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Modelling the effect of electric aircraft on airport operations and infrastructure

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ABSTRACT

Electric aircraft offer the potential for emissions savings towards decarbonising air transport and reducing its contribution to climate change. However, the characteristics of these novel technologies pose questions about how they can be integrated with existing airport infrastructure. Key considerations relate to the time needed to recharge electric aircraft whilst on the ground without adversely affecting operational capacities, and the requirement for airport operators to install electric charging capabilities. The paper applies queuing theory and simulation modelling techniques to help identify potential battery charging regimes for electric aircraft based on potential forecasts of the future electric aircraft fleet. An initial prototype discrete event simulation model was developed to simulate impacts of short-haul electric aircraft on airport capacity to help determine future infrastructural requirements. Computational optimisation techniques were used to determine optimal configurations of single purpose and converted dual purpose aircraft parking stands under different scenarios and charging regimes. The model demonstrated that a future increase in electric aircraft equating to 25% of the global aircraft fleet required the conversion of only 13% of existing parking stands, while maintaining airside capacity and operational efficiency. The findings have important implications for air transport planners and decision makers in the transition to zero emissions and flight.

1. Introduction and context

It is widely recognised that the established, deeply embedded reliance on the burning of fossil fuels for air travel is unsustainable. Notwithstanding the recent impacts of the COVID-19 pandemic and the reduction in air travel demand, up to 2050 it is forecast that greenhouse gas emissions from international aviation will increase by a factor of between 2 and 4 times over 2015 levels (Fleming and de Lépinay, 2019). The challenges associated with combatting climate change and the specific role of major polluting industries like aviation in meeting emission reductions targets were reiterated during the recent COP26 UN Climate Change Conference held in Glasgow in 2021.

Consequently, there is an increasing focus on the potential environmental benefits of transitioning to new sustainable forms of aircraft propulsion technology, including electrically powered and hydrogen powered aircraft. Of these technologies, electrical propulsion is arguably the more mature, with a number of test flights of both pure-electric (powered solely by electrical motors using batteries) and hybrid-electric aircraft (powered by a combination of electricity from batteries and fuel burnt in an internal combustion engine) having taken place in recent years. Notable recent examples include the first test flight of a hydrogen fuel cell powered aircraft operated by the firm ZeroAvia at Cranfield Airport in September 2020. In August 2021, the US company Ampaire successfully completed a series of test flights of its hybrid electric EEL aircraft on a route between the Orkney Isles and John O'Groats in Scotland as part of research project examining the commercial viability of passenger routes served by electric aircraft.

While electric aircraft have significant benefits over traditional systems in terms of environmental performance, their development and adoption has so far been limited by the vastly inferior energy density of

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batteries relative to kerosene, and the additional weight these bring to the airframe. As of 2019, the most advanced Li-Ion battery cells had energy densities of 250 Wh/kg, equating to 1.7% of the equivalent jet fuel energy content. By comparison, a short-range electric aircraft demands battery-pack energy densities of 750-2,000 Wh/kg, or 6-15% of the existing jet fuel energy content. While annual increases in the energy density of batteries has increased around 3-4% annually since 2000 (Schafer et al. 2019), there is still a need for significant progress in battery technology before electric aircraft could compete directly with traditional aircraft on these terms.

For these reasons, the short to medium term to 2030, the prospect for electric aircraft is focussed on their application for shorter range mission profiles (50-400km) in the small and regional (max 19 seats) aircraft market, as a well as for general aviation and pilot training. By contrast, the prospect of medium and longer-range electric aircraft operating in the next 10 to 20 years is far more limited for narrow body aircraft, and almost entirely out of the question for wide body aircraft (Reimers, 2018).

Like electric road vehicles, batteries for electric aircraft are likely to be integrated or 'fixed' within the airframe (known as Battery Charging Systems); requiring an aircraft to be 'plugged in' to a power source once the battery has been discharged. In comparison, for Battery Swapping Systems the batteries are removed from the airframe to be charged remotely, and then 'dropped' back into the airframe once fully charged. While Battery Swapping Systems may reduce the amount of time needed to recharge an aircraft, they are likely to require new specialist equipment for replacing and moving batteries around the airfield and add complexity to existing airport operational procedures. There are also potential safety concerns with these systems, where sparks from exposed electrical contacts may pose an added fire risk (Roland Berger, 2018).

While the key drivers for the development and adoption of electric aircraft focus on their environmental benefits over traditional systems (e. g. lower levels of emissions, reduced noise and lower energy consumption), there are important unanswered questions regarding their potential logistical and operational impacts for airports, as well as the associated infrastructural requirements. Principally, these questions relate to the amount of time required to charge the aircraft's batteries while on the ground, and the need for specialist charging infrastructure on the aircraft parking stand.

As is well established in the air transport literature airline business models rely on high aircraft utilisation and efficient turnarounds (Lange et al. 2019). This is especially true in short-haul markets (<3 hours flight time), which is where electric aircraft are expected to operate when they first enter the market. This is also an important consideration for airport operators, especially at the busiest airports and/or those with limited stand capacity, where longer turnaround times can have knock-on impacts for overall capacity and the number of arriving aircraft that can be serviced on stands within a given timeframe (Schmidt, 2017). The effects of delays and airside congestion can have important knock-on impacts for the logistical operation of an airport, given the need to co-ordinate flows of passenger, baggage and cargo, as well as the various equipment and service vehicles needed to service an aircraft while it is on the ground. Hence, the ability to 'turn around' an electric aircraft in a timeframe that does not compromise either the airline or airport operator will be a key determinant of their future adoption and success.

The time required to charge the batteries of an electric aircraft depend on several factors, including the current state of charge of the battery, ambient conditions, and the charge/discharge rate of the battery (referred to as the battery 'C-rating'). A battery with a C-rating of 1 can be charged in 1 hour, a rating of 2C can be charged in 20 mins, and a battery with a rating of 5C can be charged in 12 minutes (Buchmann, 2017). The automotive industry is targeting fast charging as high as 10C, which could result in a charge to 80%-90% state of charge in just 5 minutes (Reimers, 2018).

While increasingly rapid charging of batteries may be technically possible, consistently fast charging batteries in this way will degrade the battery and reduces its longevity (referred to as the battery 'cycle life') much quicker than if it were charged more slowly. This could mean batteries would need to be replaced relatively frequently, with associated financial implications for battery purchasing, maintenance, and the time the aircraft would need to be out of service whilst this procedure took place. While slow charging is the most efficient way to charge a battery and leads to the slowest rate of battery degradation, a charge time of several hours (for example) is unlikely to be a commercially viable or operationally feasible proposition for either airlines or airport operators.

Consequently, there is a need to better understand the balance of operational, logistical and commercial implications associated with charging electric aircraft linked to the amount time needed to recharge these aircraft. Additionally, as electric aircraft will require the provision of new specialist charging infrastructure, there is a need to determine the rate at which existing aircraft stands should be fitted with electrical charging capabilities while balancing financial and operational considerations for the airport operator.

To this end, the paper uses Discrete Event Simulation (DES) models formalised through queuing theory to help assess battery charging regimes for electric aircraft and their impacts on airside stand capacities under different simulation scenarios. Specifically, the analysis sought to determine to what extent longer recharging (and hence, turnaround times) could be accommodated for electric aircraft without compromising overall airport capacity, and the rate at which an airport would need to convert existing aircraft stands to accommodate charging infrastructure for electric aircraft as demand for these aircraft grows. While the analysis uses London's Heathrow Airport as a basis for the study, the findings and recommendations are broadly applicable to other airports, given many are at a similar early stage in planning for the introduction of electric aircraft.

The following sections of the paper are structured as follows. In Section 2 a succinct literature review of computation simulation modelling approaches for airport operations is provided. In Section 3, the formal modelling methodology based on the application of queuing theory is presented; In Section 4 a description of the prototype simulation model is supplied. An analysis of the model in understanding the impact of different battery charging times potential infrastructural requirements scenarios regarding the optimum configuration of stand infrastructure under various scenarios is provided in Section 5; In Section 6 optimal stand capacities are determined for different scenarios and charging regimes through the application of computational optimisation strategies. A discussion and recommendations for policy and practice on the projected impact on electric aircraft on airport capacity management and planning is provided in Section 7. Finally, concluding remarks and areas for future research are provided in in Section 8.

2. Literature review- airport simulation modelling

Computational models have been widely used to simulate various aspects of airport operations. A multi-fidelity modelling approach to managing airline disruptions combining integer programming and simulation optimisation is proposed in Rhodes-Leader et al. (2018). In Adacher et al. (2018) the routing and scheduling of aircraft ground movement operations based on real data is modelled and optimised to minimise total routing taxiing delays and reduce pollution emission by optimising waiting time during which the engines are turned on.

Agent Based Models (ABMs) have also been used widely in this context. These models are typically decentralised systems with 'intelligent' decision-making software agents representing primitive behaviors and interactions of people, organization and other real-world entities. For example, Bouarfa et al. (2012) use ABMs to model airside operations with a view to model and optimize behaviour against multiple Key Process Areas, including safety, capacity, economy, and sustainability. In Chen el al. (2018) an ABM is used to investigate the relationship between terminal design and retail performance through different simulated scenarios. Finally, in Noortman. (2018) ABMs are used in the modelling of an airport's ground surface movement operations.

