Title

Reducing Emissions through Monitoring and Predictive Modeling of Gate Operations of Idle Aircraft: A Case Study on San Francisco International Airport

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Reducing Emissions through Monitoring and Predictive Modeling of Gate Operations of Idle Aircraft: A Case Study on San Francisco International Airport

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Abstract

The use of airport gate electrification infrastructure in the form of ground power (GP) and pre-conditioned air (PCA) systems can reduce energy and maintenance costs, emissions, and health risks by limiting the use of aircraft auxiliary power unit (APU) engines at the gate. However, their benefits can only be gained when they are actually being used; otherwise, pilots keep APUs on to fulfill their aircraft's demands for electrical power and air conditioning. GP and PCA systems require a large initial infrastructure investment to increase energy efficiency, and they are installed with the assumption that they will be highly utilized. In this report, a method is developed to examine how much and why GP and PCA are not used to their full potential when they are readily available.

Maximizing the use of gate electrification infrastructure is a fragmented, interdependent, and dynamic management challenge. The processes of using GP and PCA fit tightly into an intricate sequence of connected and concurrent activities required to complete an aircraft turnaround operation. Each process depends on close communication, collaboration, and shared responsibility among airports, airlines, ground crews, and pilots. The circumstances and schedule of each operation can change unexpectedly while it unfolds, with limited time to react. The lack of responsiveness in such a tangled system allows for any issue to interfere with the effective use of GP and PCA (e.g., technical problems, resource constraints, scheduling conflicts, and behavioral issues). Many unique circumstances that result in APU overuse can be attributed to the unexpected incidents that caused it. However, these incidents should not be interpreted as isolated accidents; they could be recurrent symptoms of neglect, lack of prioritization, or lack of adaptability for maximizing energy efficiency at airport gates.

A case study on San Francisco International Airport (SFO), using 2019 databases, confirms that underuse of ground power is a broad and heterogeneous problem. More than 83% of turnaround operations analyzed used their APUs for more than 15 minutes while at the gate, a common threshold found in other relevant papers and stringent airport policies. 20% of turnaround operations never used gate electrification infrastructure throughout their turnaround. GP utilization rates of individual operations were associated with the aircraft model and gate. Most interestingly, performance across large samples of operations varied significantly, depending on the airline, with the best-performing airline having a utilization rate up to approximately 5 times greater than the second-worst (the worst one barely used GP).

The lack of energy-use monitoring and data sharing among airports, airlines, pilots, and ground crew workers perpetuates inefficiencies. Without measurements to hold individual operations accountable for their energy use, any enforcement or policy remains shortsighted and ineffective. Without being able to track long-term performance or set a standard, successful practices or systematic problems remain hidden. Without a method to predict and manage the energy being used at the gate, highly fluctuating energy demand from airport gates becomes an additional challenge. An integrated monitoring solution would enable airports not only to enforce policies to restrict the use of APUs but also to gain a proactive management role in the airline's use of gate electrification infrastructure. By ensuring all gate turnarounds abide by a maximum APU use time of 15 minutes, airports could achieve a further 70% reduction in airline fuel costs and

carbon emissions from current levels at airport gates, with an average fuel cost saving of $50 and 180 kg CO_2 per turnaround operation.

The monetary and environmental savings of gate electrification are not independent from many other costs of turnaround operations. Maximizing energy efficiency at the gate should not come at the expense of other priorities. There are many factors in assessing the performance of a turnaround operation, some of which are far more consequential than the use of gate electrification infrastructure, such as safety, on-time departure, or passenger experience. For this reason, it is important to assess turnaround operations with a method that is both comprehensive enough to represent the multifaceted costs and simple enough to be systematically applied. Furthermore, the costs involved apply differently to each responsible party (i.e., airline, airport, ground crews, pilots). With an understanding of the relationship between inputs (e.g., equipment, schedule, work sequence, staffing) and the costs in an operation, the groundwork is laid to predict, optimize, and incentivize effective energy management for ground handling operations. In this report, a method is developed that formulates a life cycle inventory on GP, PCA, and APU use, and evaluates energy use for turnaround operations in terms of their financial, global, and local impact. The method was applied to SFO as a case study. Each operation was associated with a breakdown of monetary and CO_2 costs, including initial and non-operational costs. In addition, a dispersion analysis and health risk assessment are used to estimate the health impact of local air pollutants on apron workers.

The value of being able to monitor, predict, and optimize operations depends on how quickly these tasks can be performed to provide actionable results. With a retrospective assessment of historical data, a broadly optimized management of a turnaround operation can provide moderate savings, satisfying the need for resiliency by placing contingencies in the plan. A turnaround operation manager can coordinate the ground crew as the operation unfolds, but all humans are limited in their ability to monitor, predict, and optimize. By streamlining the process of data acquisition, prediction, optimization, and simulation through a real-time computerized system, it is possible to design a decision support tool that can quickly adapt to the unfolding circumstances of each operation. This report outlines the architecture of an automated computerized system that can support scheduling and decision making for turnaround operations. By prototyping and running the system in a simulated environment, this report demonstrates that computerized adaptive scheduling can unlock monetary and environmental savings through increased resiliency, reduced uncertainty, and increased collaboration between stakeholders.

This research lays down the foundations for data-driven monitoring, modeling, and management of gate operations, specifically with a focus on GP use. It shows how airport databases can be integrated to produce insightful results in an immediately feasible and replicable way. It tests several modelling and evaluation techniques that dissect turnaround operations with unprecedented detail. It indicates how maximizing GP use is in part a risk management problem and proposes an active solution to address it within the framework of a larger interconnected system. Furthermore, it proposes future research directions to advance and expand the existing body of knowledge related to enhancing aircraft turnaround operations.

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Acronyms & Abbreviations

ACA	Airport Carbon Accreditation
ACDM	Airport Collaborative Decision Making
ACI	Airports Council International
ACRP	Airport Cooperative Research Program
ADG	Aircraft Design Group
ADS-B	Automatic Dependent Surveillance Broadcast
AEDT	Aviation Environmental Design Tool
AI	Artificial Intelligence
AIP	Airport Improvement Program
ANN	Artificial Neural Network
AOBT	Actual Off Block Time
API	Application Programming Interface
APU	Auxiliary Power Unit
ATC	Air Traffic Control
CAA	Clean Air Act
CARB	California Air Resources Board
CEM	Collaborative Environmental Management
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EA	Environmental Assessment
ECS	Environmental Control System
EIS	Environmental Impact Statement
EONS	Environmental Viability, Operational Efficiency, Natural Resources Conservation, and Social Responsibility
EPA	Environmental Protection Agency
EUROCAE	European Organization for Civil Aviation Equipment
FAA	Federal Aviation Administration
GHG	Greenhouse Gas
GP	Ground Power
GPU	Ground Power Unit (Mobile)
GSE	Ground Support Equipment
HC	Hydrocarbons (also VOC)
HVAC	Heating Ventilation and Air Conditioning
IATA	International Air Transportation Association
IEA	International Energy Agency
ICAO	International Civil Aviation Organization
iOPS	Airport Operations and Equipment Monitoring Technology by JBT
IPM	Intelligent Power Management (ITW GSE)
ISD	Integrated Sensing Database
ISO	International Organization for Standardization
JBT	John Bean Technologies
JIT	Just in Time
KNN	K-Nearest Neighbors

LASSO	Least Absolute Shrinkage and Selector Operator
LBFGS	Limited-memory Broyden Fletcher Goldfarb Shanno
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LTO	Landing and Takeoff Cycle
MAE	Mean Average Error
NAAQS	National Ambient Air Quality Standards
NEPA	National Environmental Policy Act
NL	No Load
NO_2	Nitrogen Dioxide
NO_x	Nitrous Oxides
PCA	Pre-Conditioned Air (Fixed)
PCU	Pre-Conditioned Air Unit (Mobile)
PFC	Passenger Facility Charge
PG&E	Pacific Gas & Electric
PIT	Pittsburgh International Airport
PM	Particulate Matter
PUC	Public Utilities Commission
RF	Random Forest
RFID	Radio Frequency Identification
RMSE	Root Mean Squared Error
RPM	Revolutions Per Minute
SCC	Social Cost of Carbon
SEA	Seattle-Tacoma International Airport
SFO	San Francisco International Airport
SIP	State Implementation Plans
SO_x	Sulfur Oxides
SVM	Support Vector Machines
TOBT	Target Off Block Time
TRB	Transportation Research Board
UF	Uncertainty Factor
U.S./USA	United States of America
VALE	Voluntary Airport Low Emissions Program
VOC	Volatile Organic Compounds (also HC)
WTP	Well to Pump
ZRH	Zurich International Airport

Glossary

Actuator
The means by which machines and software can have an impact on the real world.

Airport Collaborative Decision Making (ACDM)
"Improving the efficiency and resilience of airport operations by optimizing the use of resources and improving the predictability of air traffic," achieved by "encouraging the airport partners (airport operators, aircraft operators, ground handlers and ATC) and the Network Manager to work more transparently and collaboratively, exchanging relevant accurate and timely information." (Eurocontrol, 2023a).

Apron Area
The airport airside areas used for parking and handling aircraft between flights, typically next to the terminal building.

Criteria Air Pollutants
Pollutants that are determined to be hazardous to human health according to the EPA.

Digital Twin
An updated digital representation of a physical system for decision support and management.

Percept
The means by which machines and software can infer what is occurring in the real world.

Pull System
A lean management principle that involves drawing resources when they are needed, rather than processing them as soon as possible (i.e., push system).

Turnaround Time
The time between a flight arrival and departure, marked by the in-block and off-block times.

Utilization Rate
The ratio between the actual use time of a certain resource and the maximum time it could have been used.

1. Introduction

Aviation is one of the most difficult transportation sectors to decarbonize. To date, most attention has been given to reducing carbon dioxide (CO_2) emitted by flying aircraft whose engines burn conventional (jet and aviation gas) fuels, and therefore impact the climate globally. Radically increasing efficiency for the processes responsible for the largest part of aviation emissions may appear like the most effective strategy for decarbonization. However, smaller, yet more attainable opportunities for improvement can be just as important and should be explored in conjunction with long-term goals. Airports are one of the most complex and critical elements of aviation and significant contributors to overall flight emissions. As such, they present many opportunities to decarbonize aviation. Furthermore, a component of aviation emissions relates to criteria pollutants such as nitrogen oxides (NO_x), sulfur oxides (SO_x), carbon monoxide (CO), volatile organic compounds (VOC) or hydrocarbons (HC), and particulate matter (PM). These emissions are not only largely produced at airports, but they are also important for their impact on airport airside surface areas and surrounding communities. Overall, feasible mitigation strategies for airport emissions are a salient concern for aviation sustainability.

Although airports in the United States (U.S.) do not directly control local emissions generated by aircraft operating on airfields and in the non-movement area (aprons and gates), U.S. airports do make efforts to become more sustainable. Airport sustainability reports and climate action plans are effective means to strategically plan for sustainability and reduce emissions. Airports also explore options and invest in infrastructure that decrease aircraft emissions generated in the apron areas, including emissions at gates. However, because U.S. airports lease terminal buildings and gates to airlines, the airlines are responsible for the management of their operations in the non-movement area of their leased sections of a terminal building. In their respective leased section, each airline executes its own business decisions. Information sharing with the airport and other airlines is not fully engrained, as each airline focuses on limiting liabilities and maximizing its own profit. Therefore, the overall emission mitigation strategies of operations at gates are fragmented among airlines, and consequently, emission mitigation is not done on the airport system's level.

While parked at gates, aircraft can generate electrical power and compressed air (bleed air) through their auxiliary power unit (APU), a thrustless turbine located at the tail end of an aircraft that generates tail-pipe emissions and primarily initiates the main aircraft engines. Even when the aircraft is idle at a gate, many of its electrical subsystems and its air conditioning must stay active for some amount of time, especially for intraday turnarounds with a short duration. Instead of having aircraft default to the APU, an airport may provide more efficient external energy sources for power and air conditioning. Mobile equipment such as ground power units (GPU) and pre-conditioned air units (PCU) may satisfy these needs, and these are typically powered by a diesel generator. Alternatively, a growing number of airports have installed highly efficient gate electrification infrastructure in the form of fixed ground power (GP) and fixed pre-conditioned air systems (PCA), as illustrated in Figure 1.

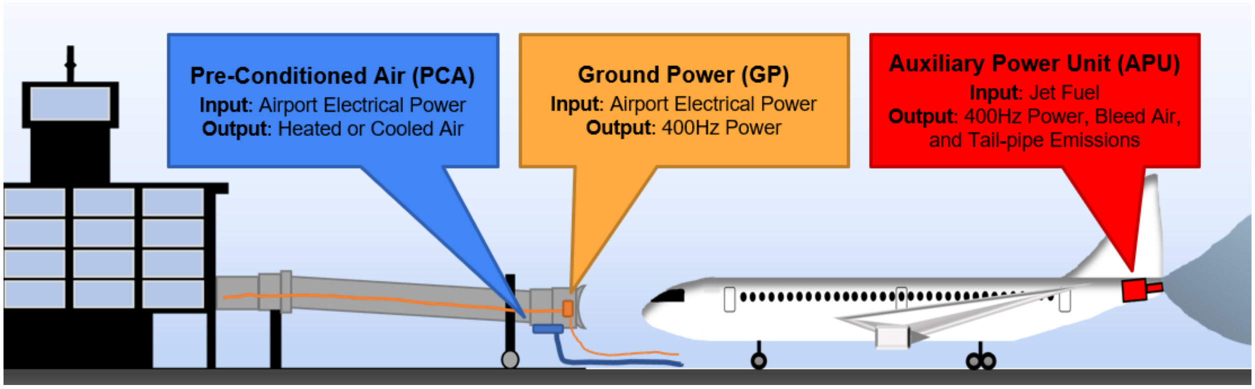


Figure 1: Pre-conditioned air, ground power cable, and auxiliary power unit

During aircraft turnaround operations, pilots and ground crew use external systems, achieving different levels of energy efficiency. After an aircraft arrives and parks at a gate, ground crew connect the cable(s) and hose(s) provided by the airport to the receptacle(s) that are typically located underneath the aircraft fuselage. A pilot can then switch off the APU engine and use the external electrical power (i.e., GP). Prior to departure, while the aircraft is at a gate, a pilot initiates the APU engine. Once the APU can generate power and bleed air, the pilot switches the power source from the GP to the APU, after which the ground crew can physically unplug the GP cable(s) and PCA hose(s) and stow them away from the aircraft. Consequently, GP use is increased by shutting down the APU as soon as possible and turning it on before departure as late as possible.

In the complex and dynamic ecosystem of airport operations, (i) technical issues, (ii) resource constraints, (iii) scheduling conflicts, and (iv) behavioral choices can impact the efficient use of GP and PCA systems. When gate infrastructure is not adequately monitored, pilots and ground crews interpret circumstantial failures as isolated accidents, while systematic issues remain unmitigated. Fragmented management practices and inconsistent policies between airports and airlines further exacerbate the lack of enforcement standards and mechanisms. Ultimately, GP use of individual turnaround operations cannot be evaluated or benchmarked, sustaining practices that result in unreliable performance and inefficient energy use.

This report pursues the following research goals:

1. Predicting GP instantaneous power demand for individual turnaround operations.
2. Advocating for the measurement of GP use for individual turnaround operations.
3. Identifying trends for GP use across large samples of operations.
4. Estimating APU fuel costs and emissions for individual turnaround operations.
5. Estimating air quality impacts and health hazards posed by APU emissions.
6. Performing a granular life cycle cost assessment for the use of GP, PCA, and APU.
7. Designing and demonstrating a scheduling system that improves GP and PCA use.
8. Identifying future solutions for improved GP, PCA, and APU management.

This report addresses the problems associated with gate operations by (i) providing an airport-centric, data-driven foundation for a monitoring system, (ii) defining a holistic cost assessment methodology, and (iii) proposing an adaptive ground handling management system that leverages artificial intelligence and includes sustainability as a decision-making criterion.

Although these sections are elaborated independently, they are highly interrelated and meant to be applied with concerted effort by airports. A case study on San Francisco International Airport (SFO) is used to illustrate and validate the research. This research is the first attempt to show the benefits of centralized monitoring, modeling, and management of gate electrification infrastructure so that emission mitigation can be done on the airport system's level. Through transparency, accountability, and collaboration, aviation stakeholders can define a unified approach towards addressing the efficiency and sustainability of gate turnaround operations.

The body of the report is composed of seven sections. After the introduction (Section 1), a literature review illustrates the inspiration and importance of this work (Section 2). A thorough analysis of GP use highlights the magnitude and complexity of the problem while providing a foundation for an airport monitoring system (Section 3). A cost assessment and health risk evaluation further expand on the impacts of variable use of PC and PCA systems (Section 4). Then, a real-time computerized scheduling system as a potential solution is defined (Section 5). An overarching discussion describes the synergies and challenges associated with the implementation of the proposed systems (Section 6). The conclusion summarizes the most important results, outlines the contributions to knowledge, and discusses further avenues for related research (Section 7).

2. Literature Review

The provision of ground support equipment for improving aircraft turnaround operations has been an industry topic for decades. Many articles and documentation have been developed on the topic, especially to justify the initial investment in the infrastructure. Monitoring, modelling, and managing ground support equipment is at the forefront of current research due to advancements in integrated data collection and increased sensitivities towards aviation sustainability. To contextualize this report, a review of academic literature, some current industry projects, and relevant methodologies is provided.

