufacturing [26]. In addition, such improvements compare favourably with the latest findings reported in the state-of-the-art. For example, the authors in [9] reported a financial gain of less than 3% from implementing a similar approach. Other studies have, however, achieved higher improvement in CO₂e emissions. For example, the authors in [8] achieved an improvement of 17% in CO₂e emissions per unit product. Their approach, however, onsite generation of renewable energy resources, which requires considerable capital cost in energy-intensive industries such as manufacturing.

The simulation results under DoE helped capture interaction effects, which makes it easier for decision-makers to better understand the implications of each scenario. Some scenarios perform worse in terms of productivity but better in terms of sustainability (e.g., scenarios 3 and 4), and being aware of such trade-offs uncover important insights when implementing new strategies. The results indicate that changing the priority rules (Factor A) to consider shipping requirements had the

highest impact on reducing lead times. This is expected as it helps avoid bottlenecks right before shipping by ensuring a balanced production of all variants. Implementing this new priority rule could significantly improve productivity. The production period (Factor C) was most influential in decreasing CO₂e emissions by avoiding electricity during peak hours, which has a higher carbon intensity. While overall productivity, which represents the mean of the cycle time of all components, declined due to idle machines, the sustainability gains were substantial. This highlights the potential trade-offs between productivity and sustainability that manufacturers will need to consider. Overall, the combination of changes in Scenario 8 (new priority rules, full machine loads, and off-peak production) led to the best results on both fronts. While this scenario may not be feasible to implement all at once, it provides insights into the factors with the highest impacts. An important practical implication that can be concluded from this observation is that manufacturers can use these learnings to prioritise incremental changes with the most benefit.

6.2. Statistical validation

As for the validation of the simulation model and the overall experimental framework, different approaches were employed. For the iterative verification and validation of the simulation model, subject matter experts review of the results, model walkthroughs with those directly involved in production within the company, experimenting with extreme values, and tracing individual entities in the model were all used to increase confidence in the model [34]. For the DoE framework and ANOVA model validation, statistical tests were carried out in order to establish the validity of the overall experimental approach and the results.

In order to do so, regression models were developed, and then residual plots (the difference between an observed value and the corresponding fitted value, the one predicted by the model) for the two responses were traced as displayed in Fig. 11. These allow the verification of whether the framework generates valid results in line with the expectations. The normal probability plots show a trend meaning that the residual follows a normal distribution. The two versus graphs show that residuals are randomly scattered around zero, highlighting a constant variance of the residual. These results indicate the validity of the statistical models that converge to a statistically reliable response.

6.3. Sensitivity analysis

Although the simulation model is stochastic, further examination of uncertainty from a proactive perspective is necessary, especially since a number of assumptions have been made due to either lack of data or due to the relevance of the assumptions to the intended domain of the model. In order to enhance the validity of the model, sensitivity analysis for key parameters is carried out. In sensitivity analysis, the impact of changing the values of certain, key, parameters is examined in order to reveal more information about possible future scenarios, or to help decision-makers assign values to these parameters more carefully in a proactive manner [36]. In particular, many assumptions have been made with regard to the energy consumption of the production equipment (primarily CNC machines) due to the lack of metering equipment to measure energy.

The energy consumption for one of the inspection processes, non-destructive testing (NDT), has been estimated based on a different (relatively similar) process and is therefore considered uncertain. The carbon intensity data was also linearised, which also adds to the uncertainty of the results. Furthermore, the demand is expected to rise by 22% in the next year that this research was carried out. This forecasted increase in demand, and the subsequent increase in production rate, can also have a significant impact on CO₂e emissions, especially when implementing off-peak production. It is therefore important to ensure that the measures taken will enable the Company to meet its primary

Table 4
P-values, effects and interaction effects of the experiments' outcomes.