Another commonly used modelling paradigm is Discrete Event Simulations (DESs), which model the operation of a system as a discrete sequence of events occurring over time. In DESs each event occurs at a given instant in time and marks a change in the state of the system (Robinson, 2004). Researchers have applied DES to estimate the potential effects of changes in airport infrastructure, operating procedures, and traffic intensity upon system performance using multivariate statistical analysis. Here the influence of design capacity, airline scheduling practices and uncontrollable events on flight delays as well as the impact of selectively removing airport assets for maintenance is assessed (Douglas-Smith et al 2015). In Malandri (2018) a detailed DES model of inbound baggage handling at a large regional airport is used to identify bottlenecks and critical operations. The model is validated by comparing the simulation results with real data. Both ABMs and DESs are compared and applied to model passengers flows in Metzner, (2019). The simulation models can be used to explore correlations between terminal resilience indicators and terminal configurations in order assess their overall efficiency.

A third type of simulation model available in the repertoire of tools is System Dynamics (SD). This is an abstract modelling methodology used to understand the nonlinear behaviour of complex systems over time, based on states of objects at a given moment in time, the rates at which entities in the model change, and feedback of information over time. In Biesslich et al, (2014) SD has been used to combine airport operational parameters such as aircraft movements, passenger flows with economic features such as cash flows. There are also examples in the research where hybrid models have been developed that combine the advantages of these various paradigms for different application domains (for example, Brailsford et al, 2019).

There are also some limited examples of simulation modelling being used in the context of infrastructure planning requirements for novel aircraft technologies. Notably, Salucci et al, (2019) developed an optimisation model based on sizing requirements for Athens International Airport to investigate the infrastructural needs to support hybrid-electric aircraft operations. The paper focussed on issues around the number and type of charging points, as well as related electrical consumption and the number of spare batteries needed to ensure smooth operations in the case a battery swapping system is employed. A similar study was conducted by Bigoni et al (2018), examining infrastructure requirements needed to support small general aviation (GA) hybrid-electric aircraft operations at Milan's Bresso Airport. Both these studies where later consolidated as part of Airport Recharging Equipment Sizing (ARES) which is a mathematical model that combines knowledge about the airport flight schedules together with the composition and specifications of the aircraft fleet, to determine number of batteries, chargers, and aircraft required for operations. The proposed optimisation algorithm provides battery infrastructure sizing solution with the scheduling of charging operations according to the predetermined flight schedules at an airport, while minimizing procurement and operational costs. The method further allows consideration of plug-in charging and battery swapping, either together or as alternatives (Trainelli et al, 2021).

In Justin, et al, (2020) the authors develop algorithms based in scheduling theory for power optimized and power-investment optimized strategies for electric aircraft battery swaps and recharge. The approach enables the estimation of peak power demand, energy expenditures, and capital expenditures used for implementing the strategies and is applied to the operations of two commuter airlines in comparison with a benchmark non-optimized power-as-needed strategy.

This paper seeks to build on this research by exploring the use of simulation models for modelling and investigating the impact of electric aircraft (incorporating both pure and hybrid-electric aircraft) at a major hub airport. We further use the generated simulations to determine the optimal numbers of stands required under different charging regimes using computational metaheuristic-based optimisation strategies.

Up until the COVID-19 pandemic, Heathrow Airport was one of the largest airports in the World in terms of passenger numbers, handling around 80 million passengers annually. The airport also traditionally operated constantly at near 100% operational capacity under an imposed upper limit of 480,000 air traffic movements per year (roughly 650 arrivals and 650 departures per day) (Heathrow Airport, 2019). By means of comparison, in 2019 the second largest airport in the UK, London Gatwick Airport, handled around 285,000 aircraft movements and 46.6 million passengers, compared with 478,000 movements and 80.9 million passengers at Heathrow. Globally, in 2019 Heathrow ranked as the 7th busiest airport in terms of passenger numbers (Hartsfield- Jackson Atlanta International Airport in the US was the first with 110,530,000 passengers) and 15th in terms of aircraft movements (Chicago O'Hare in the US with 920,000 movements was first) (Airports Council International, 2020). For the purposes of this study, it made sense to 'stress test' the model at an airport where capacity (and thus sensitivity to alterations in aircraft turnaround times) was already an acute issue. By comparison, this is generally less of an issue at smaller, less congested airports with spare capacity, where alterations can typically be accommodated more easily. In effect, if the paper can show that recharging of electric aircraft can be accommodated at a busy, congested airport like Heathrow, then it figures that other airports would also be able to accommodate these aircraft with little detriment to their current operation. Consequently, in this paper the simulation model baseline was adapted to represent the existing passenger serving aircraft parking stand capacity at Heathrow Airport (197 in total, of which 133 contact stands and 64 remote stands).

In the following sections, a description of the formal and simulation methodologies used to develop the prototype model is provided.

3. Airport stand modelling methodology

The airport stand simulation problem can be formally expressed though queuing theory, an operational research methodology used to study the impacts of queuing scenarios (Yang, 2014) (Jaroslav, 2015). This can be applied to the servicing of arriving units (aircraft) requesting for services (stands). Queueing theory is used to determine the formal foundations of the proposed simulation model for defining interdependence between arriving aircraft, their wait for a stand, on-stand processing time, and departure (Krpan, 2017). The methodology comprises of the following elements:

3.1. Distribution of arrivals

The distribution of arriving aircraft determining the request for stands is defined by the time interval between two successive arrivals of aircraft to the airport. In this simulator the arrival of each aircraft α_v is based on a fixed rate λ_v defining the number of aircraft received by the simulation in each unit of time where $v \in \{kr, ec\}$, kr represent kerosine fuelled aircraft and ec represent electric aircraft respectively. The interarrival times $t_{arr\,v}$ between successive arrivals of each aircraft type is however stochastic so $t_{arr\,v}$ represents a mean interval between arrivals within the rate λ_v.

The proposed simulation problem is assumed to be an open system where λ_v is not dependent on any other state of the system. Furthermore, the arrival of aircraft over a particular period of time does not depend on the number of aircraft that previously arrived. Therefore, for our simulation problem the arrivals of aircraft are considered flows without consequences (Krpan, 2017).

3.2. Distribution of service times

The distribution of serving times of aircraft on a stand τ_v is defined by the length of time it takes for one aircraft to be turned around at an occupied stand. The stand turnaround times in the proposed simulation problem will be modelled as T_{ser_v} for each aircraft type. The time duration for carrying out a service can be a constant or a random value determine from a probability distribution. Using T_{ser_v} the average number of aircraft served in a unit of time termed μ can be calculated based on equation 1:

$$\mu_{n_i} = \frac{1}{T_{ser_v}} \tag{1}$$

where $n \in \{sn, du\}$, sn represent single purpose stands serving only kerosine fuelled aircraft and du represent retrofitted dual purpose serving both kerosine and electric aircraft types respectively. Here i is the stand index where $i = 1, \dots, m$ and m is the total number of stands.

A stand has a capacity that can be expressed by μ_{n_i} which can also be depicted as the stand's intensity of service. As our model assumes multiple stands for serving aircraft and we can determine capacity for the total number of stands from equation 2.

$$\mu = \sum_{i=0}^{z} \mu_{sn_i} \quad + \sum_{i=0}^{y} \mu_{du_i} \tag{2}$$

where z and y are the numbers of single and dual purpose stands respectively such that $z + \ y = m$.

Using the parameters λ_v and μ the load on the airport can be calculated based on ρ which is the quotient of the intensity of the flow of arrivals and the intensity of serving over all the stands as derived from equation 3.

$$\rho = \frac{\lambda_{kr+ec}}{\mu} \tag{3}$$

If $\rho < 1$, arriving aircraft will be serviced sooner or later, depending on the availability of stands. However, if $\rho \geq 1$ the load on the airport will increase over time leading to congestion from queuing aircraft. Therefore ρ should not be greater than or equal to 1, which implies that λ_v should be smaller than μ. If this is not the case, the number of stands should be increased to satisfy the condition for maintaining system stability (Krpan, 2017).

3.3. Illustrative example for calculating load ρ

As an example, to illustrate how to calculate ρ assume a regional airport has a stand capacity of 20 single purpose stands where $T_{ser_{kr}}$ is 45 minutes and the rate λ_v of inbound aircraft is 20 per hour. The model assumes equal $t_{arr\,v}$ between consecutive aircraft, no variability on turnaround times or other stochasticity. ρ can then be derived as follows based on equations 1, 2 and 3:

$$\rho = \ 0.75 = \frac{20}{\left(\frac{1}{45/60}\right)20}$$

Though deriving ρ provides a mathematical basis for determining stand capacities, a simple formalism of it does not fully account for model stochasticity from variability in t_{arr} between arriving aircraft, variability in taxing times and variability in turnaround durations for kerosine aircraft. Additionally, ρ values are based on separately calculating the collective capacities for single and dual stands for their respective aircraft types with respect to λ_v. However, kerosine aircraft can access dual purpose stands leading to a reduced capacity for electric aircraft. Equally, if electric aircraft have occupied dual purpose stands for longer durations of changing times, this removes capacity of these stands for kerosine aircraft to use. These dynamics are harder to fully define requiring more data on stand occupancy behaviour of the model from which probability distributions can be defined affecting shared stand capacities. They therefore lead themselves to be modelled through simulation studies. However, ρ can be used to provide initial comparisons with respect to distribution of arrivals and capacities with other airports.