2.1 Sustainability at Airports

Airports are a vast, diverse, and vital component of our modern society, with their societal importance spanning beyond their critical role in today's transportation network. The world hosts around 40,000 airports (CIA, 2016), of which the top 2,500 have accommodated over 4 billion passengers (IATA, 2018). In 2019, the number of domestic and global airline flights was 38 million (IATA, 2021). Despite the major setbacks through the COVID-19 pandemic, commercial aviation is set to recover, with passenger traffic predicted to grow annually by 3.6% over the next 20 years (Airbus, 2023). Air-cargo transports $6 trillion worth of goods, or approximately 35% of world trade value (IATA, 2022), and is set to grow annually by 3.2% (Airbus, 2023). Some airports have grown to become as large as cities, and they function as catalysts for the economic, logistical, and social development of their region (Appold & Kasarda, 2013). As a critical spearhead of worldwide and regional growth, airports are top players in our society's Triple Bottom Line: environmental stewardship, economic growth, and social responsibility.

Environmental stewardship, in some ways, is a relatively new concern for airports. The biggest environmental issues faced by airports are aircraft noise, carbon emissions, and local air pollution. Over the last 20 years, the following milestones occurred regarding regulations of aviation emissions: (i) 2004 - the airline industry started addressing carbon emissions (ICAO, 2004); (ii) 2009 - the Guidance Manual on Airport Greenhouse Gas Emissions Management was released (ACI, 2010); and (iii) 2016 - ICAO issued an agreement for controlling carbon emissions from international flights (ICAO, 2016).

On the ground, the sustainability efforts are unique and tailored around the specific nature of each airport and region (SAGA, 2019). Several worldwide research institutions and programs to promote sustainability have developed metrics based upon which airports can assess their performance and set new goals. Airport Council International (ACI) uses the EONS categorization (i.e., economic viability, operational efficiency, natural resource conservation, social responsibility). Airport communities recognize the key role that they play in promoting beneficial environmental and human health outcomes, but the way the public sector addresses airport sustainability is fragmented and lacks rigorous appraisal of suggested best practices (Greer et al., 2020). Despite the newfound relevance of sustainability at airports, the current state and outlook are not as hopeful as one would wish.

Without radical systematic and technological changes, the growing and energy-intensive aviation industry will continue to increase its impact on climate change (Lee et al., 2009; Bravo et al., 2022). The problem is that current aviation emissions not only contribute to 2.5% of greenhouse gas emissions and 5% of global anthropogenic radiative forcing, but they also have regional air quality impacts that are detrimental to human welfare (Grobler et al., 2019). It is expected that such emissions will increase in the future due to increases in travel demand and the continued use of traditional fossil-fuel-based aircraft engines (Gössling et al., 2009; ICAO, 2010; IATA, 2017).

A significant and somewhat neglected portion of the problem occurs at airports. Airports contribute approximately 15% of aviation greenhouse gas (GHG) emissions (Greer et al., 2020), but this percentage varies depending on the scope of the analysis. To date, most attention has been given to reducing carbon dioxide (CO_2) emitted by aircraft engines that burn conventional (jet and aviation gas) fuels due to its impacts on the climate. However, another large part of the problem lies in local air pollutants such as NO_x, SO_x, CO, HC, and PM (Greer et al., 2020).

Masiol & Harrison (2014) found that operational emissions of local air pollutants from engine exhaust and non-exhaust sources have not received adequate attention in the literature, despite their high negative impact on ground-level air quality. Repeated occupational exposure of ground workers to criteria pollutants indicate an increased risk of cancer, heart disease, mental illness, and respiratory symptoms, but insufficient epidemiological data and studies prevent these risks from being quantified (Merzenich et al., 2021; Møller et al., 2017). The exposure and impact of criteria pollutants on the communities surrounding airports remain underexamined despite measurements of high down-wind concentrations of ultrafine $PM_{2.5}$ particles and nitrogen dioxide (NO_2) concentrations that exceeded those measured at regulatory monitoring sites (Hudda et al., 2020). Environmental and health costs are a major drawback to an airport's triple bottom line, so they must be studied further, accounted for, and addressed.

Some of the negative externalities of airport operations are difficult to address because they lie at the interface of many different stakeholders with intersecting spheres of influence (Perez, 2015). In contrast, some can be easily controlled and attributed to a specific party. Airport Carbon Accreditation (ACA) is a voluntary emission reporting and certification program that has categorized airport emissions into three scopes, as shown in Table 1 (Airport Carbon Accreditation, 2020). Emissions from facilities owned and operated by the airport (Scope 1) can be directly attributed to and influenced by the airport, and for that reason, they are one of the first to be mitigated according to ACA's multi-step certification. Emissions from purchased electricity (Scope 2) are not directly managed by the airport, but they can be directly managed and mitigated. Outside the scope of airports, many externalities associated with aircraft flights can be directly attributed to airlines. In contrast, it is those emissions that are associated with airport processes but not controlled by them (Scope 3) that are more challenging to mitigate. Scope 3 emissions lie in a grey area where airports do not directly own or control certain sources of emissions, but they can influence their mitigation. These sources include emissions from the Landing and Takeoff cycle (LTO), aircraft operations in non-movement areas (i.e., aprons), ground support equipment, and vehicles circulating on airside premises (e.g., sweeper trucks, crew buses, catering trucks, cargo tractors).

Table 1: Airport emission sources by scope (Airport Carbon Accreditation, 2020)

Scope 1 Emissions from Airport Controlled Sources	**Scope 2** Emissions from Purchased Electricity	**Scope 3** Emissions from Other Sources Related to the Activities of an Airport
● Vehicles/ground support equipment belonging to the airport ● On-site waste management ● On-site wastewater management ● On-site power generation ● Firefighting exercises ● Boilers, furnaces	Off-site electricity generation from: ● Heating ● Cooling ● Lighting	● Landing and Takeoff (LTO) Cycle: aircraft landing, taking off, ground movements ● Auxiliary power units ● Third-party vehicles/ground support equipment ● Staff commute ● Passenger travel to and from the airport ● Off-site waste management ● Off-site water and wastewater management ● Staff business travel

One airport process lies at a dynamic intersection among scopes 1, 2, and 3: providing energy and air conditioning for stationary aircraft. That makes it one of the hardest processes to attribute to a responsible party, measure with relevant performance indices, and address. The next sections of the literature review further magnify work regarding the use of energy use at airport gates.

2.2 Apron and APU Emissions

Although aircraft operations from the LTO cycle represent the largest contributor to airport air pollution, as defined by Scope 3, ground handling operations are the second largest, representing approximately 8-28% of total emissions, depending on the emission type (Fleuti & Hofmann, 2005). Many of these sources are stationary, concentrating harmful chemicals in small volumes where breathing could become more hazardous than airport-wide daily-average measurements indicate. For example, at Copenhagen International Airport, significantly higher concentrations of ultrafine particles were measured next to the gates, where ground-handlers work, demonstrating strong exposure across the airport (Møller et al., 2014). Chouak et al. (2022) performed dispersion modelling to show how plumes of exhaust emissions next to terminal buildings may create persistent hot spots with high concentrations of pollutants depending on wind direction and airport configuration.

Exhaust from APUs is one of the most concerning sources of fuel emissions and costs during ground handling operations. APUs require a high fuel flow to operate but have a low operational efficiency (approximately 10%) at the gate (Fleuti & Ruf, 2018; Renouard-Vallet et al., 2010). For example, a stationary A320 aircraft will consume 80-130 kg/hr of fuel depending on its setting (Padhra, 2018). Larger aircraft and older APU models typically require higher fuel flows, up to an average of 220 kg/hr for jumbo-wide body aircraft (ACRP et al., 2012). In 2023, the price of jet fuel is $0.91/kg (IATA, 2023), implying that APUs running at the gate are burning approximately $70-250/hr for each aircraft. The longer the APUs run, the more they require maintenance work, exacerbating the direct costs incurred by airlines. Indirect external costs are caused by CO_2 emissions and other criteria air pollutants, such as NO_x, CO, VOC, SO_x, and PM (ACRP et al., 2012; Balli & Caliskan, 2022; Lobo et al., 2015; Padhra, 2018; Xu et al., 2020). APUs are designed to run at high energy when they start up the main engines. When these powerful engines run at a fraction of their maximal output and start out at cold temperatures, the incomplete combustion leads to disproportionately high emission rates, as exemplified by their contribution to 53% of inner apron PM emissions (Winther et al., 2015). According to the Alternative Aviation Fuel Experiment campaign conducted by NASA, the APU's highest emission index was measured for CO, ahead of SO_x, NO_x, HC, and PM (Kinsey et al., 2012). An additional harmful APU impact on human health is the noise caused by the combustion of APUs that can lead to cardiovascular, hearing, and psychological damages (Münzel et al., 2014; Tubbs, 2000).

Overall, APUs are a critical component of modern aircraft; removing them would reduce safety and operational redundancy. However, APUs may also be used for the non-critical purpose of providing electrical power and conditioned air when parked at airport gates. Within the scope of turnaround operations, concerns with APU fuel costs, GHG emissions, air quality implications, noise, and health impacts are warranted.

2.3 Gate Electrification

Gate electrification in the form of ground power and preconditioned air provides a feasible and cost-effective alternative to the use of APUs (Greer et al., 2021). It is a successful energy efficiency and cost reduction strategy for airport operations (ACRP et al., 2010). ACRP et al. (2012) provided a method to make an airport-wide estimate of the fuel and emissions savings from the use of these systems that justify installation costs.

Similarly, from an environmental standpoint, gate electrification is an important GHG and local pollution reduction strategy (Barrett, 2019). Even though the emission footprint of gate equipment depends on original airport electricity energy and installation, GP and PCA systems consistently outperform APUs in terms of life cycle monetary and GHG costs (Greer et al., 2021). Mobile diesel-powered GPUs and PCUs mitigate the fuel costs and emissions of some APU pollutants, but they still produce significant tail-pipe emissions on the apron area (Altuntas et al., 2014). Especially at a local level, gate electrification reduces APU exhaust and its air quality and health implications (ACRP et al., 2019; Benosa et al., 2018; Fleuti, 2018; Sadati & Cetin, 2020).

Replacing APU times with fixed GP and PCA results in highly fluctuating loads on the airport electricity demand. Gate electrification infrastructure can contribute up to 87% to an airport's peak demand for power, having significant implications on the design of the airport's energy grid and on electricity pricing (Sadati & Cetin, 2020). Overall electricity costs contribute to approximately 10-15% of an airport's annual operational expenses (ACRP et al., 2010; Sadati & Cetin, 2020), excluding infrastructure installation and maintenance costs. Because gate electrification is an on-demand resource, it is unpredictable, and drastic fluctuations can result in a financial and infrastructure challenge for airports.

The benefits of gate electrification infrastructure can be obtained only if such infrastructure is used. Gwilliam (2010) identified a systematic problem with inefficient ground operation procedures and APU use times that have "not been reduced more aggressively." Few airports have policies to limit APUs reflected in their gate lease agreements, and most have no effective monitoring and enforcement mechanisms (ACRP et al., 2012). Padhra (2018) stated that some airports have restricted APU usage to 5 minutes after arrival and 5 minutes before departure, although different airports have different policies. He calculated that compliance with airport APU regulation occurs, on average, in only 6% of aircraft turnaround operations. Padhra dissected the problem using the data from A320 aircraft from two airlines, showing how the emission rates were highly dependent on the circumstances of each operation (timing, APU setting, ambient temperature). In addition, he found that most of the excessive APU use times and emissions occur in the pre-departure phase of a turnaround operation, often because of lacking coordination among the stakeholders involved. By conducting a high-resolution analysis of the consumption data of single operations, he quantified inefficiencies in detail, identified and compared trends, and formulated strategies to solve them. His method should be extended to include more aircraft models and airlines, but the current state of airline data collection and sharing does not enable that. A method to evaluate APU impacts that is both representative of the broader aviation industry and granular enough to assess individual operations has yet to be developed.

ACRP et al. (2019) provided a comprehensive list of challenges with the use of ground power and proposed a framework for resolving them. They identified use tracking as a functional near-term solution that can help assess the problem, but their suggested method lacks the resolution to look at individual operations (i.e., they constructed a ratio between the average time of equipment use and the average estimated time the equipment could be used for every gate at an airport). They suggested that a long-term solution would use sensors that enable real-time monitoring, automated tracking, reporting, and dissemination of use data, but they did not provide a blueprint for such a system. This report aims at providing a feasible foundation for such a system that is both detailed and comprehensive, leveraging data directly available to airports from existing systems.

The progress made in increasing gate electrification use should be benchmarked to provide a standard on which to improve. However, current benchmarking studies in aviation do not capture this well. Benchmarking studies on airport management, airport operating efficiency, and ground handling do not mention APUs and ground power at all (Adler et al., 2013; Oum & Yu, 2004; Schmidberger et al., 2009). Kilkiş & Kilkiş (2016) specifically focused on benchmarking airport sustainability using energy consumption across the airport as a metric for efficiency but did not consider the fact that the gate electrification infrastructure is a positive driver for sustainability at the airport. Kilkiş & Kilkiş (2017) also analyzed airline and aircraft sustainability but did not consider APU use at the airport as a metric, instead focusing on the overall fuel use. Despite being a key factor in efficiency and sustainability, GP use and APU use remain a neglected sub-problem or a grey area in terms of benchmarking because it is a unique process involving many stakeholders.

The literature clearly indicates that gate electrification infrastructure is an alluring upgrade for any airport gate, promoting investment in such systems. However, there is limited quantitative research on the day-to-day operation of those systems, despite indications that their use might be suboptimal. The potential missed savings and environmental impact warrant further research and supervision.

2.4 Monitoring

To provide the details necessary to assess individual turnaround operations, airports need a reliable and systematic way to collect relevant data. Airports and aircraft have a wealth of data that is already available to better dissect the progression of a turnaround operation. With the advances in Internet of Things (IoT) technologies and artificial intelligence applications, there has been a significant advancement in the ability to leverage these data acquisitions. As real-time data acquisition methods at airport gates are proliferating, the feasibility of detailed and comprehensive monitoring of gate electrification infrastructure is also increased. Currently, no standard method exists to monitor ground power use and the flow of activities for ground handling for stakeholders involved. Listing current techniques used by airport professionals and data acquisition methodologies by relevant studies will demonstrate what is currently possible.

Airports already implement some state-of-the-art monitoring technologies. As complex logistics hubs with the highest level of safety in transportation, airports showcase real-time data collection and dissemination, systems integration, and many artificial intelligence (AI) applications (Koroniotis et al., 2020; Sims, 2019). Airports can monitor in real time (i) electricity cost and emission rates (Forsyth, 2004; Janić, 2011) and (ii) air quality, with criteria air pollutants (Popoola et al., 2018; Shirmohammadi et al., 2017; Wu et al., 2017). On the airside, airports use computer vision techniques to track the movements of aircraft and other vehicles across runways, taxiways, and the apron area (Aguilera et al., 2006; Girshick et al., 2016; Li et al., 2018; Wang et al., 2021). On the landside, airports collaborate with airlines to track the movements of their passengers at check-in, security, and gate-boarding phases (Schultz & Fricke, 2011; Mrňa et al., 2021). On the apron and at the gate, events and activities can be monitored with computer vision using cameras that may already be installed at the gate and used for other purposes. Early developments focused on larger events (e.g., aircraft arrival, pushback, taxiing), but the technology is evolving to perform high-accuracy image recognition of increasingly fine-grained processes (e.g., collision detection, tracking equipment, service detection, time stamping of actions) (Aguilera et al., 2006; Lu et al., 2016; Thai et al., 2020; Wang et al., 2021; Wang et al., 2022; Yıldız et al., 2022; Thai et al., 2022). The startup Assaia is applying these concepts to collect timestamps of operational milestones in real time and track turnaround operation workflow (Assaia, 2023; Hen, 2023). These computer vision systems can visually confirm whether GP and PCA are physically connected to the aircraft in real time, although they do not provide information on their use times and magnitudes. Zhang et al. (2014) filed for a patent that describes how infrared-thermal cameras can be used to see high-temperature exhaust from the APU as a method to monitor it, but such a system would require the installation of infrared cameras at all gates.

The monitoring of GP and PCA at airports is possible, but current solutions are fragmented, not integrated, and not applied at scale. ACRP (2012) laid out a clear theoretical basis for the monitoring of APU, GP, and PCA use for the purpose of estimating the costs of turnaround operations. The report identified that monitoring (i) the aircraft type, (ii) the APU times and modes of use, (iii) temperature conditions, and (iv) airport utility costs provide the critical user-supplied data for their estimate. They also suggested several sources to procure these databases, such as:

- Commercially available data sources, such as OAGaviation.com or airlinedata.com,
- The Airport's Noise and Operations Monitoring Systems,
- The Federal Aviation Administration's (FAA's) Enhanced Traffic Management Systems database,
- The FAA's Performance Data Analysis and Decision System,
- Form T-100 Reports, available from the Bureau of Transportation Statistics,
- Other FAA or airport-specific datasets.

However, they fell short of explaining how to monitor individual operation times and rather focused on how to manipulate the relevant data once it has been acquired. Especially when it comes to monitoring APU use time, they direct an airport to "note the amount of time on arrival and departure that the APU is in use." Such a task is complex since every operation is vastly different. That is why the above-mentioned data modules use default values in the estimate as an alternative, which goes against the purpose of monitoring operations. ACRP (2019) also had this gap in data acquisition, stating that in the ideal scenario, (i) "all electric GP and PCA units are equipped with hourly meters” and (ii) “the user already has actual APU use times available.” Even if GP and PCA systems had hourly energy meters, how would those be able to monitor the use times of equipment that is used for fractions of an hour? How would they differentiate gate operations that fall within the same hour? There is a gap in information regarding how to source the data from the airport’s perspective.