Factor	p-value (cycle time)	p-value (CO ₂ e emissions)	Effect (cycle time)	Effect (CO ₂ e emissions)
A	0.000	0.000	-1584	-2172
B	0.000	0.000	-590	-972
C	0.006	0.000	-327	-2541
A*B	0.001	0.001	-431	418
A*C	0.092	0.036	-185	237
B*C	0.014	0.151	-378	-154
A*B*C	0.006	0.022	-330	-263

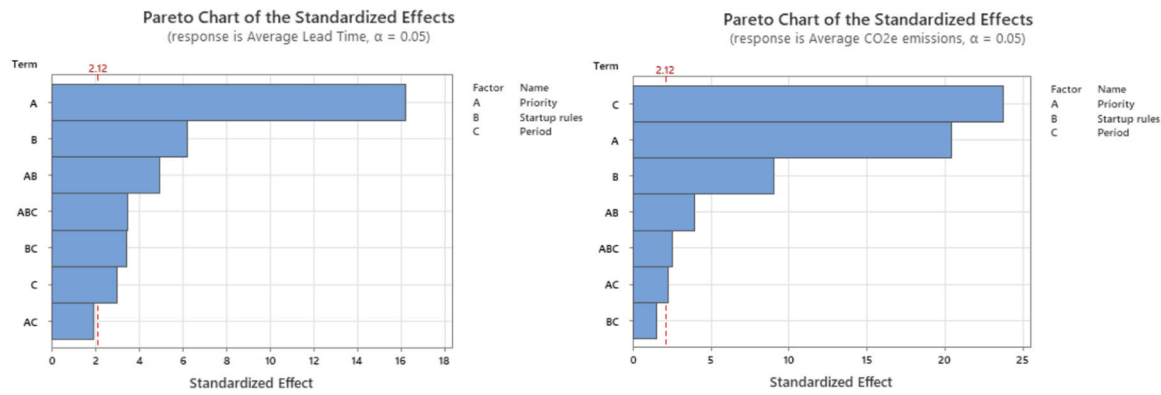


Fig. 9. Pareto charts for the standardised effects on the cycle time (left) and CO₂e emissions (right).

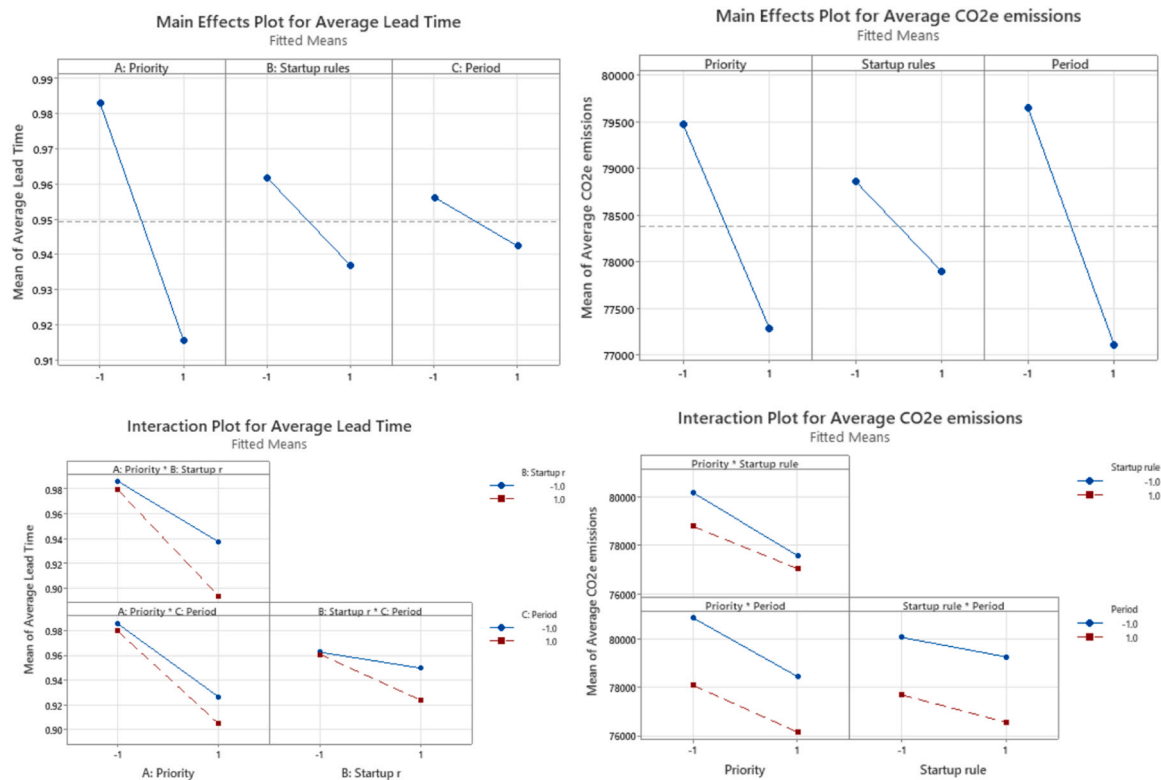


Fig. 10. Main (top) and interaction (bottom) effects plots for the cycle time response (left) and the CO₂e emissions (right).

objective of completing all orders without delay.