3.4. Number of service elements

In the proposed simulation problem, the number of sn and du stands are predefined and used to simulate the effects on congestion and the throughputs of aircraft define here as the number of arriving aircraft that have landed, been (turned around) and departed the airport within a given period of time.

3.5. System capacity, serving order and discipline

The capacity of the service system is the maximum number of aircraft that are waiting in line to be served and that are being serviced on stands. When all stands are occupied an inbound aircraft α_v that arrived will enter a queue. For our simulation problem we defined specific queues q_v for each aircraft type. This was done for purposes of simplifying the design and implementation of the simulator as our focus was on determining the optimum number of single and dual-purpose stands for minimising queuing rather than focusing on analysing the queuing regimes being employed. The way in which aircraft from each queue access the stands is based on a First-In-First-Out (FIFO) order which accounts for the order of arriving aircraft. Hence when a stand τ_v becomes vacant it will be allocated to the compatible aircraft α_v that was the first to arrive irrespective of which queue it joined.

4. Proposed DES based airport stand simulation model

DES is a modelling methodology widely used in logistics and supply chain management. DES models comprise of entities, attributes, events (modules), resources and queues where time is an essential component for describing the order in which modelled events take place. Entities interact to simulate the operational workflow being modelled. As the system evolves over time, changes of its state variables occur at separate points in time corresponding to the behaviour of the entities (Padilha, 2016). These state variables can be used to capture data from simulated runs of the model. Queues may be used to manage the interaction of entities emulating real word process flows and associated delays. Shared resources can also be used in combination with queues and delay modules to represent assets which are used, periodically held, or consumed by entities. Constructing DSE models involve identifying and representing the resources, entities, logic and flow of the entities. Stochasticity of processes involved in the model and the relationship between modelled variables are further characteristics of this technique (Padilha, 2016).

4.1. DES airport stand model elements

Using a DES modelling methodology, the modular workflow elements for modelling aircraft recharging/refuelling times based on the introduction of short-haul electric aircraft as a proportion of non-electric aircraft flight operations was determined. The DES modelled separate workflows for electric and kerosene aircraft entities where both workflows were dependent on the proportion of each aircraft type entering the model and on the shared number of aircraft parking stands. The workflow elements comprised of the following modules as depicted in Fig. 1:

4.1.1. Entry module

Modelled the hourly rate of inbound flight arrivals of both electric and kerosene aircraft. For our model the short-haul electric aircraft type was modelled on an existing small twin engine, 50 seat aircraft (Bombardier CRJ 100 series). This aircraft type was selected purely indicatively and for the purpose of physical sizing and operational parameters for the simulations only. In the absence of a commercially operational electric aircraft, it was decided that an existing aircraft with a comparable sizing, operational and performance profile to potential future electric aircraft was selected. It was not the intention to select an

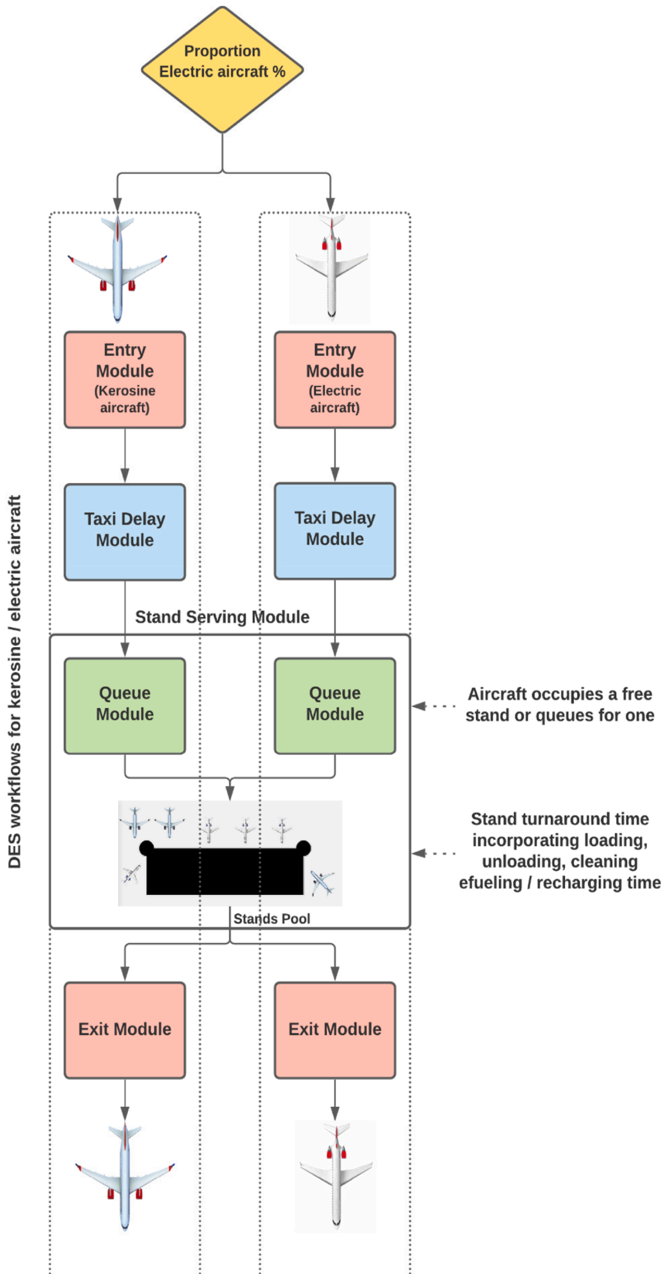


Fig. 1. DES workflow for both electric and kerosene aircraft showing the model elements.

aircraft type that would likely mirror the look or specifications of a future electric aircraft entering the market (for example, a CRJ-100 is a jet aircraft, whereas it is likely that the first electric aircraft entering the market will be propeller turbo-prop aircraft).

Here the number of short-haul electric aircraft flights were modelled as a percentage of total hourly flight arrivals. These numbers were then adjusted to model different projected increases in electric aircraft in the market. The hourly rate of inbound flights was also adjustable to model airport specific flight volumes based on aircraft movements during a standard operating day.

Formally the model determines the number of inbound kerosene and electric aircraft to generate per hour of simulation time based on their percentages to be modelled using equations 4 and 5 as follows:

$$\lambda_{kr} = \lambda_v * \left(1 - \left(\frac{eAircraftPercent}{100}\right)\right) \tag{4}$$

$$\lambda_{ec} = \lambda_v * \left(\frac{eAircraftPercent}{100}\right) \tag{5}$$

where λ_{kr} and λ_{ec} refer to the fixed hourly rate of kerosene and electric aircraft respectively, λ_v refers to the total fixed hourly rate of inbound flights as introduced in Section 3, for the given airport and *eAircraftPercent* is the projected percentage of electric aircraft.

The time interval between each arriving aircraft is distributed based on an exponentially distributed interarrival times t_{arr_v} with a mean of $1/\lambda_v$ (Cansiz, 2021). This distribution can be calculated based on equation 6.

$$f(x;\ \lambda_v) = \left\{ \begin{array}{cc} \lambda_v e^{-\lambda_v x} & x \geq 0 \\ 0 & x < 0 \end{array} \right\} \tag{6}$$

where $f(x;\ \lambda_v)$ is the probability density function and x is a random variable.

For example, if λ_v defines a rate of 20 aircraft arrivals per hour, the mean t_{arr_v} is $1/20 \times 60 = 3$ minutes between arriving aircraft over the course of 1 hour.

4.1.2. Taxiing delays module

Approximate aircraft taxiing times for movements from the runway to/from stands were also accounted for in the simulation. These were assumed to be in the range of 5- and 10-minutes reflecting estimates obtained from the airport.

For each aircraft the simulation randomly selects taxing times (measured in minutes) based on a continuous probability distribution. A triangular Probability Density Function (PDF) with a peak *(mode = 7.5)*, minimum *(min = 5)* and maximum *(max = 10)*, end points were used due to limited sample data, defined in equation (7).

$$f(x) = \left\{ \begin{array}{c} \dfrac{2(x - min)}{(max - min)(mode - min)} \\ \dfrac{2(max - x)}{(max - min)(max - mode)} \end{array} \right\} \begin{array}{l} min < x \leq mode \\ mode < x \leq max \end{array} \tag{7}$$

where $f(x)$ is the probability a random variable falls into a certain range that may be less, greater than or between a pair of values defined by x. Each aircraft's taxing delay time will be based on the simulation randomly selecting a value x from the distribution.

4.1.3. Stand serving module

Modelled a variable number of single and converted dual purpose aircraft stands τ_v as a shared resource to which arriving aircraft would be assigned. The serving model comprised of two elements:

4.1.3.1. Queuing module. Modelled FIFO aircraft queues q_{kr} and q_{ec} with unlimited queue lengths. The queues provide an indicator of congestion which can be monitored based on the adjustment of other model parameters, namely: number of stands (single or dual purpose), turnaround times for electric aircraft and kerosene aircraft, hourly rates of aircraft arrivals and the proportion of short-haul electric aircraft as a percentage of total inbound flights.