The simplest level of APU monitoring is that of a human inspector or manager on the apron floor. There are cases in which airport, airline, and government officials walk out on the apron to inspect and ensure that APUs are turned off whenever possible. To provide a rough diagnosis across a larger sample of operations, airport officials have manually recorded APU use times (SeaTac, 2019). Although such approaches lack the breath, detail, and data recording capabilities required to understand the problem in detail, manual input of data from humans on the apron can be effective. For instance, the ground handlers and pilots have been directly involved in generating data by self-reporting the completion of their activities through handheld devices that communicate with centralized data acquisition software (Wu, 2008; Makhloof et al., 2014).

The best data to understand the APU power setting, emission rates, and usage times of GP and PCA at airport gates can be collected directly from aircraft. Existing aircraft sensors are highly precise, measure direct consumption quantities, collect data regularly on an integrated system, and can transmit that information in real time (Amrutha et al., 2019; Wu, 2008). Padhra (2018) and Sadati & Cetin (2020) performed their detailed analyses by leveraging data shared retrospectively by airlines on a subset of operations. Some airlines have developed streamlined proprietary software to track APU, GP, and PCA use while sharing it with all relevant airline stakeholders (Alaska Airlines, 2019). Application programming interface (API) solutions like APiJET’s Turnaround Management tool would enable more airlines to self-monitor their APU, GP, and PCA performance (APiJET, 2023). However, airlines do not consistently record this data and are often unable, unmotivated, or reluctant to share it. In the future, adoptions of open real-time sharing of aviation data between all stakeholders might unlock this direct data with exciting potential (Lootens & Efthymiou, 2021).

If APU use times cannot be measured from the aircraft directly, they can be inferred by measuring the power being supplied to the aircraft by the airport. Monitoring the energy consumption from airport ground handling equipment can provide reasonable approximations of GP and PCA use times, which are directly related to APU use times and modes. Airport electrical meters record data on an hourly, daily, or yearly basis, often for the purpose of pricing airlines for their energy use. However, for the purpose of monitoring use, sufficient granularity in the data is required to identify events that could happen in minutes. If that data can be combined with the airport’s aircraft monitoring database, which provides data on the aircraft and their movement, enough data is present to dissect the energy use during the operation. Achatz Antonelli et al. (2019) applied this concept to a case study on San Francisco International Airport (SFO) to validate the problems with gate electrification use by using 5-minute energy metering data. That is also the methodology behind estimating current average utilization rates of gate electrification (70%) at CDG airports in Greer et al. (2021), who then expanded the scope to determine the global impact of gate electrification while considering different airport circumstances and use scenarios.

Airport equipment manufacturers are exploring a similar idea. John Bean Technologies (JBT), specifically its Aerotech branch, is developing a real-time monitoring system for gate operations that use their gate infrastructure called iOPS (JBT AeroTech, 2023). Their product has already been successfully applied to large-scale hub airports, including Houston International Airport. Their IoT-enabled gate infrastructure has precise interconnected sensors that collect data on the power consumption of GP systems, PCA systems, jet bridge systems, and more. They can collect the timestamps of activation for each individual system. This information helps to identify breakages or immediately reveal an operation that is not using gate resources correctly so that the relevant stakeholders (typically the ground crews) can be contacted to correct the situation. They use the data to approximate APU consumption and estimate the relative costs. Another ground equipment manufacturer, ITW GSE, is developing their own similar power management solution named Intelligent Power Management (IPM) that would monitor energy use and proactively limit power loads during an operation (Aviation Pros, 2023; ITW GSE, 2023). Neither iOPS nor IPM integrate with airport databases with information about the aircraft and the airline. Despite being effective at monitoring energy use and providing strategies to address gate issues in real-time, they do not offer the ability to monitor the larger trends of apron operations, such as the airline's performance, their emissions, or their regard for airport policy.

A promising technique to monitor engine use at the gate is real-time sound analysis using artificial intelligence. Different engines in the apron area that produce diverse characteristic sounds not only reveal the use rates but also provide diagnostics on engine malfunctions (Tam et al., 2013; Ahmed et al., 2021). With an array of microphones installed across the apron area, artificial intelligence algorithms can determine the source and location of noise (Ogata et al., 2000; Von den Hoff et al., 2021), providing an effective way to monitor APU use at the gate. This is being applied in practice by the University of Washington in collaboration with Microsoft X and Seattle-Tacoma International Airport (SEA) (Liang, 2023). Assaia, in combination with their computer vision system, also uses microphones as their way to infer APU use at airport gates as part of their APU Emissions Detector software service (Assaia, 2023).

Solutions already exist to monitor GP, PCA, and APU use at airport gates, without the need for new technological advancements. Some of them provide greater insight, some require low initial investment, and some do not require airline data sharing. Establishing feasible, consistent, insightful, and integrated monitoring for the use of gate electrification infrastructure is an emerging and fertile opportunity in the aviation industry.

2.5 Energy Prediction Modelling

Monitoring provides value by generating information on the past and present and by yielding data on which predictions can be made about the future. Predicting energy consumption is important to design the control and optimization of airport energy systems. Several studies focus on predicting electrical loads on the terminal buildings, especially in relationship to the heating, ventilation and air conditioning systems, the building design, and the weather conditions (Chen & Xie, 2013; Huang et al., 2015). Kang et al. (2017) used regression models to show how the Pittsburgh International Airport (PIT) building energy demand is related to weather conditions and the flight schedule, which is representative of passenger flow. Interestingly, PIT is equipped with GP and PCA systems at all gates, which consume airport power depending on flight schedule and ambient temperature, which could be a significant confounding factor for power demand prediction. Airports have been able to effectively predict many of their more consistent energy loads, while the highly variable loads coming from the gates have a less predictable energy demand.

In the context of airport gate electrification, Sadati & Cetin (2020) applied multiple linear regressions to identify trends in consumption from GP and PCA systems. They stated that both their research with manufacturers and their data-driven analysis point to the fact that ground power consumption is correlated mostly to the aircraft subtype, although their results are "not consistent with the typical power demand of GPU provided for different aircraft types, which states that the larger the aircraft size, the higher the typical electricity demand." In the article, they hypothesized that the difference could be due mostly to different electrical equipment. However, they did not consider the confounding implications of (i) the variable use times of GP vs. APU, (ii) the variable consumption rate within each operation that often peaks at the beginning and end, and (iii) the variable duration of the overall turnaround operation that is often correlated with aircraft size. For the PCA consumption, the researchers were able to fit regressions to show how the ambient temperature affects the total demand, both for heating and cooling functions. The ability to predict consumption, accurately store energy, manage multiple energy sources, and even out erratic consumption patterns could lead to monetary and environmental benefits for airports.

Monitoring, predicting, and managing energy consumption is a developing field of study that leverages data-driven machine learning methods. Amasyali & El-Gohary (2018) reviewed many of the different model types that can be used and explained their advantages and disadvantages. All the energy consumption prediction model types described are made through supervised machine learning algorithms on historical data, and their performance can be assessed using metrics related to accuracy, precision, and overfitting. Since machine learning models have not been applied for the purpose of predicting power demand from GP systems at airport gates, several models should be evaluated to see which one is most representative for this report scope. The model structures that are developed and tested in this report are: (i) decision tree regression, (ii) neural network regression, (iii) k-nearest neighbors regression, (iv) linear regression, (v) lasso regression, (vi) support vector machine regression, and (vii) random forest regression. Table 2 lists succinct explanations and reference papers that inspire the application of each modelling technique for the problem of aircraft gate power prediction.

Table 2: Supervised machine learning models used to predict GP demand

Model Structure	Model Structure and Explanation	Relevance of Model for Aircraft GP Demand Prediction at Gates
Decision Tree Regressor	Amasyali & El-Gohary (2018) Decision tree algorithms use a tree to map instances into predictions. In a decision tree model, each non-leaf node represents one feature, each branch of the tree represents a different value for a feature, and each leaf node represents a class of prediction.	Domingos (2012) Decision trees is a flexible algorithm that could grow with an increased amount of training data. Tso & Yao (2007) A major advantage of the decision tree […] is that it produces a model which may represent interpretable rules or logic statements.
Artificial Neural Net Regressor (ANN)	Amasyali & El-Gohary (2018) ANN is a non-linear computational model, inspired by the human brain. A typical ANN includes three sequential layers: the input layer, the hidden layer, and the output layer. Each layer has several interconnected neurons, and each neuron has an activation function.	Ahmad et al. (2014) Since the complexity of building energy system is very high […], the ability of ANN in performing non-linear analysis is an advantage in executing buildings energy consumption forecasting. Tso & Yao (2007) They are especially useful for prediction problems where mathematical formulae and prior knowledge on the relationship between inputs and outputs are unknown.
K-Nearest Neighbors Regressor (KNN)	Fan et al. (2019) The principal mechanism of the K-NN algorithm is that all samples have the same characteristics while they are classified in the same category in a feature space, which the category contains the k most neighboring samples.	Valgaev et al. (2017) This technique is common for data classification, but can also be extended to forecast functional time series. KNN forecasters in general, are attractive because of their simplicity and the ability to predict complex nonlinear behavior, such as the one expected of a building load.
Linear Regression	Fumo & Biswas (2015) Regression analysis is a methodology that allows finding a functional relationship (model or equation) among response or dependent variables and predictor, explanatory or independent variables.	Edwards et al. (2012) Linear Regression is the simplest technique, and can provide a baseline performance measure. Tso & Yao (2007) Regression analysis is one of the most popular techniques for predictive modeling.
Lasso Regression (Least Absolute Shrinkage and Selection Operator)	Ranstam & Cook (2018) LASSO regression aims to identify the variables and corresponding regression coefficients that lead to a model that minimizes the prediction error. This is achieved by imposing a constraint on the model parameters, which shrinks the regression coefficients towards zero, by forcing the sum of the absolute value of the regression coefficients to be less than a fixed value (λ).	Ranstam & Cook (2018) LASSO limits the complexity of a regression model. A particular advantage with this technique is that it reduces overfitting without restricting a subset of the dataset to sole use for internal validation.
Support Vector Machine Regressor (SVM)	Amasyali & El-Gohary (2018) SVM solves a non-linear problem through transforming the non-linearity between features and target using linear mapping in two steps. First, it projects the non-linear problem into a high-dimensional space and determines the function $f(x)$ that fits best in the high-dimensional space. Second, it applies a kernel function to make the complex non-linear map a linear problem.	Ahmad et al. (2014) Since it can be used to solve nonlinear regression estimation problems, SVM can be used to forecast time series. […] SVM so far has been widely used in various analyses such as regression, classification, and non-linear function approximation. […], it can be used to forecast energy consumption with high accuracy.
Random Forest Regressor (RF)	Breiman (2001) Random forests are a combination of decision tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest.	Wang et al. (2018) Random Forests use variable importance, a distinct characteristic of RF, to locate key impact variables and to understand building energy behaviors.

Energy is one of the many resources that can be predicted regarding turnaround operations, although currently, it appears to be studied in the least detail. In the following subsection, the literature on the prediction of activity durations, labor, and equipment use will be reviewed to provide a more complete picture of what can be predicted in this report's scope.

2.6 Scheduling Simulation, Optimization, and Control

Punctuality control over irregular operations is a major concern in aviation, as it directly relates to the throughput and economics of most flights (Scala et al., 2020; Balli & Caliskan, 2022). Flight delays, which may stem from delays in turnaround operations, are major concerns especially because of their interdependent and propagating nature (Sternberg et al., 2021). The simulation, optimization, and control of aviation schedules is a broad and evolving topic that addresses this concern.

Turnaround operations are project delivery processes characterized by their fast pace, the high variability in the durations of their activities, and the likelihood of last-minute unexpected changes. For these reasons, turnaround operations management is a major component of the larger challenge of punctuality control. Current literature and industry practice describe three main simultaneous methods to address the problem: (i) placing contingencies, (ii) identifying and mitigating the causes of schedule variability, and (iii) establishing adaptive management procedures. This section of the literature review shows how turnaround operations time prediction, simulation modelling with stochastic approaches, scheduling optimization, and machine learning are methods that are used to improve the performance of airport ground handling operations. Although these methods have been extensively applied to major components of the problem (i.e., passenger handling, luggage handling, refueling, catering, apron management, and air traffic control (ATC)), the non-critical issue of energy efficiency through APU, GP, and PCA use has been oversimplified or omitted.

Simulation, optimization, and streamlined control of turnaround operations have been of growing interest since the beginning of the 21st century, catalyzed by increased detail in data collection, the integration of systems, and the application of new technologies (Liu et al., 2023). However, the need to make reliable and effective turnaround operations schedules has been essential since the beginning of commercial aviation. That is why aircraft manufacturers provide airport planning manuals (e.g., Boeing, 2023) that describe typical schedules for ground handling using the critical path method. These schedules provide the probable sequence and duration of the activities for each aircraft type. Although these recommended schedules often include contingency time, they do not capture the highly variable nature of each operation or the propagating nature of delay. Since the activity durations are closely weaved together and their durations are uncertain, the activities that constitute the critical path often change throughout each operation, leading to uncertainty in the cause of each operation's delay (Sánchez & Eroles, 2018). Although the critical path method can provide a clear schematic schedule, deviations from the schedule are to be expected.

Predicting the occurrence of delay before it occurs enables turnaround operations stakeholders to customize their schedules and mitigate the risk of delay propagation. Machine learning models that track and predict the relationships between operational features and on-time performance can be used to estimate the probability and duration of turnaround operations delay, even if the sub-process logistics of the operations are treated as a blackbox (Gao et al., 2015; Thiagarajan et al., 2017; Yu et al., 2019; Halmesaari, 2020; Dalmau et al., 2021; Rodríguez-Sanz & De la Cruz, 2021). Detailed, comprehensive, real-time data acquisition systems on turnaround operations are challenging to implement, so estimating delay from easily obtainable features (e.g., arrival delay, weather, airport congestion level, passenger count) can be an effective early-stage strategy toward placing buffers and controlling overall delay.

Dissecting turnaround operations into interdependent and variable subprocesses can provide much more insight, precision, and accuracy into predicting possible schedules. Analysis of the component activities of an operation highlights the bottlenecks and inefficiencies associated with each activity (Schultz and Fricke, 2011; Norin et al., 2012; Schultz, 2018). Furthermore, fine-grained prediction models can be developed for individual activities in accordance with their influence factors and constraints (Schultz & Reitmann, 2019; Luo et al., 2021; Luo et al., 2022). These subprocess models are inherently uncertain, often being represented as or resulting in a probability distribution of the duration of activities. The subprocess models can then be used as the building blocks of more comprehensive and integrated models.

Simulation methods can be used to assimilate stochastic models of individual activities into larger interdependent structures, which can then be evaluated (Khoury et al., 2006; Bevilacqua et al., 2015; Mota et al., 2017; Schmidt, 2017; Korkis-Kanaan & Ramy Sfeir, 2019; Salihu et al., 2021). The most common discrete-event methods are Monte Carlo simulations (Wu & Caves, 2004a; Wu & Caves, 2004b; Sheibani, 2020; Guimarans & Padrón, 2022), fuzzy critical path simulations (e.g., Asadi & Fricke, 2022), and petri-nets simulations (Narciso et al., 2009; Vidosavljevic et al., 2010; Sng & Hansman, 2019). The resulting instances of these simulations are almost always a very large list of potential schedules. In average instances, the randomness in duration of individual subprocesses annuls itself, and the cumulative operation duration evens out into a smooth distribution (i.e., the central limit theorem). In less common but equally important instances, delays align to produce concerning edge-case scenarios. Generally, since turnaround operations present a merge bias (Wu & Caves, 2003), the most probable total operation duration is greater than the one obtained by using the critical path method.

With a representative distribution of the probable duration of a turnaround operation, strategic planners and managers can decide how much contingency time to allocate to an operation (Adeleye & Chung, 2006; Fricke & Schultz, 2009). They need to balance the need to maximize the efficient use of gate resources with the pressure to avoid propagating delays. One of the most important problems is determining the expected total turnaround operations time (and consequently the expected pushback time), because that milestone is critical to gate assignment, airside management (i.e., taxiway use, runway use, ATC) (Simaiakis et al., 2014; Narciso & Piera, 2015; Smith & Bilir, 2022), and turnaround operations resource allocation (Wu & Caves, 2003). With too much contingency time, flights are scheduled too far apart, leading to missed revenue opportunities. With little contingency time, an unexpected delay or incident might kick off a domino effect of resource demands that cannot be met, leading to scrambled management and uncontrollable costs. Since turnaround operations planners and managers do not have the benefit of hindsight, they need to speculate on the best contingency time on the basis of all possible outcomes and the average expected cost.

Cost metrics are important in weighing different hypothetical turnaround operations schedules against each other and make decisions (Wu & Caves, 2000). The totalized cost rates of a turnaround operation can be circumstantial to each operation and depend on stakeholder perspectives (Becu et al., 2003). Different cost factors can be vastly different in magnitude, so time can often be a misleading metric for comparison. For example, the cost of using the APU for an extra 10 minutes is often several orders of magnitude smaller than the cost of delaying a turnaround operation by 10 minutes. In particular, measuring the considerable cost of delay is challenging because of its stochastic and propagating nature (Evler et al. 2020). By taking a schedule and collapsing it into a relative cost with a holistic cost function, it is possible to weigh different scenarios against each other and make data-driven decisions based on multiple objectives, such as selecting the optimal contingency time and performing schedule recovery (Fitouri-Trabelsi et al., 2015; Evler et al., 2021). The combination of a simulation model and a relative cost function are, in such a way, the two pillars of turnaround operation optimization.

The operation optimization problem can be expanded to include many of the decisions that occur during a turnaround operation. The procurement and time windows for ground handling equipment and activities are all control variables that face the same challenge of balancing efficient utilization with schedule adaptability (Andreatta et al., 2014a; Padrón et al., 2016; Padrón & Guimarans, 2019). For every decision added, the optimization problem increases not only in opportunity but also in complexity, quickly reaching very large solution spaces. Whereas optimizing one variable with a convex cost function is fairly simple, adding more variables renders a problem that is far less intuitive and calculable. Including stochasticity in the optimization problem adds even further complexity, as it requires many more iterations to associate a set of decision variables with an expected cost.