Sensitivity analysis experiments on energy consumption and carbon intensity were carried out to reveal the potential subsequent variability in the results in terms of CO₂e emissions for the best scenario i.e., scenario 8. Another set of sensitivity analysis experiments was made for the demand and the bottleneck process time with respect to the lead time. Table 5 and Table 6 contain the different values tested and their impact on cycle time and CO₂e emissions, and Fig. 12 visualises the outcomes of the sensitivity analysis for both cycle time and CO₂e emissions. The values of the parameters increase/ decrease were primarily based on analysis of historical data, comparison with data logs of similar processes, and expert judgement.

The sensitivity analyses displayed in Fig. 12 above highlight the importance of accurate carbon intensity forecasts. The high sensitivity to NDT energy consumption also indicates this stage should be a focus for data collection to reduce uncertainty. For cycle time, with demand expected to rise considerably, it is important to monitor if the proposed

scheduling changes maintain the desired delivery performance. The sensitivity analysis figures reveal where uncertainties exist and what factors need refinement through real-world data to enhance the model's robustness. Although sensitivity analysis reveals important information about the behaviour of the modelled system, particularly with regard to uncertainty, results should still be treated with caution due to the variety of assumptions employed in the models. On the whole, the results provide useful initial estimates subject to the limitations of the model assumptions.

6.4. Final remarks

The decision-support framework can be maintained and used regularly. The simulation model, which is fully parameterised, is developed in a granular way to enable maintainability and adaptability. As more data become available, these data can be incorporated into the model to represent operations in greater detail. In addition to data, extra

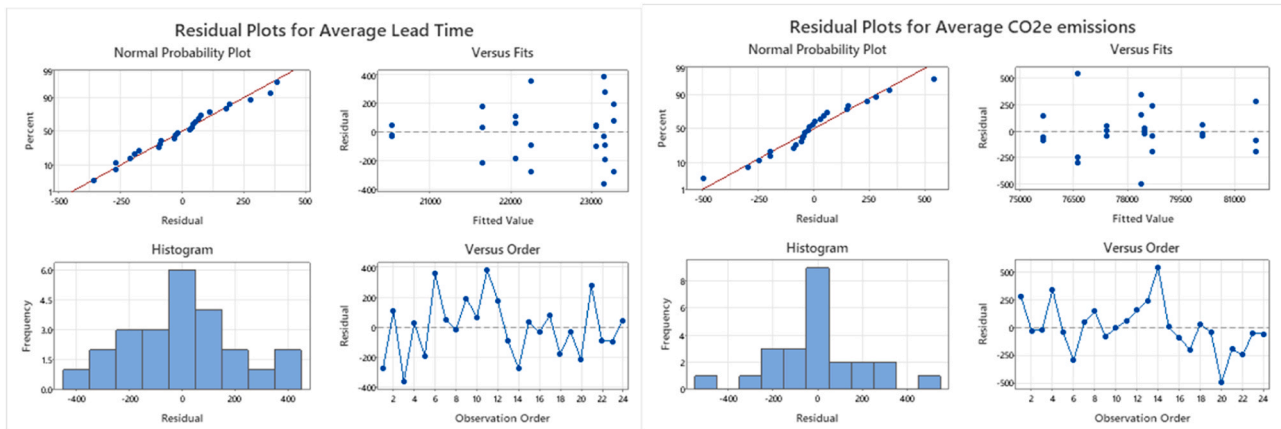


Fig. 11. Residual plots for average cycle time (left) and CO₂e emissions response (right).

Table 5

Sensitivity analysis of cycle time.

The examined parameter	Change compared with the baseline	Impact on cycle time
NDT time	-25%, + 25%	-10%, + 30%
Demand rate	-25%, + 25%	-5%, + 29%

Table 6

Sensitivity analysis of CO₂e emissions.