4.1.3.2. Stands pool. Modelled a variable number of m single and converted dual purpose aircraft stands as a shared resource to which aircraft would be assigned. The initial number of stands could be selected based on the known stand capacity of the airport in question (in this case, Heathrow). The number of dual-purpose stands could also be selected and altered to evaluate the impact of electric aircraft introduction on airside capacity (i.e., the total number of aircraft that can be serviced within a given timeframe) and operational efficiency (i.e. timely processing of arriving aircraft where congestion from queuing of aircraft waiting for a stand is minimised). Each aircraft would remain on stand for a duration of time, specified by the aircraft type (i.e. kerosene or electric) and take into account estimated times for passenger and baggage unloading, loading, cleaning refuelling or recharging in the case of electric aircraft.

The stand turnaround times for kerosene aircraft would be based on typical durations for short and long-haul aircraft and modelled in minutes as a triangular PDF. The stand turnaround times for electric aircraft was a fixed time duration in minutes comprising of battery charging times, which could be adjusted to evaluate the effect of longer or shorter charging durations. For the model, it was assumed that the recharge time for the electric aircraft reflected the overall turnaround time of that aircraft (i.e. we assumed that passenger disembarkation/embarkation, cleaning, and baggage unloading/loading processes could be conducted concurrently in the time it took to recharge the aircraft). Similarly, it was assumed that arriving electric aircraft would have fully discharged batteries that would need to be fully re-charged while on stand. While we recognise that in reality electric aircraft would arrive with varying degrees of remaining charge (much like residual fuel levels in traditional aircraft), this was not included in the model for brevity. However, this is acknowledged as a limitation of the approach.

4.1.4. Exit module

Modelling the release and departure of aircraft (electric and kerosene) once their stand servicing time was complete. As each aircraft α_v departs aircraft type specific counters are incremented and the status of these counters is recorded every hour to determine the hourly throughput. Individual aircraft can also be timestamped upon arrival and departure to record entry, exit and durations for further analysis.

4.2. Simulation modelling software

The AnyLogic software is a simulation modelling tool that supports agent-based, discrete event, and system dynamics simulation methodologies (AnyLogic). The tool is a cross platform tool built on the Java programming language and combines model optimisation capability based on the OptQuest optimization engine by OptTek Systems (OptQuest). AnyLogic was used to construct the DES stand models where Fig. 2 shows the DES user interface to the model with a graphical representation of a single pier simulation.

5. Simulation and analysis of airport stand capacities and charging regimes

5.1. Simulating impact of battery charging times

To understand the impact of different battery charging times on airside capacity an initial model was configured comprising of a hypothetical scenario were the airport operated a dedicated pier for the sole use of all-electric aircraft with a finite number of stands. The DES model assumed a rate of 10 inbound electric only aircraft per hour with an initial on stand battery charging time of 30 minutes. The initial number of stands was assumed to be 10 and an operating baseline number of stands was then determined by increasing the number of stands until all arriving aircraft could be immediately allocated to a parking stand without having to wait or queue for a stand to become available. This situation reflects the desired outcome from an airport operations perspective (i.e. no aircraft has to wait for a stand to become available upon landing). However, in a real world environment it may be necessary for aircraft to wait for a parking stand due to unplanned delays to other aircraft, malfunctions with equipment, shortages of equipment or ground crew, or other unforeseen circumstances. Hence, the baseline number of stands was determined to be 11. Table 1 shows the results after completing each simulation run in which electric aircraft charging

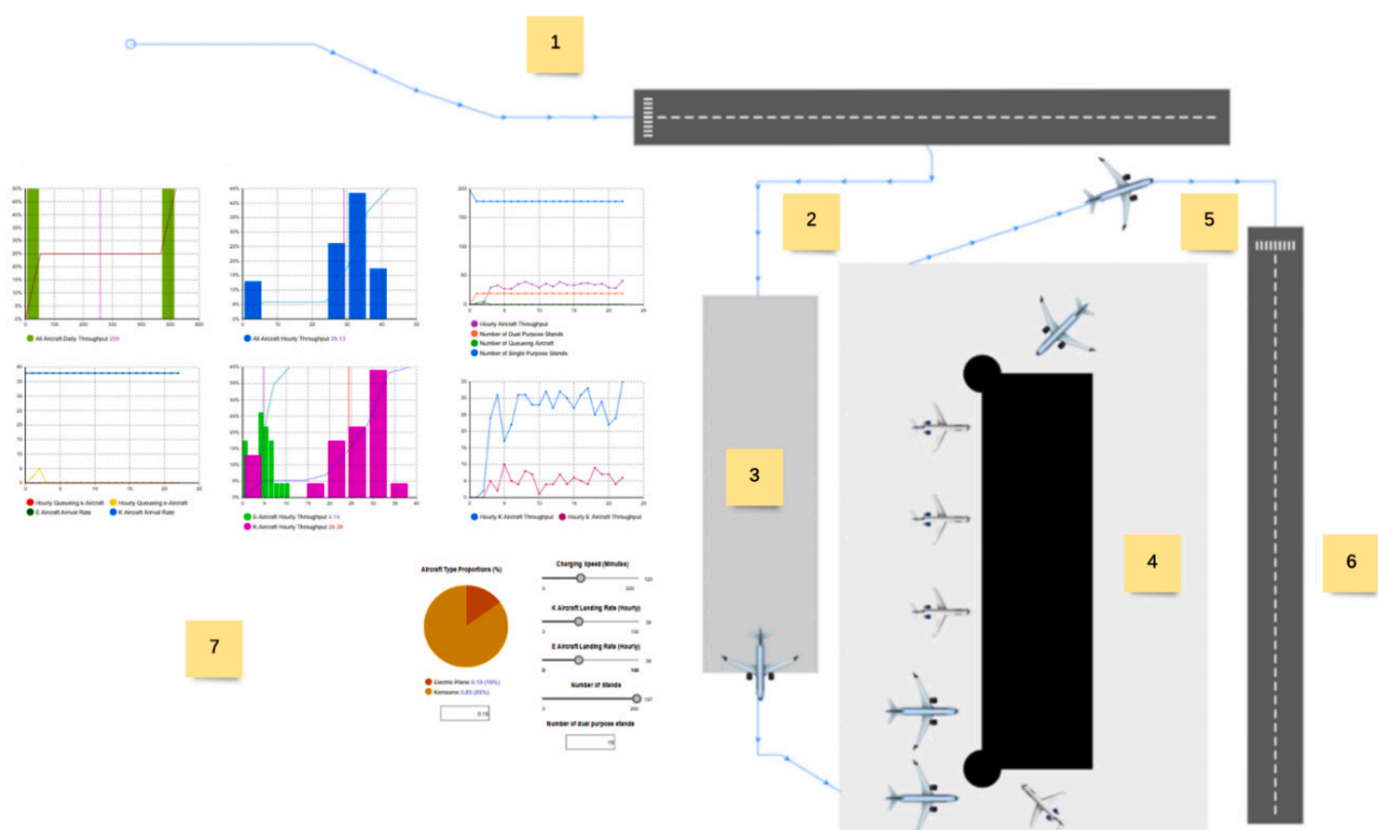


Fig. 2. Simulation user interfaces showing an airport single pier model with a number of dual-purpose stands. Based on various pre-set parameters the DES model simulates aircraft arriving (1), taxiing to stand (2), queueing for a free stand (3), refuelling/recharging (4), then taxiing (5) to the runway for departure (6). Data (e. g. aircraft throughput) is then recorded and presented graphically on plots (7) as the simulation progresses.

Table 1
Increase in electric aircraft on stand charging time vs aircraft throughput (assuming a rate of 10 inbound electric only aircraft per hour and a baseline number of 11 electric charging stands)

Electric aircraft charging times	Hourly throughput of aircraft
30 min (baseline)	9.85
60 min	9.77
90 min	7.07
120 min	5.33
150 min	4.30
180 min	3.61

times were increased by 30 minutes, up to a maximum of 180 minutes. The effect on total aircraft throughput is also shown, with increasing recharge times leading to a reduction in the number of aircraft being processed per hour.

It should be noted here that the modelling and results shown in Table 1 do not make any assumptions about the possible capacity of the batteries on the aircraft, nor the ability of the recharging and grid infrastructure to support the charging times shown. In effect, we are assuming that the charging times indicated could be supported, regardless of the size of the battery. However, we fully acknowledge that this is an important consideration when planning for electric aircraft, but this was not considered here in light of the focus on airside capacity and operations. As a means for comparison, current leading commercial electric cars commonly have batteries in the size of around 100 kWh, with charging speeds commonly available at 120-150 kW. The Eviation Alice, a 9-seater pure electric aircraft currently in development, is reported to have an 820 kWh battery (Eviation, 2021). To fully charge this battery in 60 mins (i.e. a rating of 1C), charging speeds of 820 kW would be required. If current charger technologies were used, it would take around 5 hours (300 minutes to charge) the aircraft.