There are many methods to improve the complexity of the search-simulation-optimization challenge to cut down on the solution space and computational demand. Gradient descent is a fundamental tool in systematically lowering total costs from an initial set of decision variables. This method is computationally fast due to its greedy search nature of prioritizing immediate cost savings, but without some randomization, it directs the search towards local minimums (Resende et al., 1995; Lagodimos & Leopoulos, 2000). Linear programming can be used to identify a set of decision variables within a deterministic environment that can then be evaluated for robustness within a discrete-event simulation model that includes the variability in activity duration (Lim et al., 2005; Tomasella et al., 2019; Gök et al., 2020a; Gök et al., 2020b; Wang et al., 2021; Liu et al., 2022). Genetic algorithms inspired by evolutionary biology can be used to hybridize sets of decision variables and find new effective combinations (Kumar et al., 2010; Liang, 2020; Fei et al., 2022; Bao et al., 2023). Cost heuristics can help expand the optimization search in the right direction (Deroussi et al., 2006; Andreatta et al., 2014a; Tabares & Drouin, 2021). Computational cost can also be intelligently reduced by cutting down the number of simulations (Chen et al., 2000). All these methods can inspire and combine to tackle very complex problems and produce a less computationally expensive and less localized optimum.

Once data acquisition, processing, and result delivery are streamlined, simulation and search optimization can be leveraged in real time. As real-time systems progressively incorporate circumstantial data, uncertainty in the inputs is reduced, and the results gain both precision and accuracy. Digital twins can be developed to integrate data from various sources and then be used to simulate various scenarios and optimize operations (Conde et al., 2022). Real-time monitoring and decision support tools can assist in dynamic management of systems with high uncertainty and variability (Wilkins et al., 2008; Pohling et al., 2022; Kuster & Jannach, 2006; Saha et al., 2021). The solutions that can be developed to support turnaround operations management depend greatly on the technologies that are available and can be effectively integrated. Some of the technologies considered for real-time monitoring and information sharing are: radio (Wu, 2008), radio frequency identification (RFID) (García Ansola et al., 2012), mobile phone texts (Makhloof et al., 2014), smart sensors (Fei, 2022), and computer vision (Thai et al., 2020; Assaia, 2023). The continuously developing technologies often determine the problem scope and system architecture.

The Airport Collaborative Decision Making (ACDM) framework is a leading effort in real-time optimization and management at airports. Some European and Asian airports use the ACDM framework as an information system to allow multiple stakeholders to optimize the operational efficiency across the airport through transparency, data sharing, and centralized management (Ball et al., 2007; Wilkins et al., 2008; ACRP, 2015; Eurocontrol, 2023a). That has been possible thanks to the endorsement of Eurocontrol, the European Organization for Civil Aviation Equipment (EUROCAE), and strong government regulations on airports, which have pushed airport stakeholders to accept a top-down management arrangement for airport operational efficiency. By continuously updating predictions and timestamping operational milestones, airports can optimize the use of their facilities while being resilient to deviations from the schedule. Such a collaborative and transparent process is not being implemented consistently in the US because of contractual, practical, and cultural differences (Okwir & Correas, 2014). Eurocontrol's Collaborative Environmental Management (CEM) takes the principles of ACDM further, focusing on the management of aviation networks to reduce environmental impacts (Eurocontrol, 2023b). These decision-making structures are excellent frameworks in which the use of resources can be rendered more efficiently, and they drive other initiatives towards further data integration and scope expansion.

There is a growing drive to integrate ACDM and CEM frameworks with turnaround operations management. ACDM focuses primarily on the ramp control and airside operations involving the aircraft, where there are the highest stakes in terms of costs and emissions. However, turnaround operations are a central component of airside operations, interconnected with all other airport processes. On one side, real-time monitoring and simulation are fundamental to estimate the completion of turnaround operations and consequently manage air traffic efficiently (Oreschko et al., 2012; Schultz et al., 2012; Schultz et al., 2013; Evler et al., 2018; Asadi et al., 2020; Saggar et al., 2021; Schultz et al., 2022; Assaia, 2023). On the other side, effective air traffic management needs to inform turnaround operations stakeholders so their resources can be allocated effectively (Okwir et al., 2017; Tabares & Drouin, 2021). Harmonizing the bidirectional relationships between turnaround operations and all of its interdependent systems is a great opportunity within the field of Aviation 4.0 (Schmidt et al., 2016; Tabares & Mora-Camino, 2017; Bubalo et al., 2017; Scala, 2019; Tabares, 2022), a term used to describe the integration of real-time data acquisition, predictive systems, decision support tools, and automation in aviation.

Integrated, centralized, and optimized management are paradigms of increasing system efficiency that need to be complemented with organic and decentralized solutions. A unique system that can optimize global air traffic flow, all airport airside operations, and all gate turnaround operations while accounting for ubiquitous variability is not realistic. As previously described, even much smaller scopes of centralized management present challenges with computability, implementation, and connection to the realities of airport management. Segmenting problems by reducing the scope, isolating variability, removing variables that cannot be influenced, and making assumptions is fundamental to making systems that can actually be developed. Agent-based modelling and simulations are effective at segmenting and decentralizing management problems such as turnaround operations management, enabling stakeholders to independently develop robust schedules, limiting the sharing of sensitive data, and interfacing with centralized systems like ACDM (Ip et al., 2010; Kabongo et al., 2016; Zhang et al., 2018; Baer et al., 2019; Gök et al., 2023). In such decentralized systems, the hierarchy, or prioritization of decision making, becomes determining (Weigert et. al., 2019; Jalilvand et al., 2023). To some degree, sequencing the optimization of decision variables one by one is similar to performing a gradient descent search, and hence it has similar attributes: it is fast, it is representative of the decision making of individual stakeholders, and it will also likely get stuck in a local minimum. Balancing centralized and decentralized strategies is an essential challenge in the management of large, interdependent, and dynamic systems.

In the plethora of articles about simulation, optimization, and scheduling of turnaround operations, the management of APUs, GP, and PCA is either oversimplified, omitted, or neglected. Especially when it comes to the departure sequence, the startup of the APU and the disconnection of GP and PCA are either simplified into short finalization procedures, merged with the pushback procedure, or ignored altogether. No paper has yet to address the question of when the APU should be started up, highlighting the need for more detailed data collection and relative simulation models. ACRP (2019) provided the most extensive review of potential causes for addressing gate electrification infrastructure but did not touch upon the crucial issue of schedule punctuality. Although resource allocation, data collection, automation, and communication between stakeholders and training crews are discussed, ACRP did not detail that the uncertainty and dynamic nature of scheduling and managing turnaround operations. Further, it did not mention that the operation's complexity and unpredictability could be some of the main drivers for the suboptimal use of gate infrastructure. Therefore, the turnaround operations present a considerable opportunity for improvement. Furthermore, the integrated management of APUs, GP, and PCA at the gate is a unique scope for the development of ACDM and CEM frameworks that warrants more research.

2.7 Policy

Policy, regulation, and incentives can influence the importance of sustainable and efficient operation across many industries. For example, regulation by the California Air Resources Board (CARB) has greatly accelerated the use of hybrid and electric vehicles while setting progressively more stringent requirements on vehicle emissions (Shaheen et al., 2020; Shaheen & Lipman, 2007). Their authority to define policy, enforce it, and incentivize change has shifted trends for the car industry, not only in California but also worldwide. In contrast, aviation lies in a grey area that resists scalable change. The regulatory landscape in aviation is fragmented and inconsistent because it is an industry whose operations span across different cities, regions, and countries, each with their own standards and interests. The main drivers of regulation and incentive systems in aviation are airlines, airports, government bodies and grant programs, research institutions, the United Nations, and certification programs. This section describes how policy and external incentive systems are relevant to APU, GP, and PCA use at airport gates.

The ACRP (2012) survey found that no airport mandates the use of GP and PCA by airlines, even when the equipment is available. However, some airports have policies encouraging their use. Zurich International Airport (ZRH) in Switzerland is the only airport surveyed that requires airlines to use GP and PCA instead of APUs (Fleuti, 2018). Federal regulations, such as the Clean Air Act of 1977, also apply to airport activity, and the U.S. Environmental Protection Agency (USEPA or EPA) has established National Ambient Air Quality Standards (NAAQS) for pollutants like carbon monoxide, nitrogen dioxide, and particulate matter. Areas that exceed NAAQS levels are considered nonattainment areas and are subject to controls to achieve attainment. Under the CAA Amendments of 1990, federal agencies are required to comply with State Implementation Plans (SIPs) that are designed to bring nonattainment areas into compliance with the NAAQS. For most airport projects that receive federal funding or approval, the "General Conformity" regulations apply. These regulations require an assessment to determine if a proposed project in a nonattainment or maintenance area would result in total direct and indirect emissions that exceed the annual de minimis emissions levels specified in the regulations.

Although NAAQS regulation directly affects the installation of GP and PCA systems, it does not ensure their use afterwards. If an airport is located in a nonattainment or maintenance zone, is subject to state air quality regulations, or has ambitious air quality and greenhouse gas emissions reduction goals, there may be more incentive to implement policies that encourage or require the use of gate electrification systems by airlines. Conversely, airports in regions with good air quality and no political or community pressure to address air quality may place less emphasis on the strict use of gate electrification systems. Airport operators use lease and use agreements to enforce policies that apply to tenants in different administrative and operational aspects. These policies aim to minimize emissions and noise exposure, and they may differ among airports. For instance, around 25 airports in the U.S. have implemented regulations on the use of auxiliary power units (APUs) as a means of reducing emissions and noise exposure (ACRP et al., 2012).

ACRP et al. (2012) elaborated on the National Environmental Policy Act (NEPA), which mandates federal agencies to evaluate the environmental consequences of any federal decision. The FAA is obliged to abide by NEPA requirements before undertaking any federal action. According to FAA guidelines, there are three avenues to fulfill NEPA standards: categorically excluded projects, Environmental Assessments (EAs), and Environmental Impact Statements (EIS). The usage of APUs alone does not fall under the category of a federal action. However, the installation of PCA or gate-based ground power at an airport may be considered a federal action as it could require modifications to the passenger terminal facilities and airport layout plan. While FAA Order 1050.1E does not explicitly exempt the installation of PCA and/or ground power from NEPA review, the installation of alternative systems is comparable to other actions that are categorically excluded. These systems are often used to fulfill NEPA requirements.

ACRP et al. (2012) also discussed the Voluntary Airport Low Emissions (VALE) program, established in 2004, which helps commercial service airports in designated nonattainment and maintenance areas implement emission reduction actions. The program allows airport sponsors to use the Airport Improvement Program (AIP) and Passenger Facility Charges (PFCs) to fund eligible emission reduction projects. There are conditions to obtain a VALE grant: the project must be quantifiable, the emissions would need to be surplus from other regulations, the reduction needs to be permanent, there must be sufficient support and funding, and the project must be federally enforceable. GP and PCA fall within this domain, which is why VALE is a critical driver of the requirements of those systems. As of March 2011, the FAA had funded the installation of PCA and/or ground power at 11 airports through the VALE program. However, the fulfillment of quantifiable criteria is debatable since the current monitoring and emission estimating methodologies have low resolution. Calculating monetary and emissions savings with the methodologies in ACRP (2012) and ACRP (2019) might provide a broad approximation of airport-wide savings that justify initial investment in the infrastructure, but when considering the infrastructure of individual gates and individual operations, there is a gap in information to make sure VALE investments are quantifiable, supported, and enforceable. Requiring detailed monitoring and reporting of GP and PCA use to satisfy VALE grants would ensure that the grant money is used to its fullest potential and represent the real savings at airports.

Overall, regulation and incentive systems could provide pressure for turnaround operations stakeholders to improve their gate electrification. However, without a consistent approach in the international and fragmented business of airport operations, regulatory approaches might prove challenging. Furthermore, regulatory approaches lose their influence without a systematic way to monitor and enforce them.

3. Ground Power Use Monitoring

This section of the report contains the original study that prompted a deeper investigation into the problem of gate electrification use. An initial exploratory analysis of SFO energy data in 2018-2019 revealed that approximately 20% of turnaround operations were not using any of GP provided, and many others were using it for much less time than their total turnaround operations time (Achatz Antonelli et al., 2019). We have since redesigned the analysis, further detailed the dissection of each turnaround operation, and applied the method to new data. We also provided SFO with a prototype analysis software in a Python script that could automatically perform the analysis on their databases. Although, in an ideal scenario, data acquisition for GP use monitoring would happen in real time, this retrospective analysis provides insight and a foundation for the design of a real-time airport GP monitoring system.

3.1 Introduction

Deciphering the GP under-use problem is the first step towards fixing it. Existing literature provides insights on its failure mechanisms and estimates its importance towards airport sustainability. However, any approach that is either too narrow or too broad is more of an acknowledgement than an attempt to mitigate it. Only a deeper dive reveals that the problem is highly heterogeneous, consisting of several complex details and significant variability in output performance. An integrated, recurrent, comprehensive, and high-resolution monitoring system may offer a step towards improving the use of gate electrification infrastructure. It is the key to enabling benchmarking, accountability, enforcement mechanisms, and policymaking for airports. By identifying and mitigating negative practices while making positive practices more consistent across the industry, it is feasible to shift the overall performance regarding maximizing the use of gate electrification.

The following sections will describe a detailed method of analyzing GP use (Section 3.2), results from a case study on SFO (Section 3.3), a discussion on the relevance of this work (Section 3.4), and conclusions and future work regarding GP monitoring (Section 3.5).

3.2 Methods

A detailed analysis of the consumption of GP energy aims to assess real-world gate electrification use patterns for individual operations. Instead of estimating average utilization rates for each gate, this research monitors individual operations before aggregating all the results. Although this approach greatly increases the number of inputs, it offers valuable insights not obtainable otherwise.

The methods used to conduct this analysis include: (i) data collection and cleaning, (ii) data fusion, (iii) prediction modelling, (iv) operation analysis, and (v) emission analysis. Figure 2 outlines the framework of the method, connecting databases, scripts, models, and reports. Each component is described in the following sections, both theoretically and practically. The methods are first developed generally so they can be replicated at any airport with the relevant data, and then applied to San Francisco International Airport (SFO) as a case study.

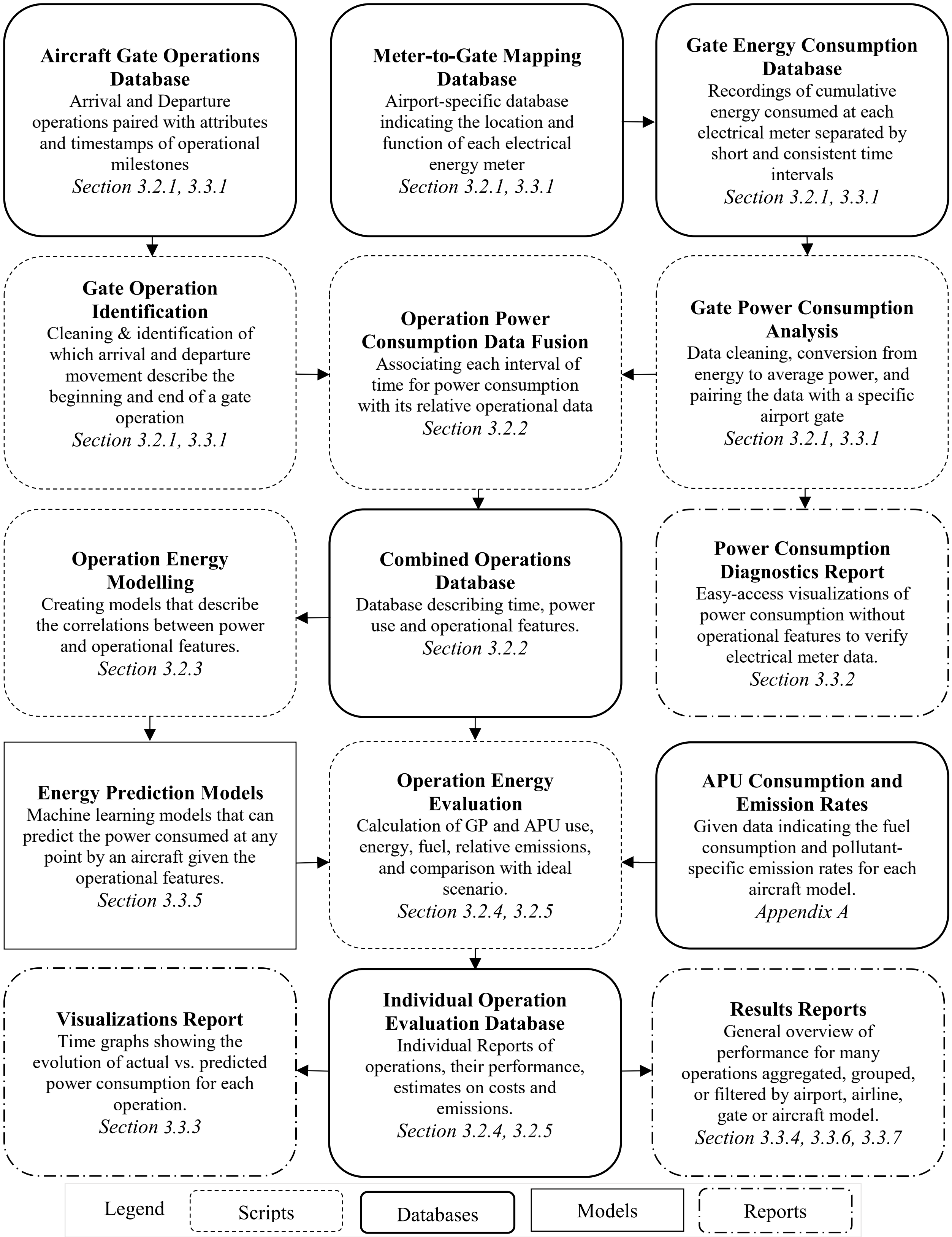


Figure 2: Framework for monitoring, predicting, and assessing GP use. Numbering refers to sections with further explanation.