The examined parameter	Change compared with the baseline	Impact on CO ₂ e emissions
Carbon intensity	-10%, + 10%	-9%, + 8%
NDT energy consumption	-50%, + 275%	-7%, + 22%

production steps or complex interrelationships can be easily incorporated into the model to examine further what-if scenarios. Moreover, due to the granular approach to model building, additional sustainability factors like material waste and water use could also be easily incorporated in the future. These features also allow the model to serve as an easy to use decision-support tool, and visualise results in an easy to comprehend way. Fig. 13 below depicts a screenshot of an example of the model's dashboard. The dashboard displayed in Fig. 13 depicts an example of the simulation model interface (with arbitrary values) which shows scenario definition, process contribution to CO₂e emissions, resource utilisation, and uncertainty analysis. Scenario definition is realised through the parameterisation of the model where the values of

key parameters are chosen by the decision maker from a set of pre-specified values available in drop-down menu. Scenario definition is implemented as described in Section 3 and depicted in Fig. 2 where scenarios are automatically built after the user chooses a series of pre-defined alternatives at model time zero. The model logic and interrelationships amongst entities are hidden, and usually the model user does not have to access them. This enables ease of use and interpretation of the model as significant knowledge of simulation modelling, or the mathematical properties of scheduling decisions, are not required. Beneath the scenario definition section in Fig. 13, the contribution of each process to total CO₂e emissions is displayed in the stack chart. This also enables ease of interpretation of the model outputs by the user. The user interface also includes a section that displays histograms of the measured KPIs (cycle times appear in Fig. 13). These histograms are important in uncertainty analysis since the simulation model, as explained earlier, is stochastic. Therefore, the model user can assess the behaviour of the modelled system with regards to uncertainty. This can also be used for building empirical probability distributions that can be used to model future scenarios. Finally, resource utilisation for the production equipment is represented in the pie charts on the right section of Fig. 13, and the total CO₂e emissions per product variant are displayed in the gauge on the left side of Fig. 13.

In order to further validate the overall approach and data source for carbon intensity, and to demonstrate the reliability of data, the absolute difference between actual and projected carbon intensities was investigated and presented in Fig. 14 below.

The UK's Carbon Intensity API website <https://carbonintensity.org.uk/> forecasts the carbon intensity 96 + hours ahead for each region of the United Kingdom. The absolute difference between forecasts and the actual carbon intensity is displayed in Fig. 14 where, apart from certain

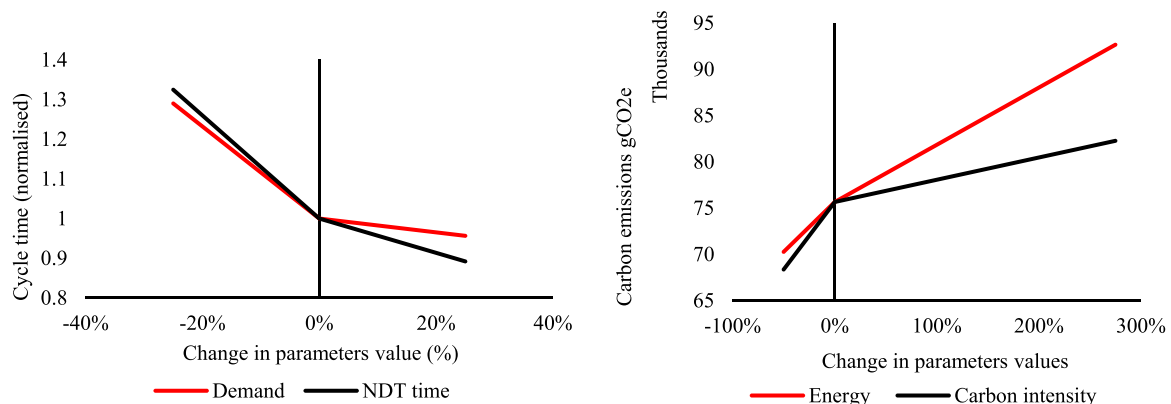


Fig. 12. Sensitivity analysis of the cycle time (left) and CO₂e emissions (right).