It was also important to understand the relationship between required electric charging stand capacities and different battery charging times for the modelled all-electric aircraft pier. The DES simulation model was then used to dynamically increase the number of stands in response to increasing charging times to minimise congestion from queuing aircraft. This aimed to illustrate the extent to which the number of stands needed to be increased to maintain operational efficiency, assuming the volume of inbound aircraft was fixed at the same rate of 10 flights per hour. Table 2 shows the results after completing each simulation run in which electric aircraft charging times were increased up to a maximum of 180 minutes and their effect on the number of stands required for minimising congestion and maintaining throughput based on the number of inbound flights. Calculated ρ values for each modelled scenario are also provided for comparison.

The simulation evidence from Tables 1 and 2 show that an increase in battery charging times can have a significant impact on throughput and required stand capacities for an all-electric aircraft pier. For example, if the electric aircraft took 90 minutes to recharge, 24 stands would be required to maintain the rate of processed aircraft. The ρ values also correspondingly show a steady increase in load with charging time. These volumes and capacities would vary if a shared pier with dual purpose stands serving both electric and kerosene aircraft were modelled, which is discussed in the next section.

Table 2
Increase in electric aircraft on stand charging time vs number of electric charging stands required to minimise congestions and maintain aircraft throughput (assuming an hourly rate of 10 inbound electric only aircraft) with ρ values based on aircraft and numbers of stands

Electric aircraft charging times	Number of electric charging stands	ρ values for inbound electric aircraft rates λ_{ec} and dual-purpose stand intensities $\sum_{i=0}^{y}\mu_{du_i}$
30 min (baseline)	11 (baseline)	0.45
60 min	16	0.63
90 min	24	0.63
120 min	29	0.69
150 min	32	0.78
180 min	40	0.75

5.2. Determining stand capacity using DES model parameters representing a single pier

To assess the number of single and dual-purpose stands required to maintain airside capacity (reduce congestion) under scenarios of increased introduction of electric aircraft, the simulation model made the following assumptions as shown in Table 3.

The aircraft turnaround times would combine the fuelling / charging times with typical unloading and loading times and the initial number of single and dual-purpose stands was not defined. A baseline stand capacity of 20 single purpose stands for kerosene aircraft was initially established by reducing congestion to a minimum, based on assuming an initial rate of 20 inbound kerosine aircraft per hour. This can be shown from the green plot in Fig. 3 showing an increase, peak and decrease in queuing aircraft as the number of stands (shown in the blue plot) are increased from 8 to 20. The purple plot gives the throughput of processed aircraft every hour over the full simulation run for 75 hours.

The DES simulation model was then used to determine the total number of single purpose stands (i. e. kerosene only) that would need to be converted to dual purpose stands (i. e. kerosene and electric charging) to maintain capacity and keep airside congestions levels to a minimum. To do this, the proportion of electric aircraft relative to kerosene aircraft was separately modelled for 5%, 10%, 15%, 20% and 25% of hourly inbound aircraft. These figures reflected indicative scenarios for low (5%) to very high (25%) scenarios for future uptake of electric aircraft in the market up to 2040, based on industry literature regarding the uptake of electric aircraft (ICAO, 2019, Reimers, 2018, Roland Bergher, 2018). Fig. 4 below shows selected generated plots over an entire simulation run for a 10% increase in the proportion of electric aircraft movements and their effect on capacity and congestion, where the simulation was run for 375 hours.

Table 4 below shows the required increase in single and dual-purpose stand capacities required (as both exact numbers and percentage increases) to meet the demand for the higher proportions of electric aircraft movements based on the values obtained at the end of each respective simulation run. Note that these capacity increases are based on starting with 20 single purpose stands, representing a typical airport pier. The number of single and dual-purpose stands can be seen from the blue and orange plots in Fig. 4 (a). The increase in stand capacity still resulted in some congestion from queuing of predominantly electric aircraft, which on average was reduced to 5 aircraft or less per hour as the simulation was run. This can be seen in the green plot for all aircraft in Fig. 4 (a) and more specifically in the yellow plot for e-aircraft in Fig. 4 (b). This could be reduced or eliminated by increasing the stand capacity further, although the purpose here was to try and determine the minimum increases in stand capacity from the baseline model.

Table 3
DES model parameters representing a single airport pier

DES modules	Parameters
Stand serving module: short haul kerosene aircraft	Turnaround time of between 30 to 60 minutes (mode = 45 minutes), in line with current turnaround times for short-haul aircraft
Stand serving module: short haul electric aircraft	Recharging and turnaround time of 120 minutes. This time was chosen as a compromise between minimising the turnaround time and maximising battery cycle-life conservation
Stands pool module	Baseline stand capacity of 20 single purpose stands for kerosene aircraft
Entry module	20 aircraft per hour
Taxing delay module	5 to 10 minutes (mode = 7.5 minutes)

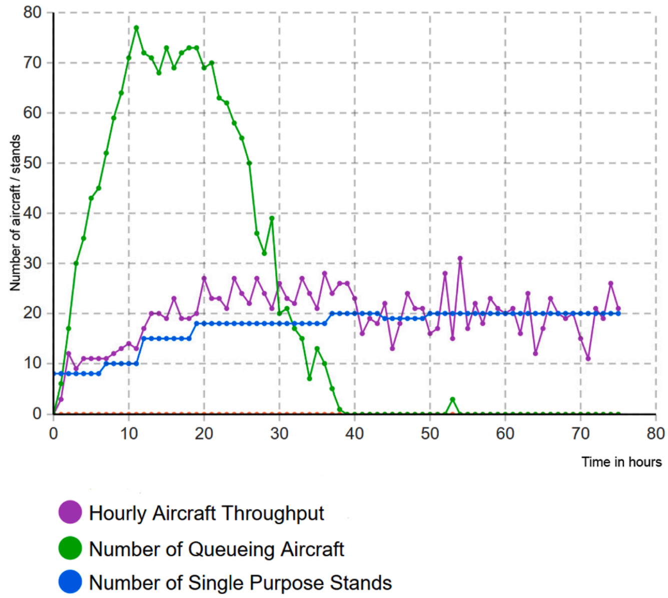


Fig. 3. Hourly throughput of all aircraft, number of queueing aircraft recorded per hour, number of single purpose stands (y-axis - number of aircraft/stands, x-axis - time in hours)

The results in Table 4 suggest that in the single pier case, there has to be a 50% increase in stand capacity, and where 50% of those stands have to be converted to dual purpose in order to meet the capacity demands for a 25% increase in electric aircraft movements. This is because given the relatively small number of stands to start with, both kerosene and electric aircraft compete for limited resources. Increasing the number of dual-purpose stands means kerosene aircraft have to share more stands with electric aircraft that require longer turnaround times. Consequently, there needs to be an increase in the number of single purpose stands to maintain capacity of the remaining higher proportion of kerosene aircraft. This can also be seen from the red plot in Fig. 4 (b) which shows some congestion for queuing kerosene aircraft requiring the number of single purpose stands (blue plot Fig. 4 (a)) to also be increased by 3 stands as is shown in Table 4 for a 10% increase in electric aircraft. Table 4 also provides calculated ρ values for each modelled scenario that in part follow the required stand increases to satisfy load for initial increments and conversions from the baseline. However, for higher percentage increases in electric aircraft, ρ diverges slightly from the required stand increases possibly due to model variabilities encountered in the simulation runs.

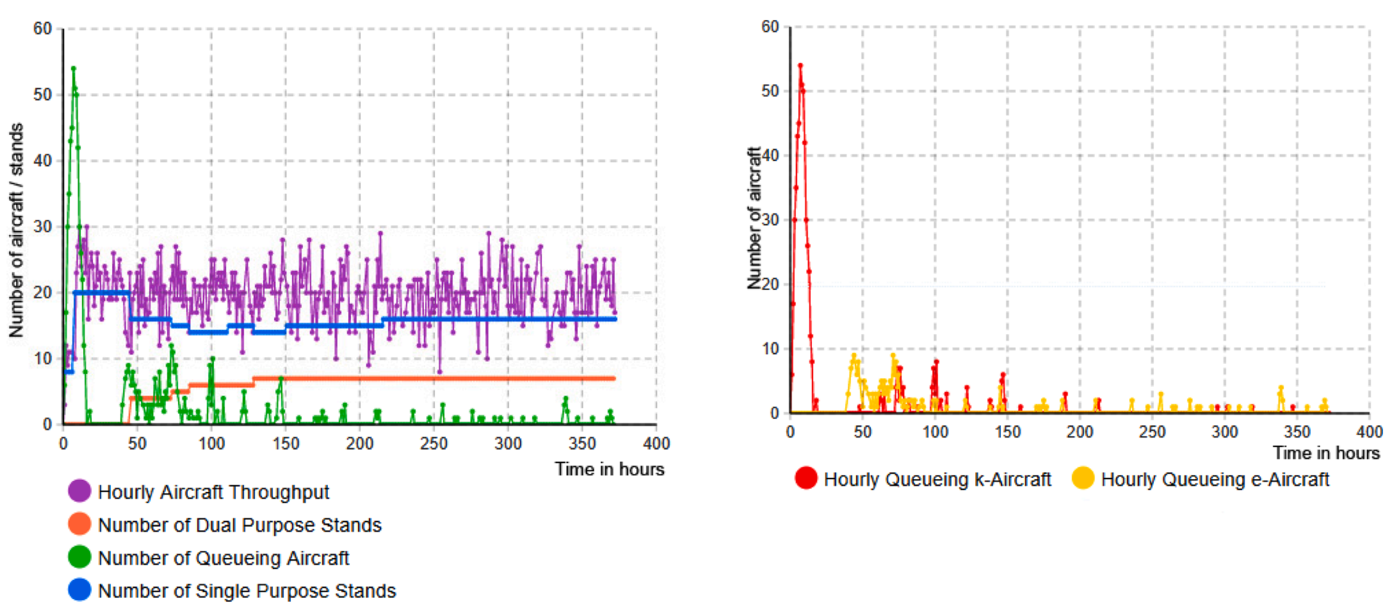
5.3. *Determining stand capacity using DES representing airport level parameters*

Having demonstrated the efficacy of the model for a single pier operation, the model was then developed further to assess the number of single and dual-purpose stands required to maintain capacity (reduce congestion) increases in electric aircraft operation for the entire airport. Assuming the simulation based on Heathrow Airport, the new model made the following assumptions as shown in Table 5.