3.2.1 Data Collection

After identifying a case study airport, the first step is to acquire the relevant databases. This analysis can be replicated for any airport that provides access to the following databases.

Gate Energy Consumption Database

The gate energy-use database is recorded from meters that measure the cumulative energy consumption for the 400 Hz GP supply for a single gate (Figure 3). Metering is done in timesteps, e.g., every 5 minutes. The average power consumption for each timestep can be computed from the cumulative energy at each timestep. These data points need to be recorded in intervals smaller than or equal to the typical durations of GP use and the minimum time between two consecutive gate operations; otherwise, it is impossible to differentiate whether the power was consumed by two aircraft that share the same metering timestamp. GP meters have often been installed at gates for electricity pricing purposes and usually only record data every hour, which is not sufficiently granular. We recommend data points that represent at most an interval of 10 minutes; otherwise, the interval might include consumptions from separate operations.

Additionally, note that this metering does not include any electricity supplied by potential mobile GP units (GPUs). If a gate is being powered significantly with mobile GPUs, inferring APU use by the lack of GP use would not be appropriate. Furthermore, measurement outliers and system errors are common. A simple diagnostic of the consumption can help identify any broken or flatlining meters, which must be excluded from the analysis. The times for which the power consumption measurements spike to unrealistic magnitudes (extremely large or negative for a brief period) and the hours surrounding a daylight savings change should be marked as measurement errors and be excluded from the analysis.

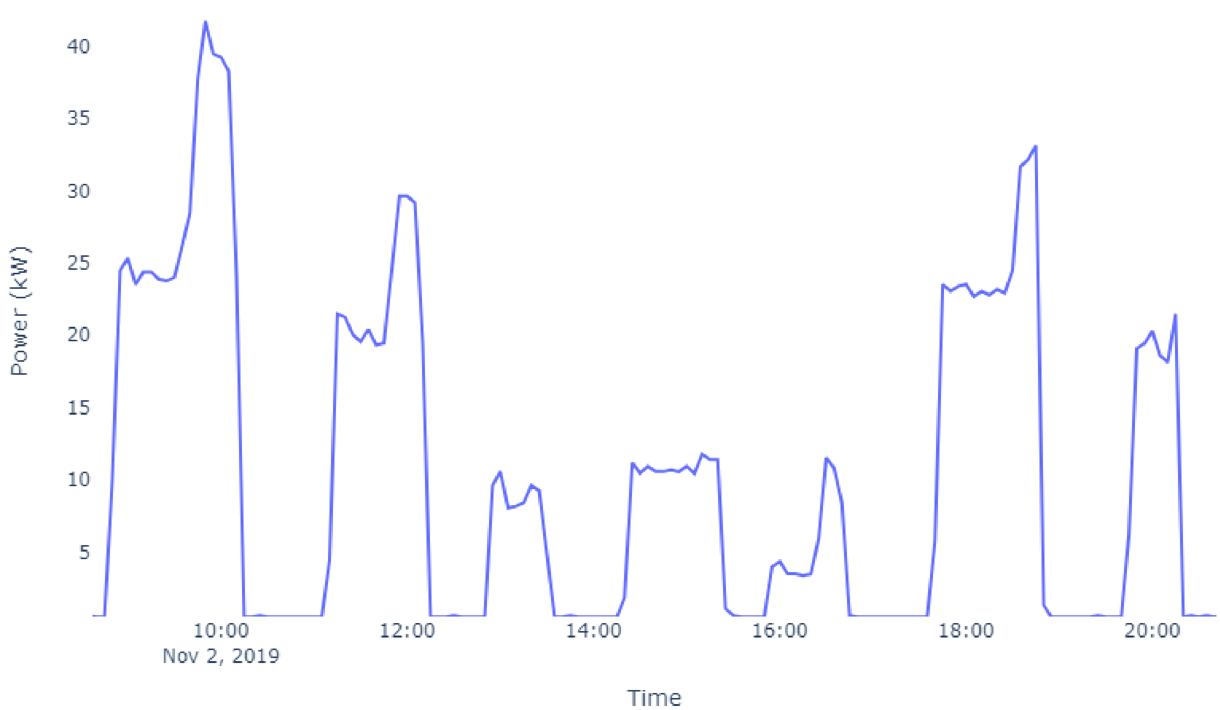


Figure 3: Sample power metering data for 12 hours of operations at a single gate

Meter-to-Gate Mapping Database
The meter-to-gate mapping database maps a gate name to its respective GP meter. This information can be found in airport documentation or by inquiring with the electrical engineers responsible for the 400 Hz GP systems. It must consider any name changes in the data collection period, should there be any.

Aircraft Gate Operations Database
The aircraft gate operations database describes aircraft movements across the airport, from gates to runways. Each arrival or departure is represented by a row in the database with reference numbers, flight information, aircraft model, gate, airline, flight reference numbers, scheduled in-block and off-block times, and actual in-block and off-block times. In-block and off-block times refer to the times at which the chocks for the aircraft wheels are inserted and removed, respectively, and they mark the beginning and end of a turnaround operation. The aircraft operation database typically provides separate rows for the arrival operation and the departure operation, so they need to be combined into a single row so that gate and reference numbers match. Any operation without the required data needs to be excluded from the analysis. Turnaround operations with durations greater than 3 hours should also be excluded from the analysis, because, in such cases, it is likely that an aircraft is shut down entirely.

3.2.2 Data Fusion

Both the metering and operational databases index their data based on the event time and gate at which the event occurs. By mapping gate names to their respective energy meters, aircraft operations at the gate and their energy use can be merged. As a result, if energy is consumed in a time interval, it can be directly associated with a specific aircraft reference number, aircraft model, gate, airline, scheduled in-block and off-block times, and actual in-block and off-block times.

The in-block and off-block times of a gate turnaround operation often do not align with the time intervals from the metering database, leading to some intervals being only partially occupied. To address this misalignment, a new parameter called $Ratio_{gate}$ is added to represent the fraction of time within a time interval for which an aircraft was present at the gate. For example, if an aircraft parked at 10:03, the data point representing the time interval between 10:00 and 10:05 will have a gate-in ratio of 0.4.

The merged database describes the effective measurement of GP utilization rates. All data points representing time intervals in which significant power was drawn indicate that GP was being used. By inspecting the lowest consumption rates across many gates, 2 kW was identified as an effective threshold to differentiate base fluctuations from idle systems from times power is being drawn. This database can be used (i) to provide statistics on power use for single or multiple operations and (ii) to estimate GP use for an operation by adding up all the time intervals in which its use was recorded. However, detail can be lost using this simple sum because of the granularity of the data. If some electrical meters collect data every 15 minutes, the uncertainty with the beginning and end of GP use would be large, especially when considering operations under an hour. Any time interval with partial power consumption would be associated with full GP consumption, systematically overestimating the actual GP use time. Additionally, such a procedure leaves little room for consideration of the actual magnitude of power demand. Any interval with partial GP consumption would be represented by an energy-consumption measurement that is less than the actual power demand. Predicting the instantaneous magnitude of GP demand will provide the missing information to address this granularity problem.

3.2.3 GP Prediction Modelling

Using machine learning techniques, a procedure is proposed to estimate the utilization rates of GP with a higher precision than the granularity of the metering data. Accurate prediction models enable airports to forecast future power demand and estimate the instantaneous power consumed without a direct input from the metering systems. If the consumption rate of GP for a certain operation can be effectively predicted, it is possible to interpolate the exact time at which it was turned on and off and therefore make a detailed estimate for GP utilization rate.

Before introducing any prediction models for the aircraft's instantaneous power, it is important to select the appropriate data to train them. Only data points that confidently represent full power demand across their time interval should be included in the training data. Any interval that has $Ratio_{gate}<1$ should be excluded because the cumulative energy consumption measurement would not represent power used if the aircraft is not present. Any interval with a reading under a threshold of 2 kW should also be excluded because it might represent times in which the aircraft is likely relying on the APU for its power demand. Additionally, time intervals immediately preceding or following other intervals with readings under 2 kW should be excluded because they might represent times in which GP is only partially used. Figure 4 displays the selection of training data from a sample operation. Given these exclusions, we can assume the remaining intervals contain cumulative energy measurements that can be translated into GP demand.

If the dataset includes nightly data of operations occurring between 12 AM and 5 AM, the system filters out the data points that show standby GP consumption. An aircraft that stays at the gate overnight sometimes shuts down partially or completely, reducing the aircraft's power demand to quantities not higher than a threshold of 7 kW. 7 kW is an arbitrary value obtained by visually inspecting nightly GP consumption. Nightly data is relevant, but it could also make the prediction for intraday power demand less accurate. If the nightly data is removed, intervals immediately preceding or following other intervals with readings under 7 kW should be excluded for consistency because they could represent times in which GP was only used partially. Figure 5 displays a typical nightly operation in which GP drops to approximately 5 kW.

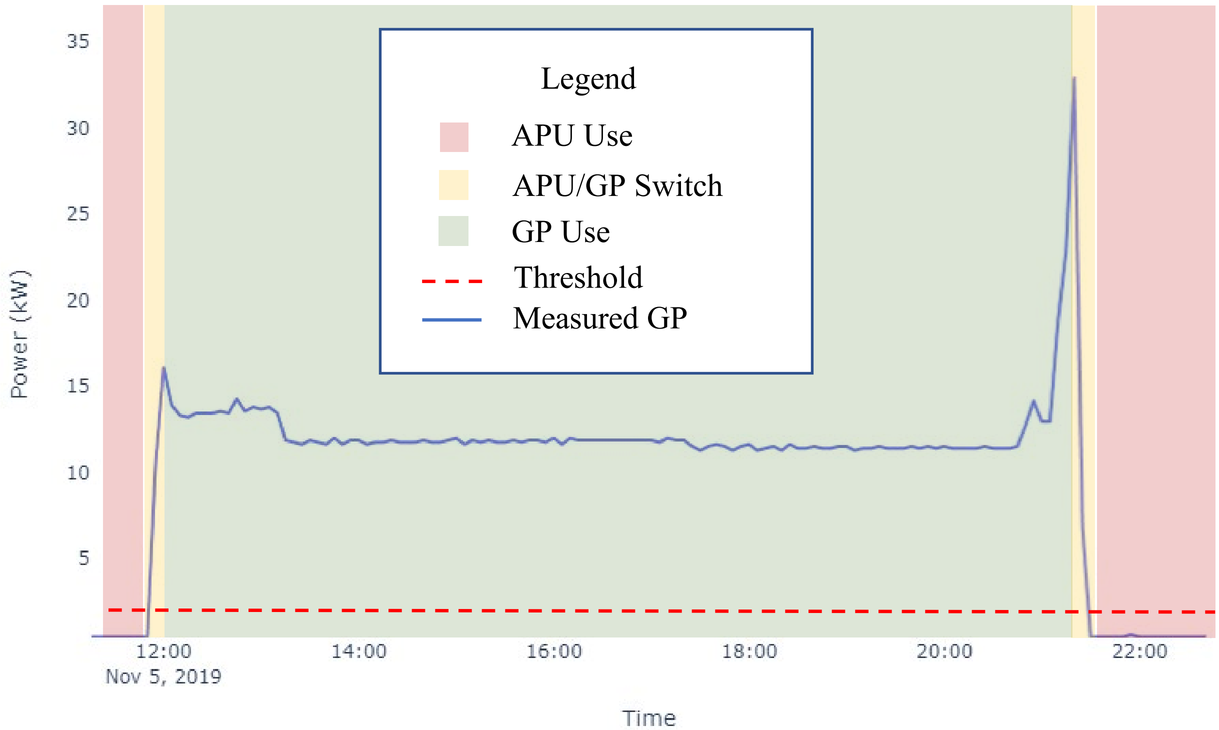


Figure 4: Selection of prediction data for a sample intraday turnaround operation at SFO

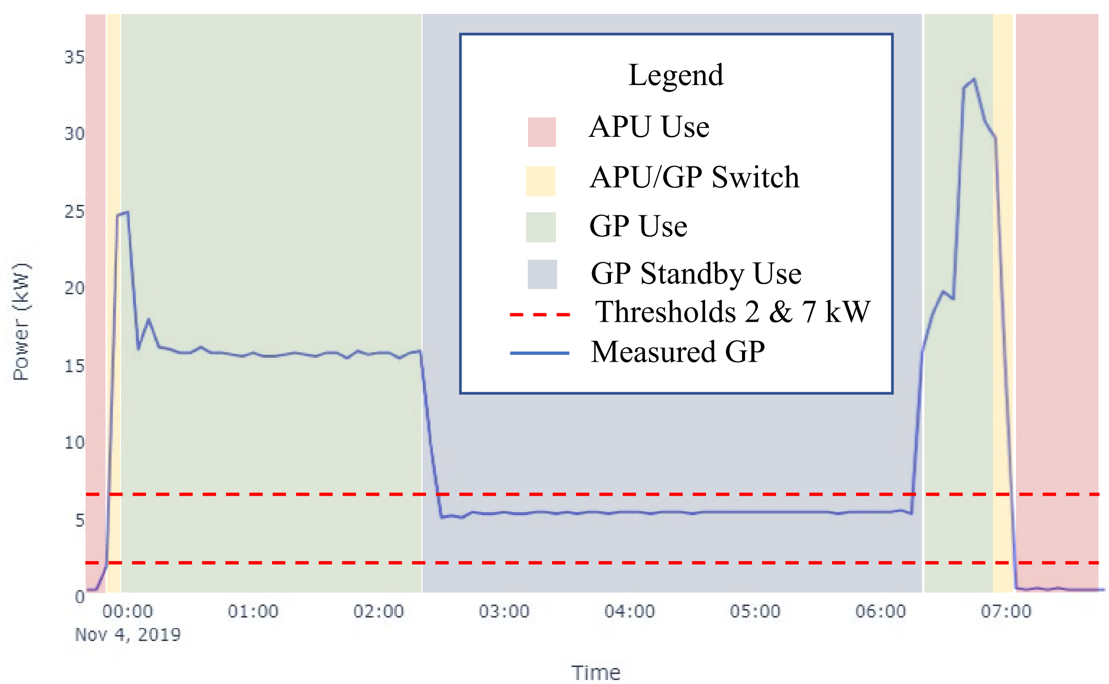


Figure 5: Selection of prediction data for a sample overnight turnaround operation at SFO

To construct prediction models, it is necessary to define each time interval as a vector that contains readings for power consumed and other relevant features. Some of the most relevant features are shown in Table 3, although only those italicized were used. To justify the testing of each feature, the right column of the table shows the potential influence mechanism that can describe the causal relationship between the feature and GP demand.

Table 3: Relevant features to predict energy demand

Feature Name	Feature Type	Influence Mechanism
Aircraft Model	Categorical	Aircraft Design
Airline	Categorical	Airline Systems and Management
Gate Number	Categorical	Gate Systems and Management
Domestic/International	Categorical	Aircraft Configuration
Time after In Block Time	Numerical	Turnaround Arrival Sequence
Time before Off Block Time	Numerical	Turnaround Departure Sequence
Total Turnaround Time	Numerical	Operation Length
Time of Day	Categorical	Hourly schedules
Day of Week	Categorical	Weekly staffing
Ambient Temperature	Numerical	Aircraft Heating Ventilation and Air Conditioning (HVAC) systems
Actual-Predicted Off Block Time	Numerical	Delay

Note: Italicized features were used to construct prediction models.

With a large set of refined and labeled data, machine learning models can be trained and tested, as can be seen in Section 3.3.5. We test 7 models: (i) decision tree regression, (ii) neural network (net) regression, (iii) k-nearest neighbors regression, (iv) linear regression, (v) lasso regression, (vi) support vector machine regression, and (vii) random forest regression. To obtain better predictive models, one must use large amounts of training data combined with cross-validation through random sampling. The dataset needs to be split into a training set, a test set, and a validation set. For each model, the validation set was used to tune the models' hyperparameters to optimize accuracy as dictated by the Root Mean Squared Error (RMSE) (Eq. 1) and Mean Absolute Error (MAE) (Eq. 2). Other criteria may also be introduced. An assessment must be made of which model performs best.

$$Root\ Mean\ Squared\ Error\ (RMSE) = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{predict,i} - y_{data,i}\right)^2}{n}} \quad \text{(Eq. 1)}$$

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{n}\sum_{i=1}^{n}\left|y_{predict,i} - y_{data,i}\right| \quad \text{(Eq. 2)}$$

Once the models are trained, providing the features of a certain time interval from an operation should output a predicted power demand, even for time intervals that were originally not included in the training set. When GP is being used, the order of magnitude of the predicted vs. actual power should be similar. In contrast, when GP is not used or is disconnected, the magnitude of predicted power demand should not resemble the one for measured GP. The RMSE and MAE are used to determine the best prediction model, which is then applied to the whole data set, not only on the vectors that were used to train the models (JJ, 2016).