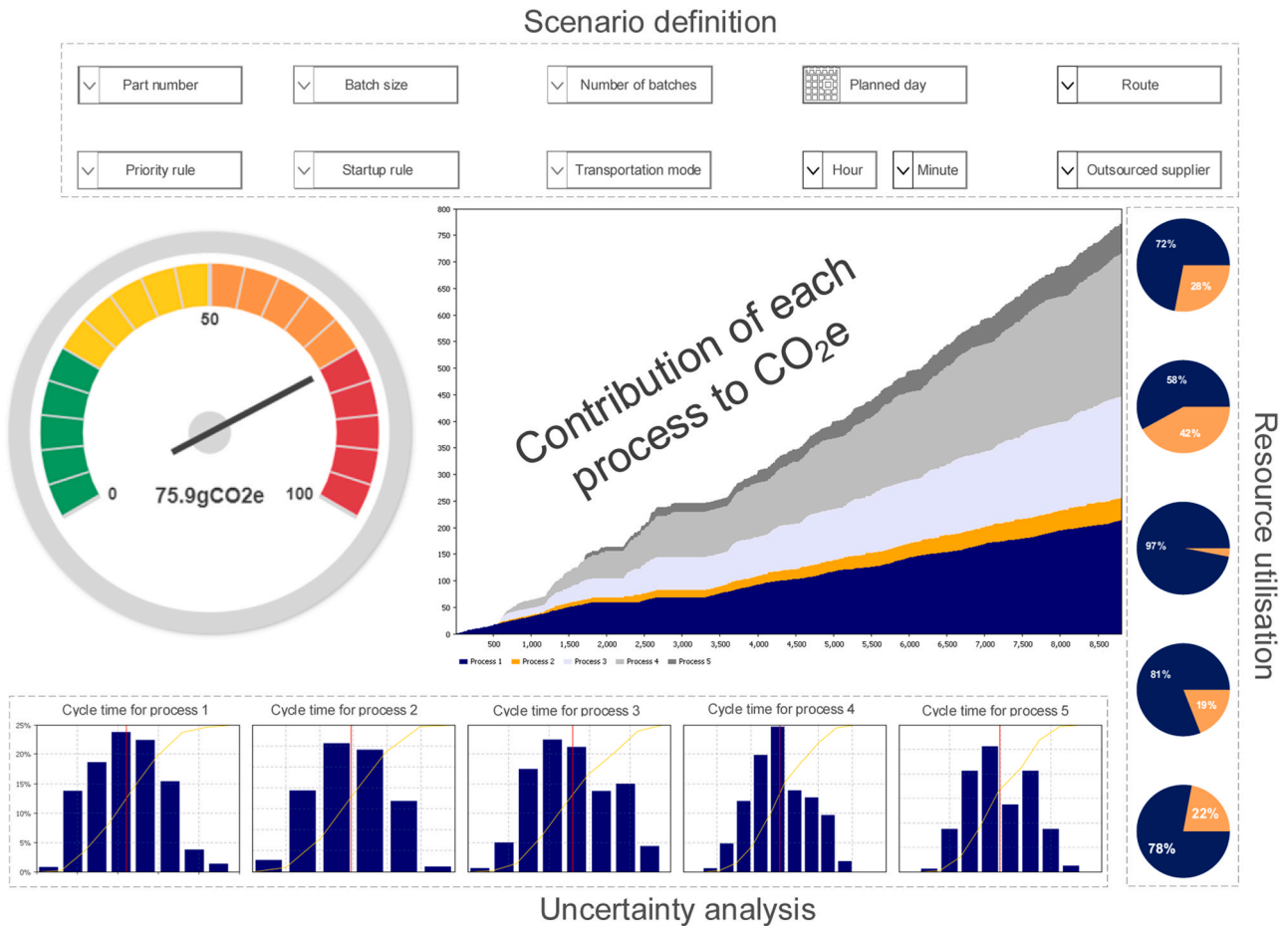


Fig. 13. Screen shot of a partial section of the dashboard of the decision-support tool.