The aircraft turnaround times would combine the fuelling / charging times with the unloading and loading times for the aircraft type. The rate of aircraft landing per hour was based on the average taken over a 17.5 hour operating day at Heathrow, using figures obtained from Eurocontrol: https://ext.eurocontrol.int/airport_corner_public/EGLL#traffi

Table 4
Single and dual-purpose stand capacity vs % increase in electric aircraft for a single pier of 20 stands or more with ρ values based on aircraft and numbers of stands

% increase of electric aircraft	Number of single purpose stands / % increase from baseline	Number of dual-purpose stands / % of single purpose stands	ρ values for inbound aircraft rates λ_v and total stand intensities μ
0% (baseline)	20	0	0.76
5%	20	4 (20%)	0.85
10%	23 (+15%)	7 (30%)	0.80
15%	25 (+25%)	10 (40%)	0.80
20%	29 (+45%)	14 (48%)	0.74
25%	30 (+50%)	15 (50%)	0.72



(a) (b)

Fig. 4. shows the following plots for a 10% increase in the proportion of electric aircraft movements: (a) plot showing: the hourly throughput of all aircraft, number of queueing aircraft recorded per hour, number of dual-purpose stands, number of single purpose stands *(y-axis - number of aircraft/stands, x-axis - time in hours)*; (b) plot showing: hourly queueing for kerosene vs electric aircraft, *(y-axis - number of aircraft/arrival rates, x-axis - time in hours)*.

Table 5
DES model parameters representing a single airport pier

DES modules	Parameters
Stand serving module: short and long haul kerosene aircraft	Turnaround time of between 45 to 120 minutes (mode = 82.5 minutes), (considering a mix of short haul and long-haul flights).
Stand serving module: short haul electric aircraft	Recharging and turnaround time 120 minutes
Stands pool module	Baseline stand capacity of 197 single purpose stands for kerosene aircraft
Entry module	38 aircraft per hour This figure is based on averaging out variations (peaks and troughs) in daily aircraft activity
Taxing delay module	5 to 10 minutes (mode = 7.5 minutes).

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DES Simulation models where then used to determine the optimal number of single purpose stands, and of those stands, the number of converted dual purpose stands that would be required to minimise congestion levels as the share of electric aircraft rose (from 5%, 10%, 15%, 20% and 25%). Figs. 5 and 6 shows selected generated plots over an entire simulation run for 10%, and 25% increase in the proportion of electric aircraft movements where each simulation was run to 325 and 800 hours respectively. This variation in simulation running times was to ascertain selected stand numbers reflected minimum congestion for each modelled scenario.

Table 6 below shows the increase in dual-purpose stand capacities required (as both exact numbers and percentage increases) to meet the demand for higher proportions of electric aircraft movements based on the values obtained at the end of each respective simulation run.

From the results in Table 6 an increase in the proportion of electric aircraft does not require provision of additional stands to maintain capacity of the remaining kerosene-based flights. This can be clearly seen from the red plots in Figs. 5 (b) and 6(b) which show no congestion of queuing kerosene aircraft for 10% and 25% increases in electric aircraft. However, we see a steady increase in the number of stands that need to be converted to dual purpose to meet traffic demands as shown from the orange plots in Figs. 5 (a) and 6(a). These increases still resulted in minor occurrences of congestion from queuing electric aircraft, which on average was 1 aircraft or less per hour as shown from the yellow plots in Figs. 5 (b), and 6 (b), and reflected overall in the green plots in Figs. 5 (a), and 6 (a). While this delay could theoretically be eliminated entirely by increasing stand capacity still further, this would represent only a marginal gain in operational efficiency. Table 6 also provides the theoretical ρ values based on inbound electric aircraft rates and the corresponding dual stand capacities given that the baseline number of single stands was sufficiently large to accommodate the load of inbound kerosine aircraft rates. ρ values are shown to follow the necessary stand increases to satisfy load from increases in electric aircraft volume.

Table 6 is especially useful for demonstrating the possible phasing requirements of infrastructural development with respect to forecasted increases in the volume of electric aircraft. Notably, it shows that even under optimistic scenarios of electric aircraft adoption in the market, the requirement for the airport to convert stands to accommodate electric aircraft remains modest, at 15%.

6. Optimisation of airport stand capacities and charging regimes

For both the airport level and single pier scenarios we further wanted to determine the optimum (minimum) number of single and dual-purpose stands required to maintain capacity (reduce congestion) over two different charging regimes for the maximum 25% projected increase of electric aircraft operations.

Anylogic provides the additional feature of running optimisation experiments comprising of adjusting simulation parameters over multiple runs where optimisation algorithms are used to find the optimum parameters for minimising or maximising an objective function. The optimisation engine is based on using metaheuristic search driven optimisation techniques combining a single solution based Tabu search and a population based scatter search algorithms (Glover, 1996) (Duarte, 2009), solution feasibility analysis with neural networks to facilitate more efficient and accelerated exploration of the search space for viable solutions (Laguna, 2011). There are a number of other popular optimisation algorithms such as genetic algorithms, simulated annealing as well as other state-of-the-art approaches. However, the purpose here was to validate the observed simulations experiments carried out in Section 5 rather than evaluate the effectiveness of different optimisation algorithms. Hence, using the above mentioned integrated optimisation