3.2.4 GP and APU Utilization Rate and Energy

Even if the data granularity is insufficiently detailed, it is possible to make estimates on the exact time GP started to be used by observing the ratio between actual power and predicted power. For example, if the expected power consumption during a 5-minute interval was 20 kW but instead was measured as 8 kW, one could estimate the power that was being drawn for 40% of the time, or 2 minutes. With this logic, the observer can estimate the beginning and end of GP use for every operation. The error in this estimation will be proportional to the error in GP demand prediction. For each time interval, $Ratio_{GP,i}$ is defined as the fraction of time that GP was used, and presented as the ratio of the measured $Power_{measured,i}$ and the predicted $Power_{predicted,i}$ (Eq. 3).

$$Ratio_{GP,i} = \frac{Power_{measured,i}}{Power_{predicted,i}} \quad \text{(Eq. 3)}$$

Since the predicted power can be estimated for each time interval i, one can calculate the predicted cumulative energy $Energy_{GP}$ for its n time intervals using Equation 4.

$$Energy_{GP} = \sum_{i=0}^{n} Power_{predicted,i} \times Ratio_{GP,i} \quad \text{(Eq. 4)}$$

The cumulative energy consumption was already provided in the original data, so it can be compared to the predicted energy consumption to assess the validity of the prediction model.

If GP cables are installed at all gates, and alternative GP unit use is rare, the observer can assume that whenever an aircraft does not use GP, it must be using its APU. $Ratio_{APU,i}$ is defined to be the fraction of a time interval for which GP was not used and is calculated across the whole dataset. Based on this assumption, Equation 5 is used.

$$Ratio_{APU,i} = Ratio_{gate,i} - Ratio_{GP,i} \quad \text{(Eq. 5)}$$

This enables us to estimate the times for both GP and APU use within each time interval i of duration d_i. Equations 6 and 7 show the calculation for GP and APU cumulative use times for n time intervals, T_{GP} and T_{APU}, respectively.

$$T_{GP} = \sum_{i=0}^{n} d_i \times Ratio_{GP,i} \qquad \text{(Eq. 6)}$$

$$T_{APU} = \sum_{i=0}^{n} d_i \times Ratio_{GP,i} \qquad \text{(Eq. 7)}$$

Similarly, the energy demand from the APU $Energy_{APU}$ can be estimated from n time intervals by using Equation 8.

$$Energy_{APU} = \sum_{i=0}^{n} Predicted_i \times Ratio_{APU,i} \qquad \text{(Eq. 8)}$$

We estimate the number of times the APU was initiated by determining the number of times there is a switch in power consumed. Before APU power is consumed, the APU needs to start so that the turbine can reach the required rotations per minute (rpm) or electrical power generation. This process can take up to 3 minutes, depending on the APU type. Based on this estimate, 3 minutes of APU time on a no-load condition were added to each operation for every time the APU was started, although the power consumed in those times originated from GP.

Figure 6 illustrates this dissection of power consumption for a partially successful operation (solid blue line) as compared to the neural network prediction model from Section 3.2.3 (solid red line). The $Ratio_{gate}$ describes the total time the aircraft is at the gate (dotted purple line), which can be associated with either APU use (dotted light blue line) or GP use (dotted yellow line) depending on whether the actual power was lower or greater than the threshold power (solid green line), respectively.

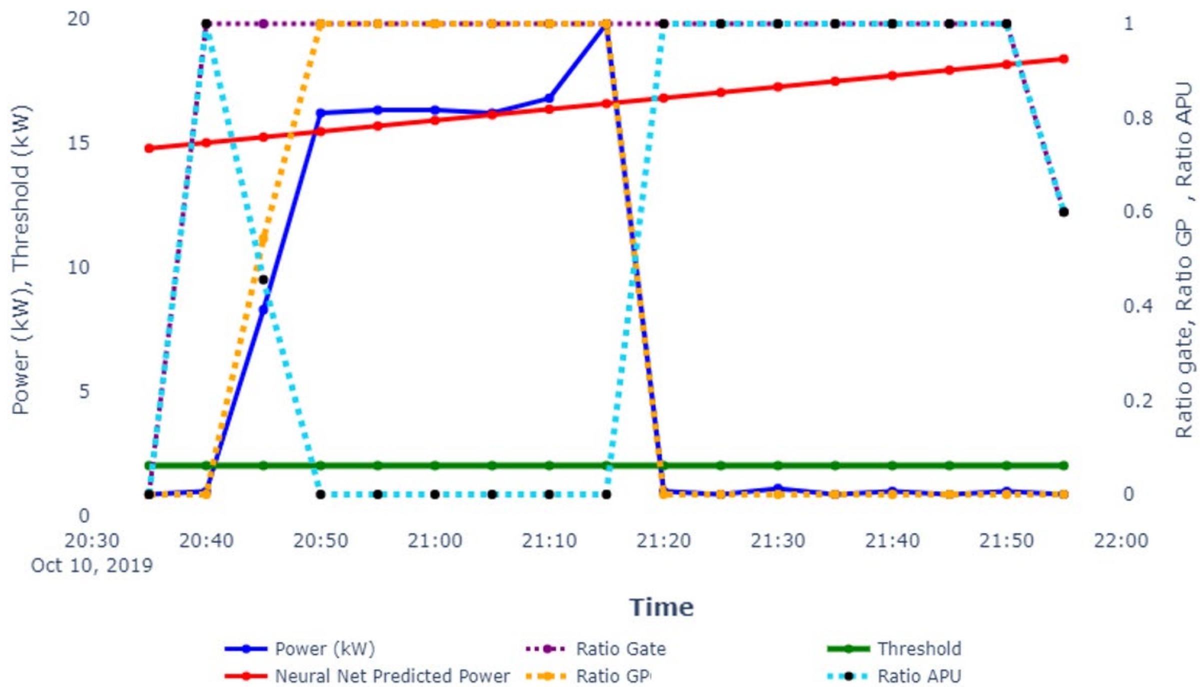


Figure 6: Power analysis for sample operation of a Boeing 737-900 aircraft with total GP time of 32.7 min and APU time of 45.28 min

Two metrics were created to assess the performance of each operation with regards to GP:

- GP Utilization Rate, which refers to the ratio of time GP was used versus the total time the aircraft was at the gate between the in-block and off-block time.
- Total APU time, which refers to the number of minutes, both in normal and start mode, that the turbine was operating.

3.2.5 APU Fuel and Emissions

The data from Section 3.2.4 can be used to estimate the total tailpipe emissions and the excess fuel consumption of the APU used at the gate by combining the deduced APU used times with APU emission rates specific to different aircraft categories. ICAO (2011), ACRP (2012), and Winther et al. (2015) provide the data for fuel flows and emissions rates, shown in appendix Tables A1, A2, A3, and A4. The pollutants were: NOx, NO_2, CO, HC (soot), and PM. The total emission estimates include both the emissions from the "start" or "no-load (NL)" modes from Winther (2015) and the equivalent "normal" or "environmental control systems (ECS)" modes of operation of the APU described in ACRP (2012). An APU startup time of 3 minutes was assumed since there are no data inputs to measure this value (ACRP et al., 2012). The total emission estimate does not capture the full cost-benefit assessment or life-cycle assessment of the gate operation, but it does provide insight into the most significant tail-pipe emissions that occur at the gate.

3.2.6 Scenario Comparison

Alternative hypothetical scenarios can be used to evaluate the potential for improvement in GP use in each operation. This report proposes two scenario models: (i) a worst-case scenario in which the operation uses the APU through the whole turnaround and (ii) an ideal scenario in which the operation uses GP for most of the turnaround except 5 minutes after in-block time and 10 minutes before off-block time (including the 3-minute spin-up). For each of these scenarios, the relative fuel and emissions were calculated. The data from the two scenarios provide a baseline to calculate the currently achieved savings and the potential savings for each operation. Although uncommon, it is possible for a turnaround operation to use APU less than what is assumed in the ideal target scenario of 15 minutes, for which the minimum potential savings need to be limited by 0 (no negative savings).

3.2.7 Aggregated Database

In the last step, a single, comprehensive database should aggregate all the information from the gate operations analyzed. This database can be filtered on attributes such as gate, aircraft model, and airline to provide customizable groupings and samples, for which values can be compared or summed. The most relevant parameters to observe are GP demand, GP utilization rate, and total APU use. Different metrics can be plotted and compared against each other to show relationships between them. Sections 3.3.4, 3.3.6, and 3.3.7 show the results that can be obtained by manipulating the aggregated database.

3.3 SFO Analysis Results

The results section applies the selected methods to a data set containing 343,721 5-minute data vectors representing 21,486 operations. All the results are indicative of the sample of operations that are analyzed and not the entire population of SFO operations.

3.3.1 Databases

SFO provided detailed data from several databases for a continuous time interval between April 1st, 2019 and January 31st, 2020. This provides a large sample of operations during which the airport was operating near its highest capacity, before the COVID-19 pandemic drastically curbed air traffic.

Ground Power (GP) Metering Database
Schneider Electric collects raw data on energy consumption from meters measuring the individual GP systems for most gates at SFO. In March 2019, for the purpose of this research, SFO reprogrammed their meters to sample total cumulative energy consumption at each meter every 5 minutes instead of every hour. Forty-nine meters were successfully identified, and their data were collected. During the data collection period, SFO had 120 commercial gates, but many were either under construction or did not have a GP meter needed for this analysis. For each gate, the average power consumption in kW was computed from the cumulative energy. A

diagnostic of the consumption was used to identify any broken or flatlining meters, which were excluded from the analysis. The rare times for which the power consumption was unrealistic (extremely large or negative for a brief period) and the hours surrounding a daylight savings change were marked as measurement errors and excluded from the analysis.

Meter to Gate Mapping
This database is a map between the gate names and their respective GP meter. This information can be found in airport documentation or by inquiring with the electrical engineers responsible for GP systems. It must consider any naming changes in the data collection period, such as the airport-wide gate renaming SFO executed on October 16, 2019.

Aircraft Operations Database
Aerobahn collects real data on the operations of aircraft at SFO through several sensors and image recognition technologies. For each arrival and departure movement at the airport, Aerobahn records the metadata of the flight and the times at which specific operations were performed.

3.3.2 Gate Diagnostics

The initial results obtained in the analysis pertain to the metering data. They revealed the poor reliability of the data, the limited scope of the analysis, and the somewhat deficient state of metering GP at SFO.

The first observation regarding gate metering data was that a lot of data were missing. We initially assumed that the data were missing because Terminal 1 was undergoing major renovations. However, many operating gates were either absent from the metering database or their readings were completely flatlining, meaning that their damaged data were not measured or lost.

Another observation was the presence of a continuous “phantom” energy load at all functioning gates. This phantom load varied for different gates but was typically around 0.88 kW consistently throughout the metering when an aircraft was not present at the gate. Table A14 in the appendix lists the phantom load for each gate. It is not possible to infer whether the phantom load also occurs when the GP system is in use. This is a small power load in comparison to that of GP systems that are in use, but because it is continuous, it represents between 10% and 30% of the overall yearly energy demand of a GP system depending on the gate.

Figure 7 shows the probability distribution of all GP readings across the whole dataset. Up to 2 kW of power consumption, the power is assumed not to be drawn. Upon inspection, power consumptions between 2 kW and 7 kW were either nightly standby operations or associated with regional jets CRJ-200 and CRJ-700, or they were associated with the Embraer 175 aircraft. For this reason, a threshold of 7 kW was chosen to separate nightly standby power from typical intra-day power consumption for most aircraft models (see Sections 3.2.3 and 3.3.5).

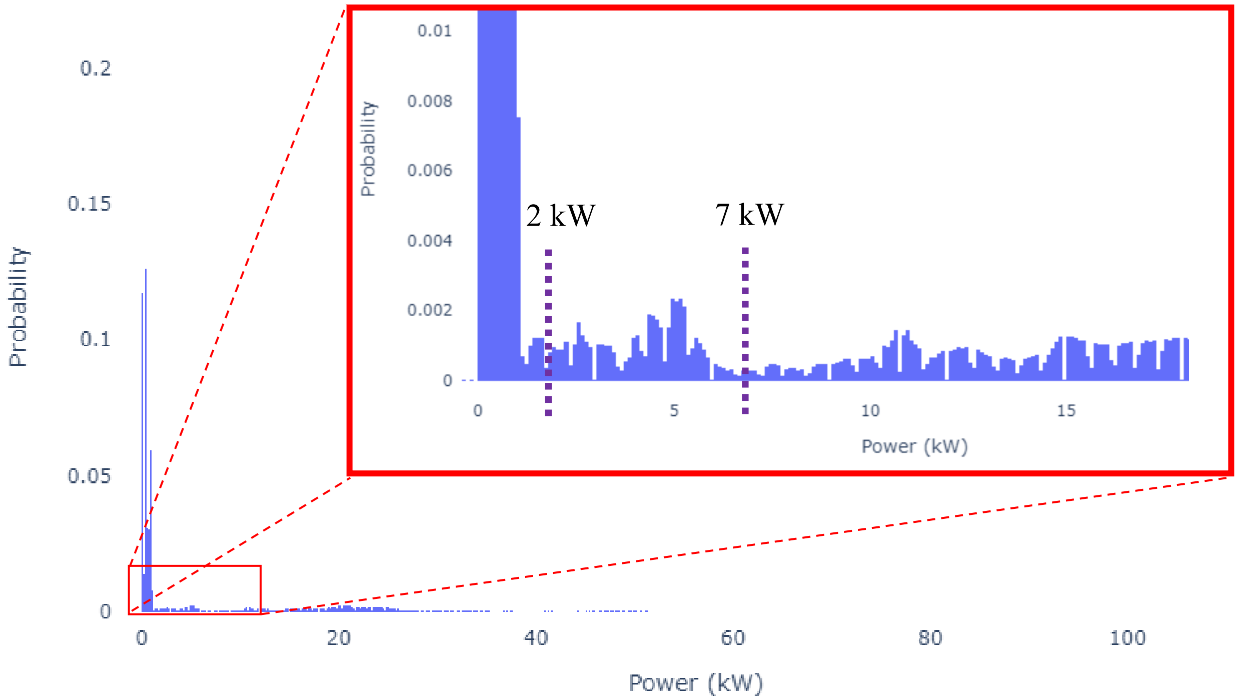


Figure 7: Probability distribution of GP measured across the sample

Throughout the metering data, occasional spikes occur in consumption beyond the reasonable limits of aircraft power demand. In some cases, the power reading becomes negative for a brief time interval, which is not realistic. Although they are rare, these measurement errors raise doubts about the reliability of data acquisition from the meter.

The granularity of the data from the metering system is not consistent. Gates record energy consumption at different intervals (1 h, 30 min, 15 min, 10 min, 5 min, and more), and even single meters could switch between different granularities. However, 98.8% of the intervals were 5-minutes long, allowing for sufficiently consistent data to train a model to perform the analysis.

3.3.3 Single Operations

Each operation is summarized with a graph and a table indicating the results. The operation in Figure 8 was a well-performing example, with GP being used during the interval that lasted between 7 min after on-block time and 11 min before off-block time. Tables 4 and 5 represent the relative estimates for energy, fuel, and emissions. Notice that when compared to the estimates for the worst-case scenario, the amounts of CO and HC emissions measured are higher. This is because the worst-case scenario does not include the APU engine startup, which is responsible for a large part of the incomplete combustion and soot generated.

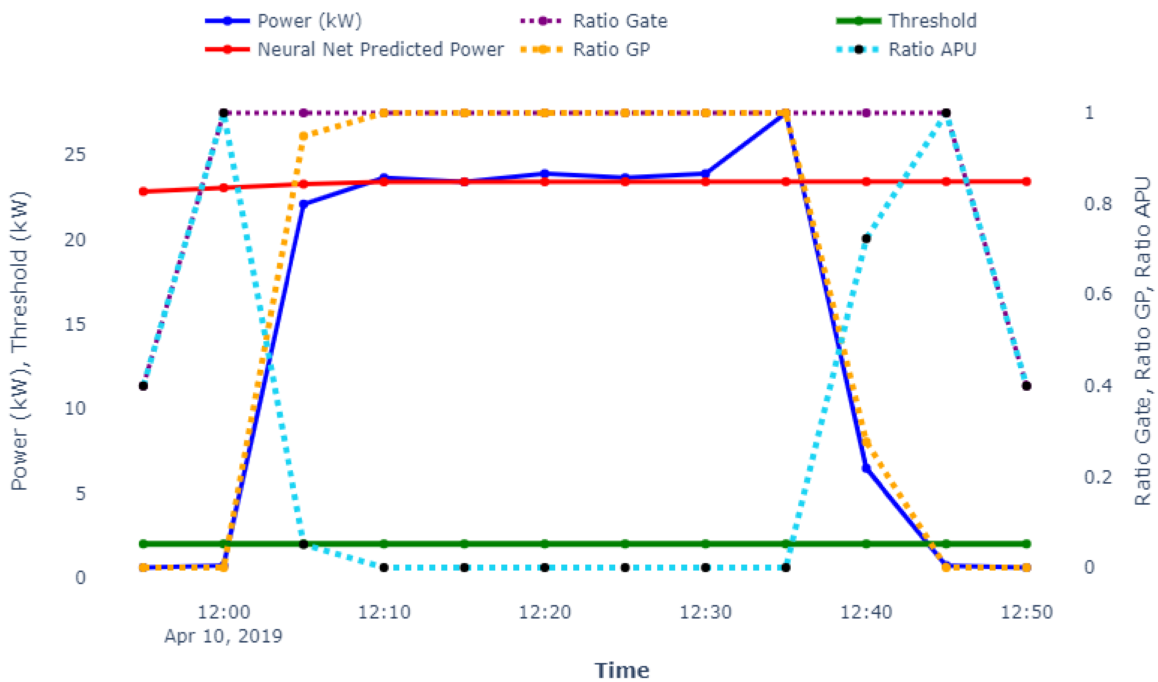


Figure 8: Sample operation of an Airbus A319 aircraft from airline J with GP use time of 36.1 minutes and APU use time of 17.9 minutes

Table 4: Energy totals for the sample operation in Figure 8

Power Prediction Data (kWh)	Value
Total Real Energy	14.76
Total GP Energy Predicted	14.08
Total APU Energy Predicted	6.924
Grand Total Energy Predicted	21.01