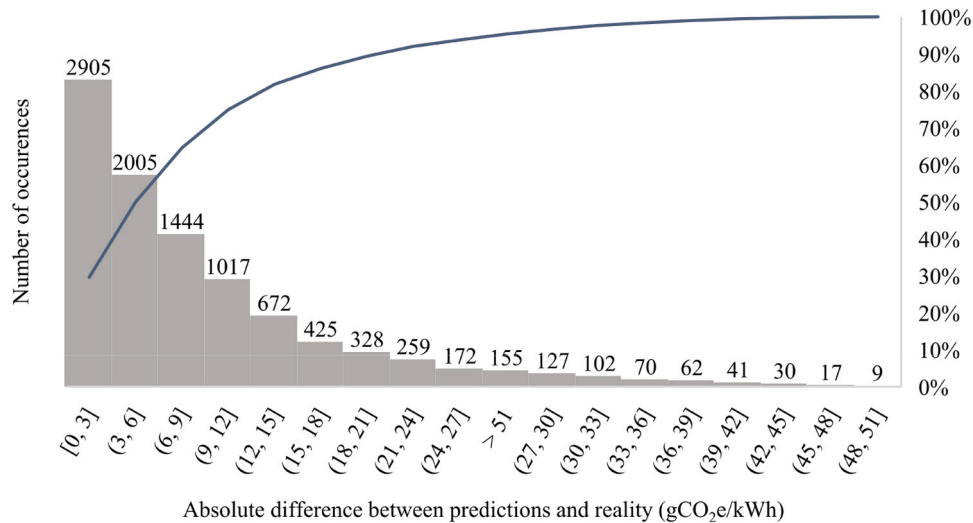


Fig. 14. Absolute difference between forecast and actual carbon intensity between 1 November 2021 and 9 May 2022.

peaks, forecasts are reasonably reliable. In Fig. 14, which shows the absolute difference between carbon intensity's forecasts (as provided by the Carbon Intensity API) and the actual grid's carbon intensity (as obtained by the National Grid ESO <https://nationalgrideso.com/>) over a six-month period from 1 November 2021 to 31 May 2022. In Fig. 14, it can be noticed that for 80% of the instances, the error in prediction was less than 12 gCO₂e/ kWh, which indicates reasonable accuracy of the

carbon intensity forecasted data that were used for decision making. With an average carbon intensity of 195 gCO₂e/ kWh, the error margin of 12 gCO₂e/ kWh is rather small, which supports the validity of the approach.

7. Conclusion

This paper proposes a stochastic simulation-based decision-support framework aimed at reducing the environmental footprint of manufacturing without incurring capital costs. The simulation model was developed in a modular manner, hence enabling adaptability to the modelled system as it evolves over time. This modularity also enables the applicability of the model to other industries. In addition, this modularity allows for the inclusion of new sustainability metrics. The proposed approach explores the prospects of energy flexibility, from a demand response perspective, in production scheduling decisions that minimise carbon intensity in the energy used to run the production processes. The simulation model was conceptualized and validated through a case study in collaboration with a UK-based aerospace manufacturing company on a family of structural aluminium components. The results highlighted priority rules and off-peak production as most influential in enhancing productivity and sustainability, respectively. A combination of changes in the optimal scenario substantially improved both objectives. Results reveal a number of important practical implications. First, results from the case study revealed that adjustment to scheduling decisions, based on time of use so that production of energy-intensive processes coincides with times of the day when carbon intensity is at its lowest, can reduce their carbon emissions by up to 7% for the given family of components. This promising finding can motivate manufacturing enterprises to explore the prospects of implementing small, operational, capital-free changes to improve their sustainability profiles on their path to net zero.

Results from the use case demonstrate a number of interesting findings. First, results highlight that changes to already established daily practices that do not require capital investment can still contribute favourably to the improvement of the environmental footprint of manufacturing enterprises. Another interesting finding of this study is that the cycle time also improved, although this finding cannot be generalised to other instances, particularly to high production rates, low lead-time, industries.

This research can be extended in a number of research directions. One possible worthy extension is through linking the simulation model with a digital twin of the shopfloor through real-time data exchange and using the forecasts of carbon intensity, the Company would be able to have a schedule updated for unexpected events and to improve its resilience. Another possible extension is the incorporation of additional sustainability metrics such as material efficiency, water footprint, and waste, amongst others. Finally, an interesting extension of this research is to complement the simulation model with a system's view of the proposed approach. For example, the model can be hybridised by the incorporation of system dynamics simulation where causality and emerging complex behaviour can be exposed. This will allow a better understanding of other pillars of sustainability, such as the impact on the social dimension, in particular workers' productivity, especially since workload might shift to unconventional times.

CRedit authorship contribution statement

Eléna Galigny De Bonneval: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yousef Haddad:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Joseph Carter:** Validation, Resources, Project administration, Conceptualization. **Mohamed Afy-Shararah:** Writing – review & editing, Validation, Resources, Funding acquisition. **Konstantinos Salonitis:** Writing – review & editing, Funding acquisition, Conceptualization. **James Artingstall:** Validation, Resources, Project administration, Conceptualization.

Declaration of Competing Interest

The co-author Konstantinos Salonitis is an Associate Editor for the *Journal of Manufacturing Systems* and was not involved in the editorial review or the decision to publish this article.

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