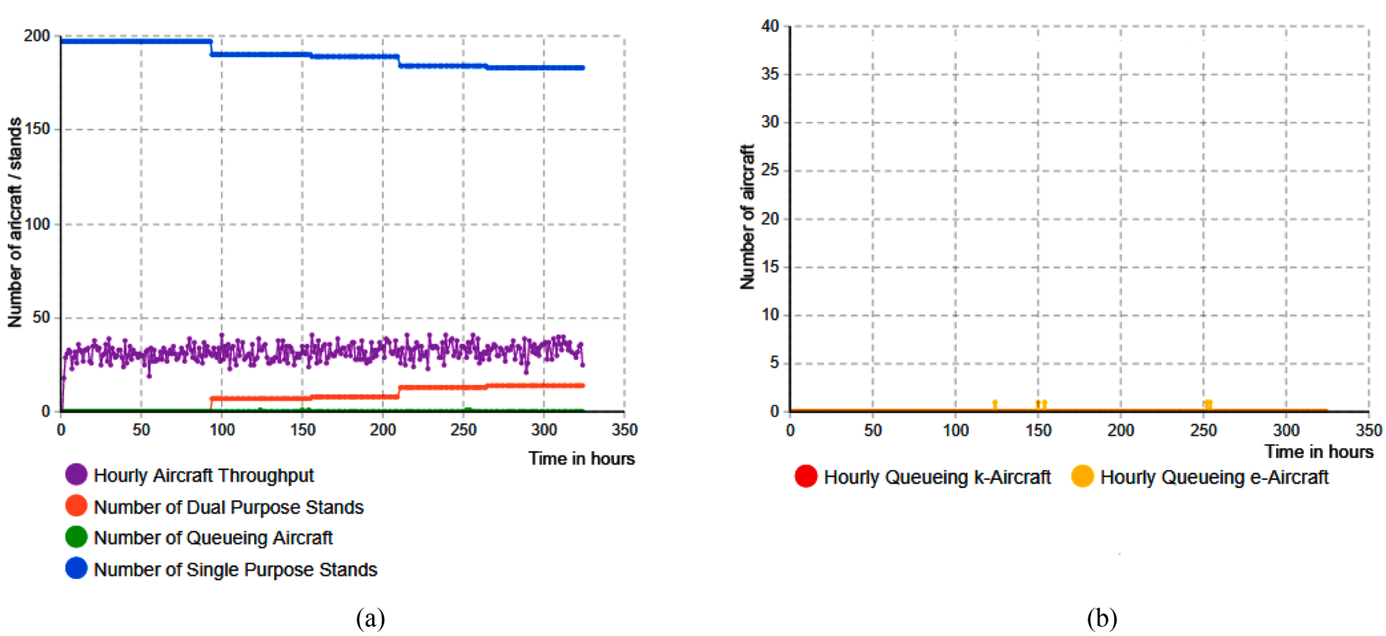
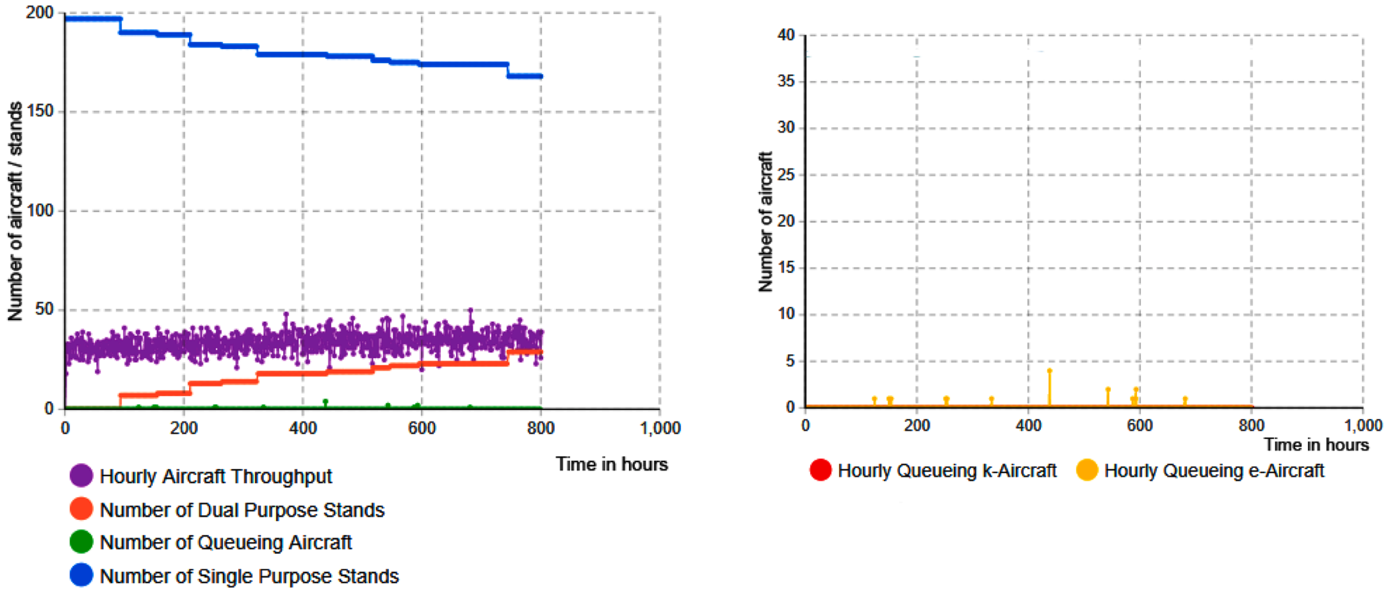


Fig. 5. shows the following plots for a 10% increase in the proportion of electric aircraft movements: (a) plot showing: the hourly throughput of all aircraft, number of queueing aircraft recorded per hour, number of dual-purpose stands, number of single purpose stands (y-axis – number of aircraft/stands, x-axis – time in hours); (b) plot showing: hourly queueing for kerosene vs electric aircraft (y-axis – number of aircraft/arrival rates, x-axis – time in hours).



(a) (b)

Fig. 6. shows the following plots for a 25% increase in the proportion of electric aircraft movements: (a) plot showing: the hourly throughput of all aircraft, number of queueing aircraft recorded per hour, number of dual-purpose stands, number of single purpose stands (y-axis – number of aircraft/stands, x-axis – time in hours); (b) plot showing: hourly queueing for kerosene vs electric aircraft (y-axis – number of aircraft/arrival rates, x-axis – time in hours).

Table 6
Single and dual-purpose stand capacity vs % increase in electric aircraft for all stands at Heathrow with ρ values based on electric only aircraft and numbers of dual-purpose stands

% increase of electric aircraft	Number of single purpose stands / % increase from baseline	Number of dual-purpose stands / % of single purpose stands	ρ values for inbound electric aircraft rates λ_{ec} and dual-purpose stand intensities $\sum_{i=0}^{y}\mu_{du_i}$
0% (baseline)	197 / 0%	0	
5%	197 / 0%	8 (4%)	0.48
10%	197 / 0%	14 (7%)	0.54
15%	197 / 0%	19 (10%)	0.60
20%	197 / 0%	23 (11%)	0.66
25%	197 / 0%	29 (15%)	0.65

techniques provide in Anylogic proved sufficient for this purpose.

6.1. *Optimisation experiment setup and objective function definition*

The experiment assumed the fixed parameters and parameter ranges previously specified for the single pier and airport level scenario (based on Heathrow Airport) descried in Sections 5.2 and 5.3. These were: The rate of aircraft landing per hour for both kerosene and electric inbound flights; on stand serving times of kerosene aircraft and aircraft taxiing times. Two distinct charging regimes of 60 and 120 minutes were evaluated for stand turnaround times of electric aircraft, representing a greater range within which battery charging times could vary due to future developments in battery charging efficiency or other forms of energy harvesting technologies. As mentioned previously, assumptions were not made regarding the prospective battery size of the aircraft in the model. However, as an indication, an 820 kWh battery charging for 60 minutes (a rating of 1C) would require charging speeds of 820 kW, while a 120 minute charge (0.5C) would require charging speeds of 410 kW.

The experiment varied the number of single purpose stands and of these the number of converted dual purpose stands to determine their optimum number for each charging regime. The goal of the optimisation algorithm was to find the right combination of single and dual-purpose stands that would reduce congestion to a minimum over a specific simulated time horizon (selected for these experiments as 72 hours representing a suitable timescale over which the simulation could be assessed). A secondary goal was to minimise the required number of converted dual purpose stands and also keep the number of single purpose stands as close as possible to their respective baselines determined in Sections 5.2 and 5.3. Based on these criteria an objective function was defined where the algorithm would aim to minimise the objective value *objValue* as depicted in equation (8):

$$objValue = ((accHourlyQueued \times 2) + (z \times 3) + (y \times 4)) \tag{8}$$

where, *accHourlyQueued* represents accumulated number of hourly queuing aircraft waiting for stands, z and y represent the number of single and dual-purpose stands, respectively (see Section 3). The objective function was handcrafted through a process of trial and error to assign the greatest weight on reducing congestion followed by the number of dual and single purpose stands, respectively. The weights were selected to give solutions comparable or better than what was observed when running simulation experiments. In addition to the objective function a requirement was specified to check the feasibility of searched solutions whereby feasible 'legal' solutions were judged as ones where the total number of stands was always greater than or equal to the converted dual purpose stands.

6.2. *Optimisation experiment results*

Four optimisation experiments were carried out, one for each single pier and airport level scenario evaluating the selected charging regimes of 60 and 120 minutes. Each optimisation experiment ran up to a maximum of 500 simulation iterations where each simulation was also replicated 10 times to account for stochastic variability of the models due to certain fixed parameters being randomly selected from ranges described in Sections 5.2 and 5.3. Fig. 7 shows the AnyLogic Optimisation experiment GUI that includes the scatter search plot of simulation solutions on the right where the x-axis represents simulation runs, and the y-axis represents current solution, best feasible solution (blue plot) and best infeasible solution (red plot) found for each simulation based

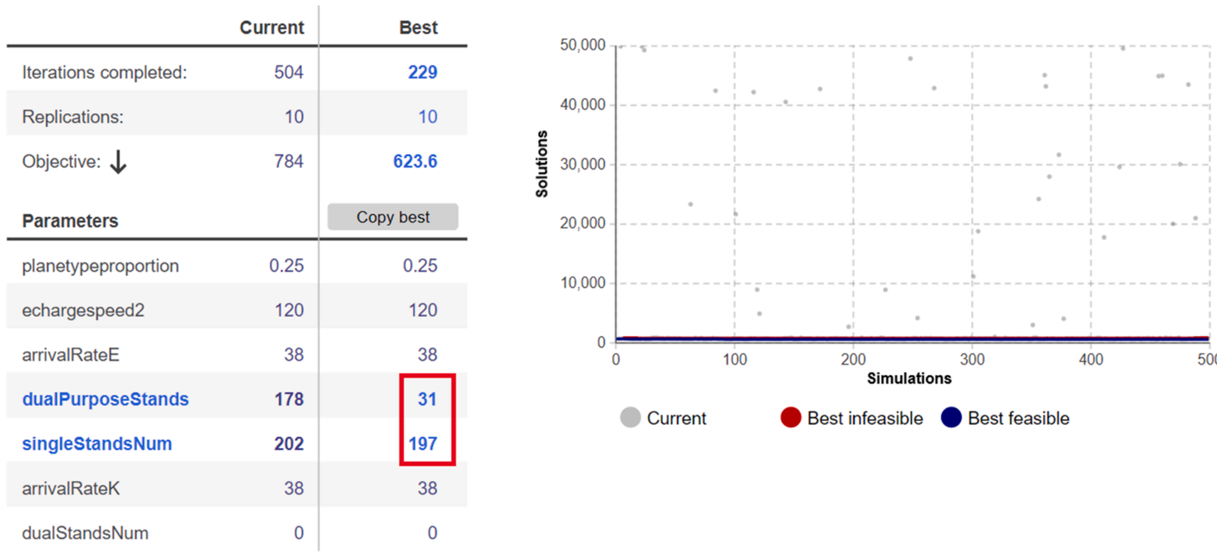


Fig. 7. shows the AnyLogic GUI containing the scatter search plot of simulation solutions (right). Here, the x-axis represents simulation runs, and the y-axis represents current solution, best feasible solution (blue plot) and best infeasible solution (red plot) found for each simulation based on their *objValue* values. The optimal best-case single / dual purpose stand numbers (boxed in red) generated during the optimisation experiment run for London Heathrow based on a charging regime of 120 minutes for a 25% increase in electric aircraft operations is shown to the left.

on their *objValue* values. To the left of the GUI the optimal best-case simulation parameters including single / dual purpose stand numbers (boxed in red) are shown, these values were determined from the optimization experiment run for Heathrow Airport based on a charging regime of 120 minutes for a 25% increase in electric aircraft operations. Table 7 shows the results for all four scenarios / charging regime-based optimisation experiments.