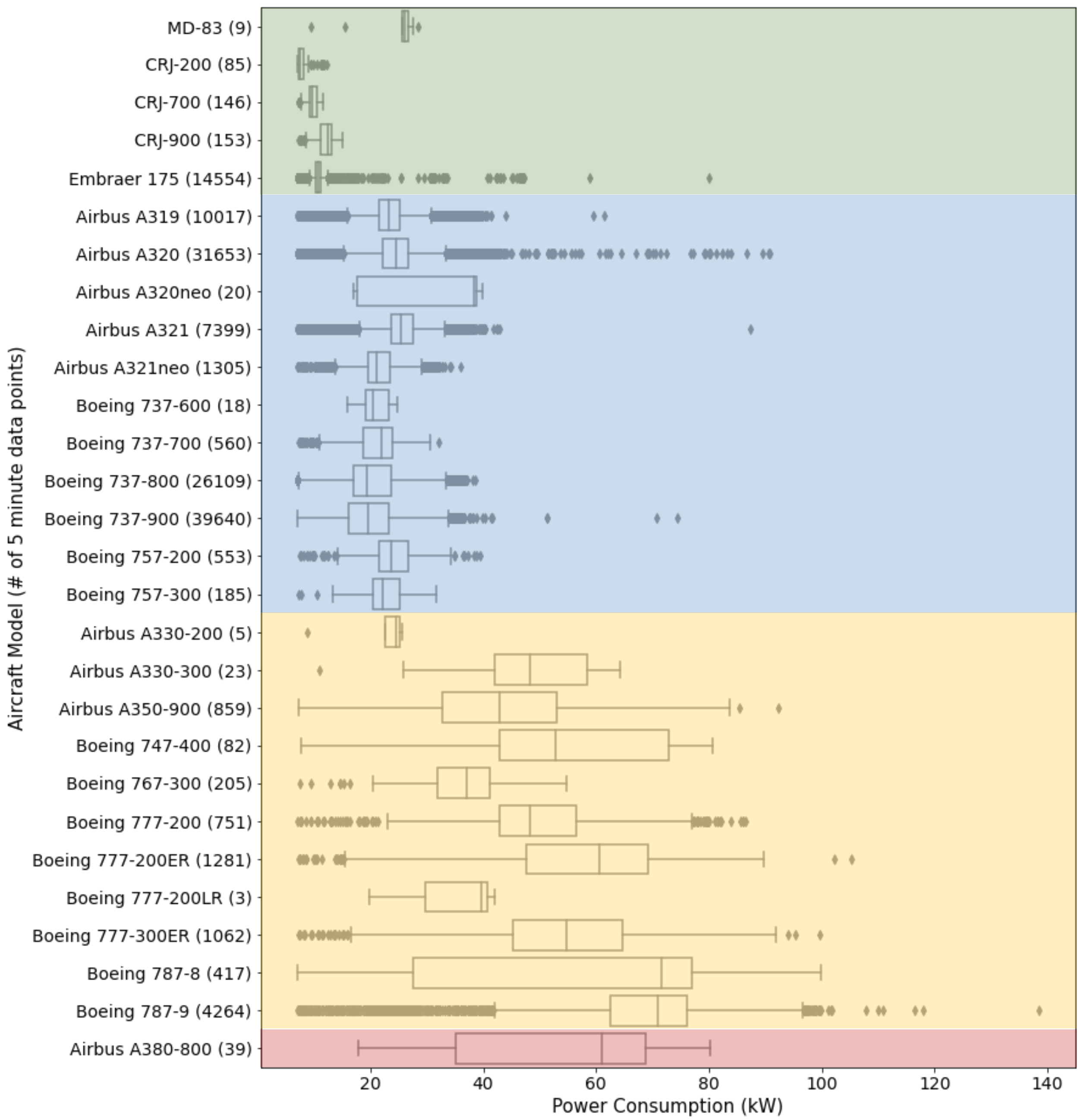
Table 5: Emission and fuel totals for the sample operation in Figure 8

Rate Source	Emission Type	Calculated from Operation Data			Scenario Totals	
		No Load (kg)	ECS (kg)	Totals (kg)	Worst (kg)	Best (kg)
Winther et al. (2015)	NO_x	0.036	0.240	0.280	0.725	0.179
	NO_2	0.012	0.082	0.094	0.248	0.061
	CO	0.370	0.120	0.500	0.377	0.271
	HC	0.270	0.028	0.290	0.085	0.152
	PM	0.0031	0.0092	0.0120	0.0279	0.0077
	Fuel	10.00	30.00	40.00	90.00	25.00
ACRP (2012) (EI=Equivalent)	Fuel	7.56	35.39	42.95	106.92	27.54
	EI-CO_2	23.85	111.64	135.49	337.33	86.89
	EI-CO	0.240	0.202	0.442	0.612	0.442
	EI-HC	0.049	0.015	0.065	0.046	0.035
	EI-NO_x	0.041	0.242	0.284	0.732	0.183

3.3.4 Power Consumption Statistics

By integrating 5-minute power measurements from thousands of operations, the resulting database can generate statistics on the consumption patterns. Figures 9 and 10 show the consumption trends relative to different aircraft models and aircraft design groups, respectively. They do not include data with power lower than 7 kW, as that would represent standby power demand that typically occurs at night. Figure 9 provides the number of data points for each aircraft model on the axis, showing that some aircraft models have few data points.

On a broad level, larger aircraft consume more power, although there is much variability for each aircraft model and even for each individual operation. Figure 11 shows a scatterplot between the passenger capacity of the operations and the observed GP demand, which demonstrates an approximately logarithmic relationship.



Legend Regional Jet Narrow Body Wide Body Jumbo-Wide Body

Figure 9: Ground power (GP) consumption over 7 kW for different aircraft models (data in appendix Table A6)

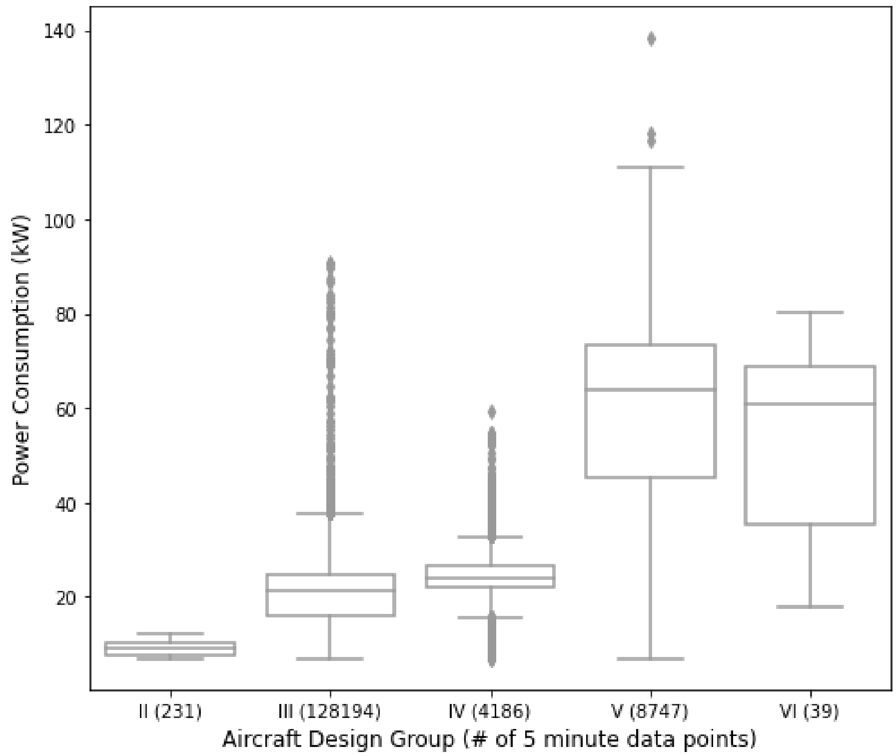


Figure 10: Ground power (GP) consumption over 7 kW for different aircraft design groups. (data in appendix Table A8)

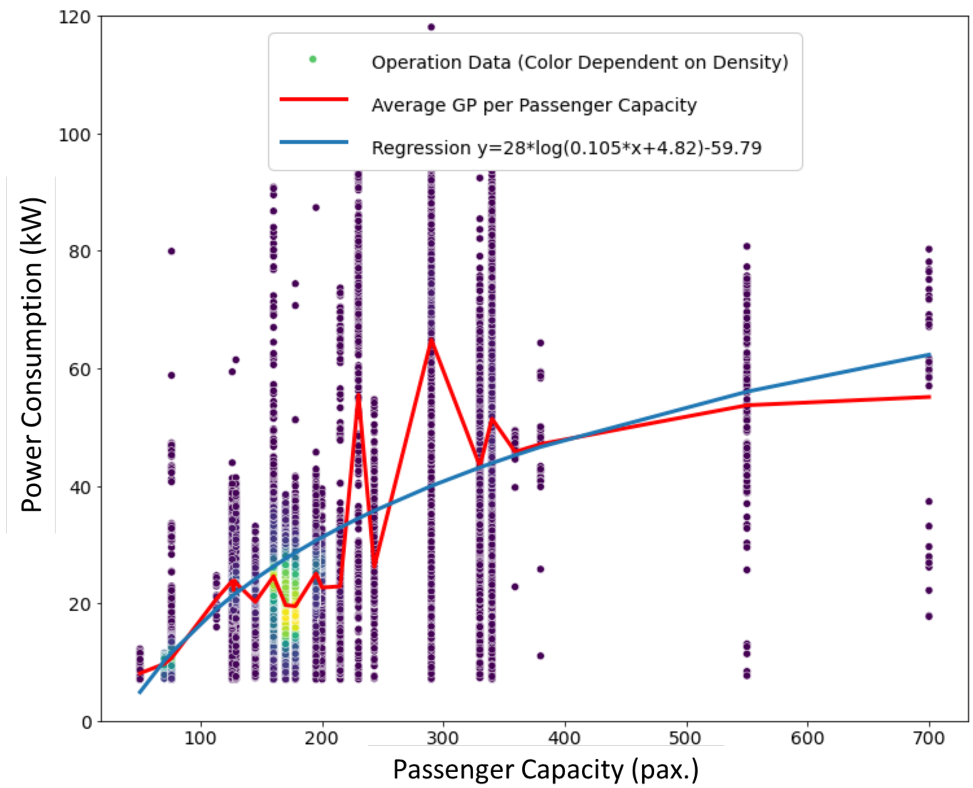


Figure 11: Ground power (GP) consumption vs. passenger capacity (with power>7 kW)

The data can also be grouped by gate, as shown in Figure 12. International gates (G91-G100) have greater power demands because they often accommodate the largest aircraft. Specific gates can accommodate the largest aircraft (A5). Energy spikes may generate outliers.

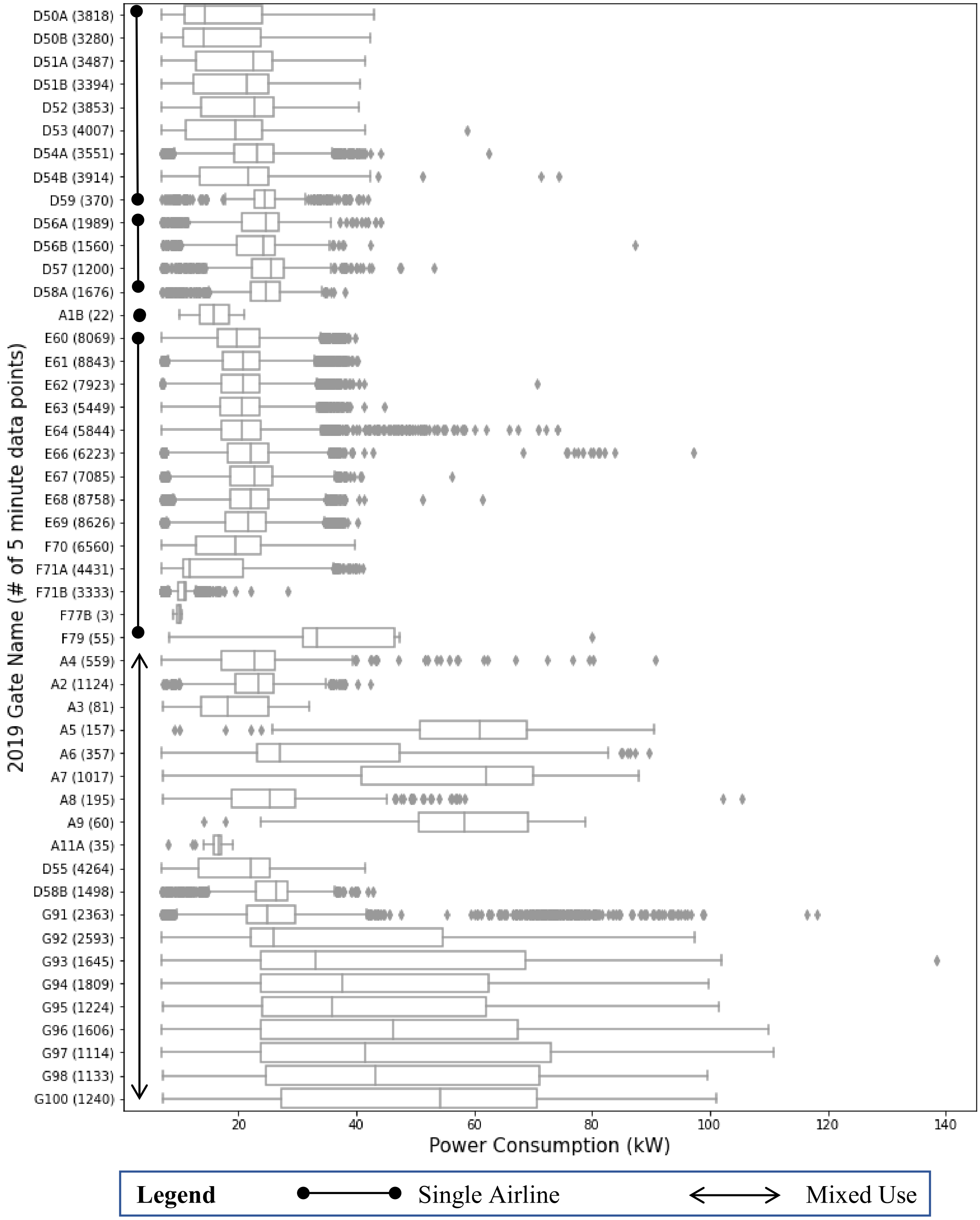


Figure 12: Ground power (GP) consumption for different gates (data in appendix Table A7)

GP demand statistics are shown for ten airlines in Figure 13. The distribution of power consumption for each airline is largely related to their fleet mix; airlines with many international long-range flights tend to have larger aircraft and therefore consume more power, as seen by comparing Figures 13 and 14.

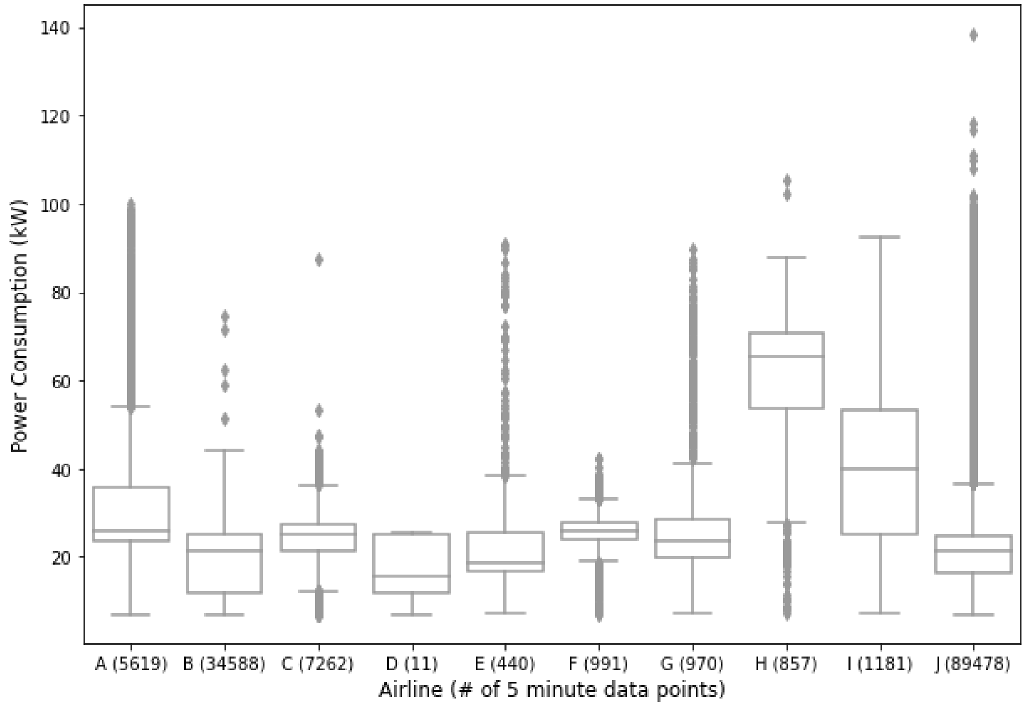


Figure 13: Ground power (GP) consumption statistics of airlines A through J (data in appendix Table A9)

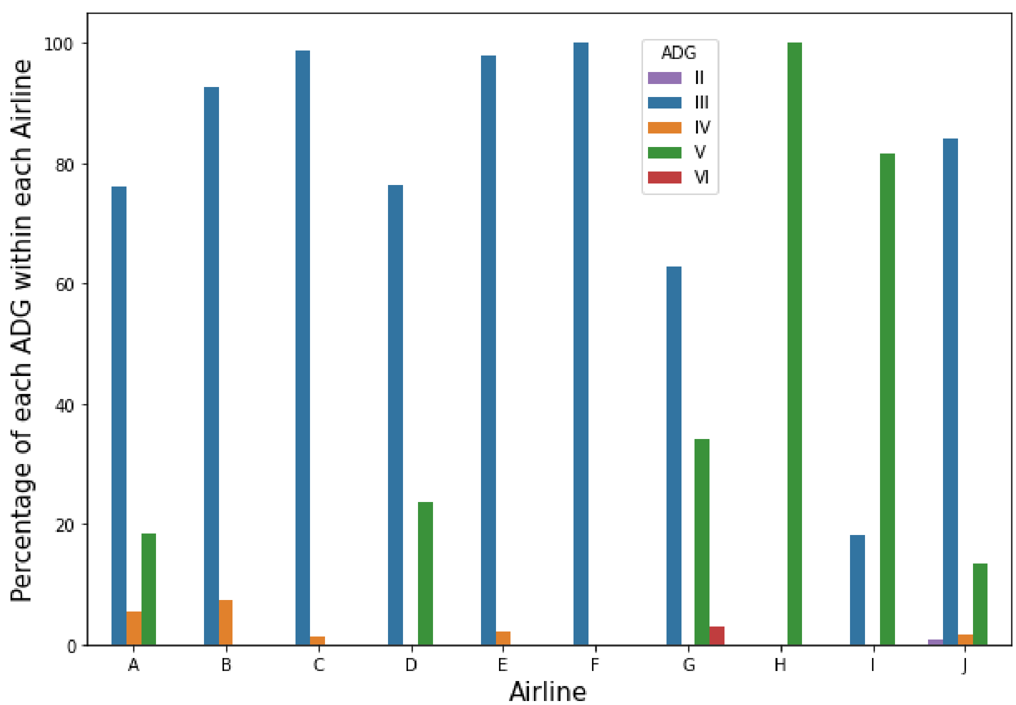


Figure 14: Aircraft design group (ADG) fleet mix for each airline A through J

3.3.5 Prediction Modelling

Seven machine learning models were trained and tuned using each model's hyperparameters. Each model was optimized using cross-validation and compared using RMSE and MAE as measures of accuracy. A visual representation of the models on a sample operation is shown in Figure 15. Table 5 summarizes the performance of each of these models over the set of valid GP consumption data. The neural network was chosen as the most responsive model to predict GP demand across the whole dataset. Its hyperparameters are a Limited-memory Broyden Fletcher Goldfarb Shanno (LBFGS) solver, a maximum iteration of 2,000, and a Rectified Linear Unit (ReLU) activation function. The neural network performs best with two hidden layers, each with five neurons.