The best-case results for the single pier scenario show a 5%, and 15% increase in the optimal number of single purpose and dual purpose stands respectively, as compared to the simulation results in Table 4, for a charging regime of 120 minutes. This is because the algorithm's optimisation strategy was aimed and minimising or eliminating congestion. As such the best-case simulation solution resulted in a greater increase in the number of stands. For the same scenario, the best-case results for a charging time of 60 minutes showed a 25% decrease and 6% increase in the required number of single and dual purpose stands respectively, given the shorter turnaround times and higher aircraft throughputs impact on reducing queuing.

The results for the airport level scenario based on Heathrow showed that for a charging regime of 120 minutes the best-case results are near equivalent to the simulation results shown in Table 6. Here, no increase from the baseline number of single purpose stands and only a 1% increase in the number of dual purpose stands were required for minimising congestion, when compared with the results shown in Table 6. For a charging regime of 60 minutes the required number of dual purpose stands decreased by 5%.

Taking the average over the results of both 60- and 120-minute charging regimes, for Heathrow the optimal number of single purpose stands required to be converted to dual purpose for accommodating a 25% increase in electric aircraft was shown to be 13% with no need to increase overall stand capacity. These results would tend to support the projection that even under optimistic scenarios of electric aircraft development in the market, the requirement for airports to make infrastructural changes is likely to remain modest. In other words, even if the market uptake of electric aircraft was relatively high, this would likely still only equateto an airport needing to convert a small number of existing stands per year to accommodate electric aircraft and would not require overall stand capacity to be increased.

7. Discussion

Electric aircraft have significant benefits over traditional kerosene aircraft in terms of environmental performance, and it seems inevitable that the development and testing of electric aircraft will continue in the coming years, as well as other forms of sustainable propulsion. Over and above the technical aspects associated with the systems themselves, there remains considerable uncertainty around the operational and commercial viability of electric aircraft. The analysis in this paper seeks to contribute to this new area of research, seeking to develop an understanding of cooperative operational and infrastructural implications of electric aircraft. Certainly, a critical issue here relates to optimal charging times and the number of aircraft stands that need to be adapted for electric aircraft recharging. Interestingly, findings from the analysis here provides a source for conservative optimism, in so much that the

Table 7
Optimal single and dual-purpose stand capacities for 25% increase in electric aircraft for single pier and airport level scenarios assuming stand baselines established in Sections 5.2 and 5.3

Model Scenario	Electric aircraft charging regimes (mins)				Average electric aircraft charging time (mins)	
	60		120		90	
	Num single purpose stands / % increase from baseline	Num dual-purpose stands / % of single purpose stands	Num single purpose stands / % increase from baseline	Num dual-purpose stands / % of single purpose stands	Avg % increase single purpose stands	Avg % dual purpose stands
Single Pier	25(+25%)	14(56%)	31 (+55%)	20(65%)	+28%	60.5%
London Heathrow	197(+0%)	20(10%)	197(+0%)	31(16%)	+0%	13%

results suggest that even a relatively high uptake of electric aircraft in the market could be accommodated without significantly affecting airport capacity or the need to rapidly convert large number of aircraft stands to accommodate electric aircraft, at least initially.

Of course, one should not lose sight of, or downplay, the other challenges and potential barriers to the wider adoption of electric aircraft technology. For example, this paper does not consider the likely utilities requirements in terms of electricity demand, nor the challenges of retrofitting legacy airports with widespread electric charging capabilities (for example, installation of high voltage cabling to aircraft stands). Nor does the analysis consider the outstanding and unresolved certification challenges around electric aircraft and its related infrastructure, or public attitudes and perceptions towards this technology. Equally, it is worth noting that electric aircraft technology is likely to form only part of the solution in terms of sustainable propulsion. For example, considerable progress has already been made in the development of Hydrogen powered aircraft and Sustainable Aviation Fuels (SAFS). These technologies will have a role to play alongside electrification, and future work needs to address specifically how these technologies may co-exist most effectively. If ever a reminder was needed, the COVID-19 pandemic has highlighted the dynamic and unpredictably nature of aviation and the challenges of planning in uncertainty. This situation is likely to persist beyond the current crisis, and it will be important that a collaborative, flexible and evidence-based approach is taken to planning for future aircraft propulsion technologies.

8. Conclusions and future work

In conclusion, the developed DES simulation models provide some novel insights on projected aircraft throughputs, capacities, and aircraft stand requirements for the possible future introduction of short haul electric aircraft operations. More specifically the models can be used to:

- Evaluate the impact of different turnaround times for kerosene and electric aircraft reflecting different charging regimes for electric aircraft.
- Determine the requirements for new and converted stand infrastructure to meet a market increase in uptake of electric aircraft while maintaining airside capacity and throughput. This in turn has important implications for future stand design and investment planning decision making.
- Find the optimal stand infrastructure requirements for minimising operational impacts of electric aircraft introduction.

The DES can also in part be formally explained through the application of queuing theory together with details provided for all model parameters making it reproducible through different programming and simulation tools.

For future work these simulations can be extended to include greater complexities with respect to representing the cooperation and interaction of more assets, operational entities, actors and external factors to make the simulation models more realistic and able to simulate more complex and holistic scenarios. These models could take the form of hybrid models (Ozturk et al. 2019) which could be based on ABMs for modelling aircraft movements between, say, Heathrow Airport and other airports. These hybrid models would likely combine sub models that use DES and SD models. Indeed, an important avenue for future work should include the investigation of requirements at a diverse range of airports, given their varying operational and infrastructural characteristics.

Here, a DES would model airport specific ground operations that include on-stand processing. In these more complex models, big data analytics (Iqbal, 2020; Iqbal, 2020) based on specific capacity, real traffic data for each destination airport and environmental factors could be used. This would allow the model to simulate contextually richer impacts of electric aircraft at both an airport specific level, as well as collectively across the entire network. These models could also consider the impact of flying time, weather and other factors on battery power consumption that could influence stand charging durations. For example, in the same way that a traditional aircraft will be fuelled according to the requirements of the particular route flown, an electric aircraft may not need to be fully charged before each flight, especially if it is a relatively short sector.

Equally, even busy airports experience uneven demand during a typical 24-hour period, with flight schedules typically concentrated into morning and evening 'peak' periods. Here it is possible that advanced modelling could be conducted to help account for prevailing real-world flight schedules at airports to help optimise the integration of electric aircraft in a way that minimises operational disruption. Further work could also include an SD or other integrated climate models to model the effects of weather and projected climate change on aircraft operations such as flying time, turbulence (Williams, 2016) (Storer, 2017) and take off / landing separation distances. These in turn could feedback to effect aircraft inflight and ground operational behaviours modelled by the ABM and DES respectively.

It is worth noting here that by only focussing on questions of the airside capacity aspects of electric aircraft, this paper does not consider important electrical sizing aspects, as well as the related supporting charging infrastructure and power demands of electric aircraft. However, it is hoped that by focussing on the operational and planning aspects of electric aircraft, the findings from the research will complement this important avenue for future research.

Future work could also more extensively apply computational machine learning and other forms of metaheuristic optimisation techniques such as evolutionary algorithms to identify optimal solutions for stand capacity and other complex resource scheduling and allocation issues for airport operations. This could include the consideration of energy storage infrastructure and distribution across different locations to provide intelligently orchestrated energy demand management across aircraft and airport assets. Additional approximate reasoning techniques such as probabilistic and fuzzy systems (Mendel, 2001) could be used to complement quantitative and sensor rich data with experiential knowledge models to handle sources of uncertainties present in modelling real world systems.

The combination of bottom-up computational methodologies such as cooperative multi-agent systems for representing the characteristics, and interaction behaviours of actors and assets with top-down machine learning and optimisation algorithms such as deep learning neural networks (Maniak, 2020), reinforcement learning, and optimisation algorithms can also be used to create high fidelity intelligent digital twins of airport operations for facilitating more effective planning and management decisions as have been recently applied in the context of complex transportation networks (Li, 2019). The potential insights offered by such an approach presents an exciting avenue for future research in this area.

Acknowledgements

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