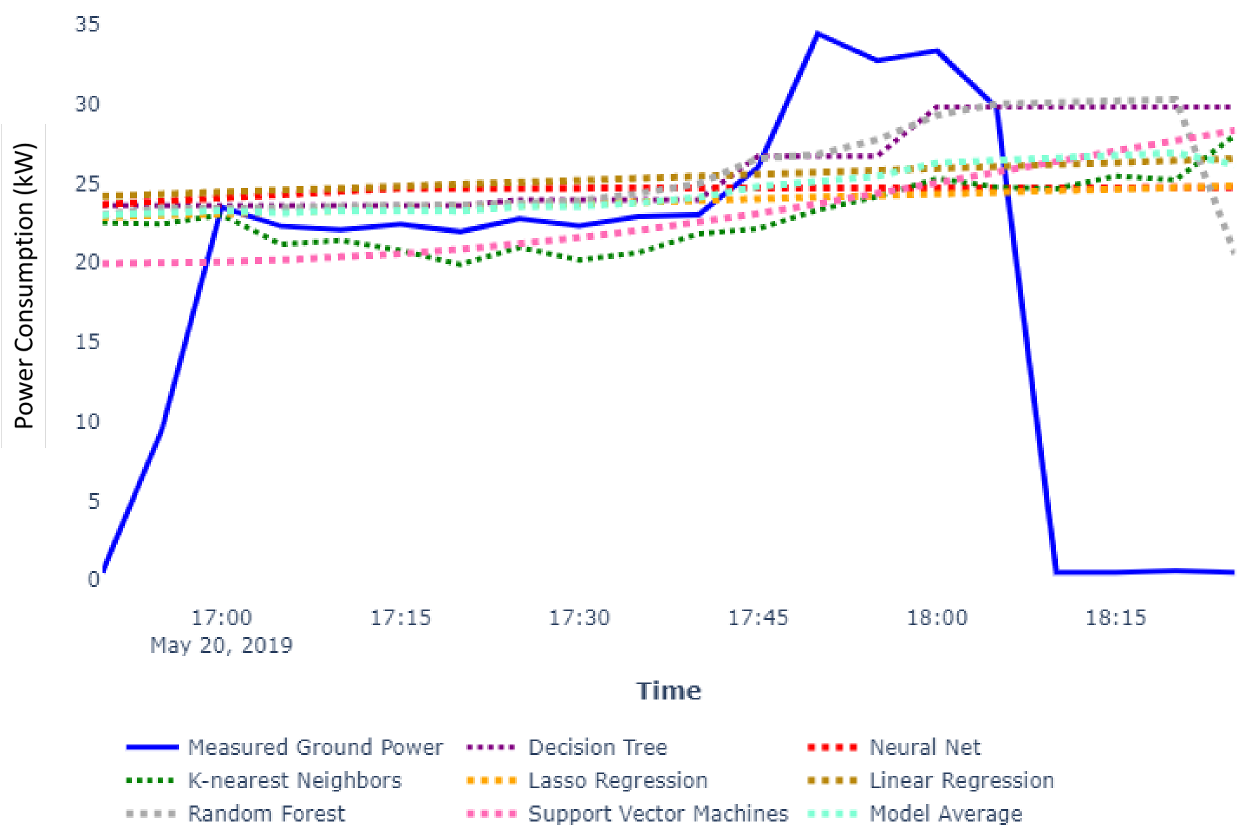


Figure 15: Time graph of predicted vs. actual GP for a sample B738 gate operation

Table 6: Summary of performance for models trained to predict power against the measured data, ordered by increasing MAE. Coloring scheme is consistent with Figure 15.

Model Type	Model Hyperparameters	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)
Neural Net Regressor	Solver = LBFGS Activation = ReLU Hidden Layers = 5,5 Max Iterations = 2000	10.882	7.715
Decision Tree Regressor	Max Depth = 20	11.230	7.853
Lasso Regression	Alpha= 0.1	12.393	8.025
Linear Regression		11.652	8.146
Model Average		11.942	8.227
K-Nearest Neighbors Regressor	K=30	12.016	8.363
Support Vector Machine Regressor	Kernel = RBF Degree = 3	13.155	8.914
Random Forest Regressor	Estimators = 100 Max Depth = 20	14.081	9.567

3.3.6 GP Utilization Rate and Total APU Time

GP utilization rate and total APU time are performance indicators used to identify if gate electrification infrastructure is being utilized to its fullest potential.

Figures 16 and 17 show GP utilization rates for the whole dataset. Figure 16 displays that approximately 36% of operations use no GP at all. Figure 17 focuses on the remaining 64% of operations and shows their smoother distribution of GP utilization rates.

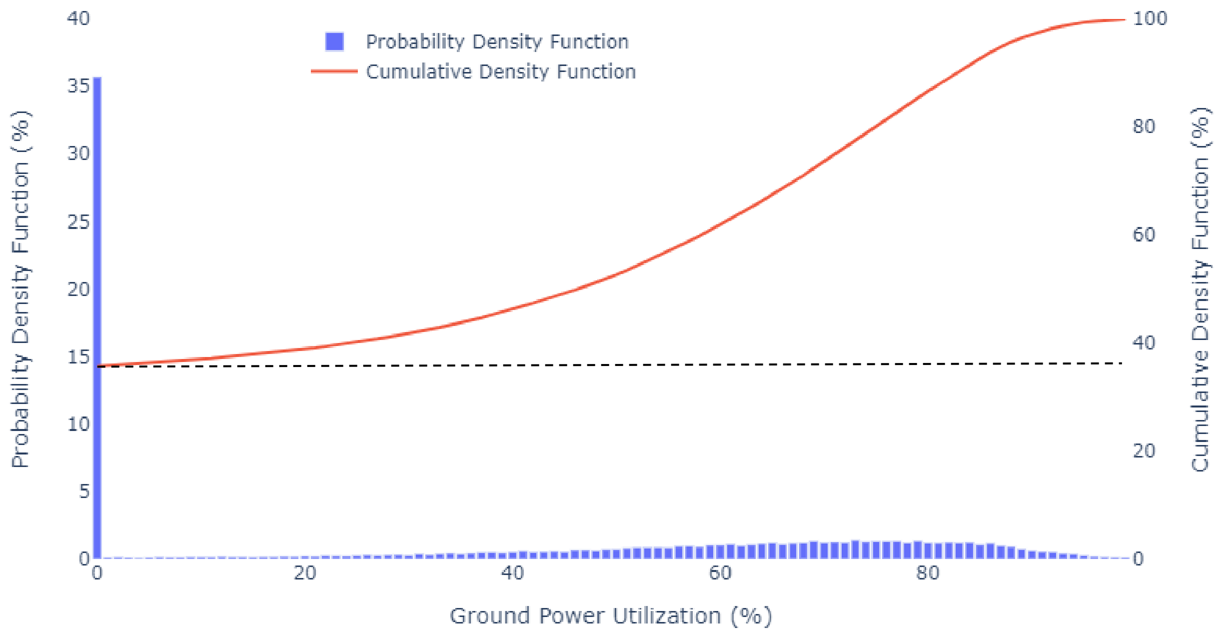


Figure 16: GP utilization rate per operation across the whole dataset with an average of 40.3% and a standard deviation of 34.4%. The y intercept of the CDF is 36.2%, showing operations that used no GP at all.

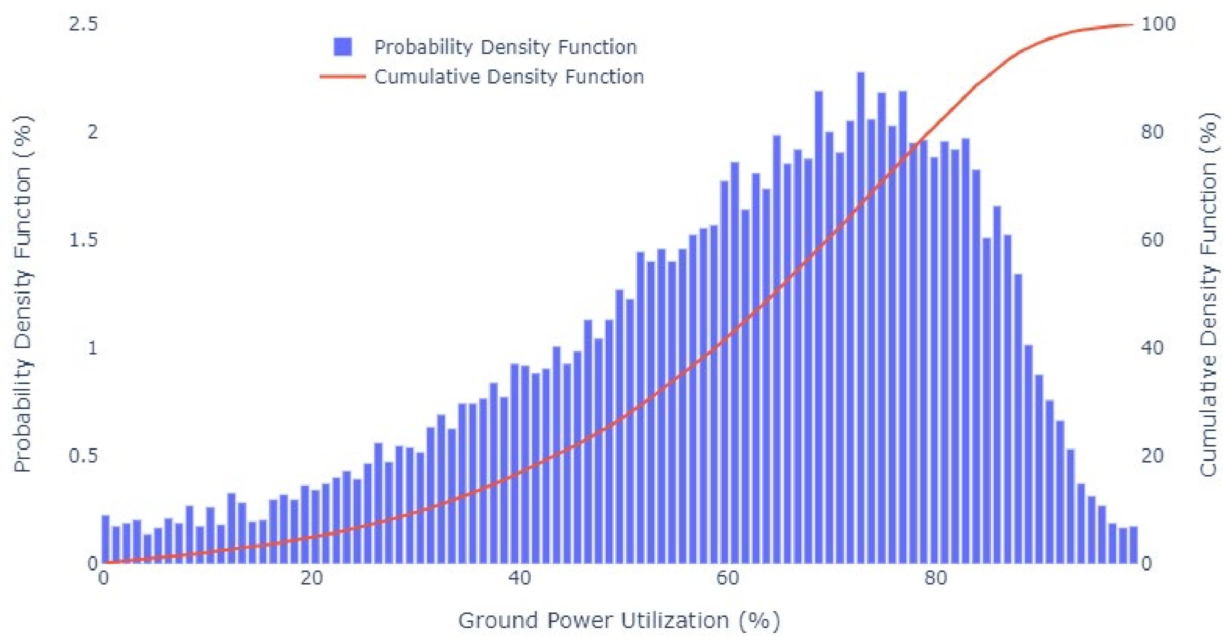


Figure 17: GP utilization rate per operation that consume at least some GP across the whole dataset with an average of 62.5% and a standard deviation of 21.2%

Similarly, Figures 18 and 19 represent the distribution of APU use time across the whole dataset. Whereas Figure 18 shows the total APU time for each operation, Figure 19 shows the APU time prior to the off-block time. Both distributions were fitted to a lognormal distribution function. Only 15.38% of operations used GP less than 15 minutes, which is an ideal-use-time policy applied at some European airports. Less than 35% of operations use the APU less than 25.63 min, which is the maximum default use time suggested in ACRP (2012) to estimate APU costs and emissions.

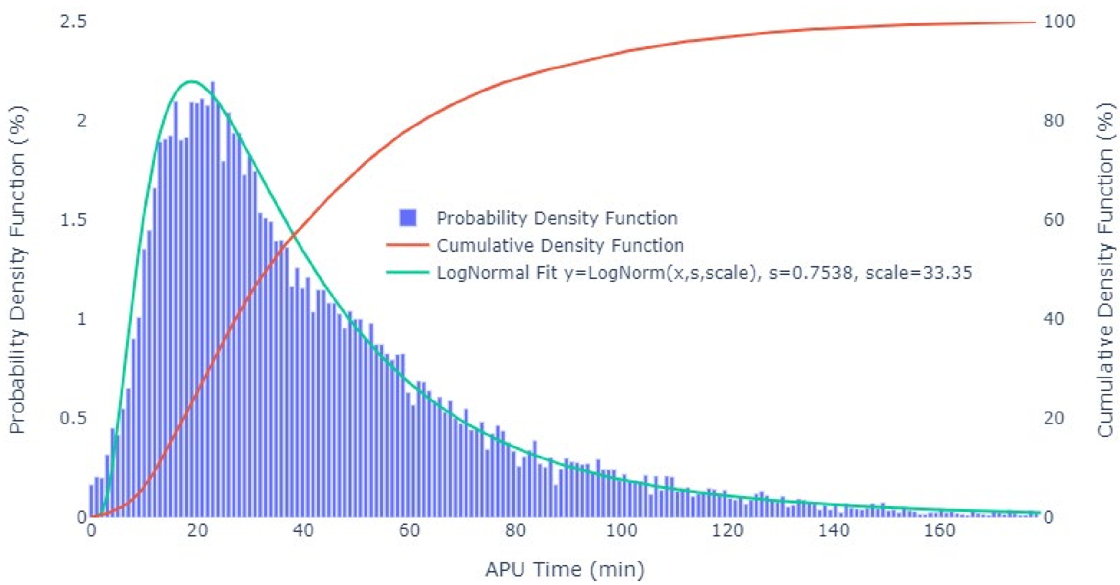


Figure 18: Total APU time per operation across the whole dataset with an average of 43.98 min and a standard deviation of 38.36 min

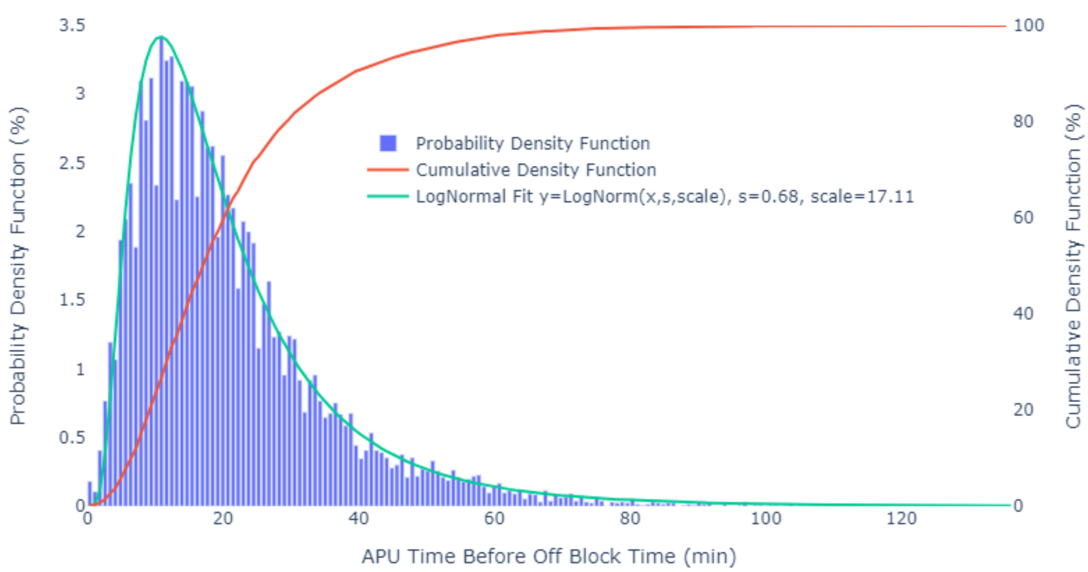


Figure 19: APU use time before off-block time per operation across the whole dataset with an average of 21.18 min and a standard deviation of 14.27 min

Figure 20 plots the APU time before off-block time against the recorded delay, which is the difference between the scheduled off-block time and the actual off-block time. The results are shown in a range of delays between -15 minutes and 55 minutes, which capture 92% of the results. A negative delay is possible, as the scheduled off-block time may be altered to optimize airside traffic; the aircraft do not leave before they are told to do so, rather, their schedules are dynamic. The average APU use before off-block time shows a strong positive logarithmic relationship with the delay. Between a delay of -10 minutes and 10 minutes, each additional minute of delay is likely to result in half a minute of additional APU use. This gradient peters out with larger delays. This result highlights how GP use is not resilient to the shifting schedules of turnaround operations, especially with short-term variability in off-block time.

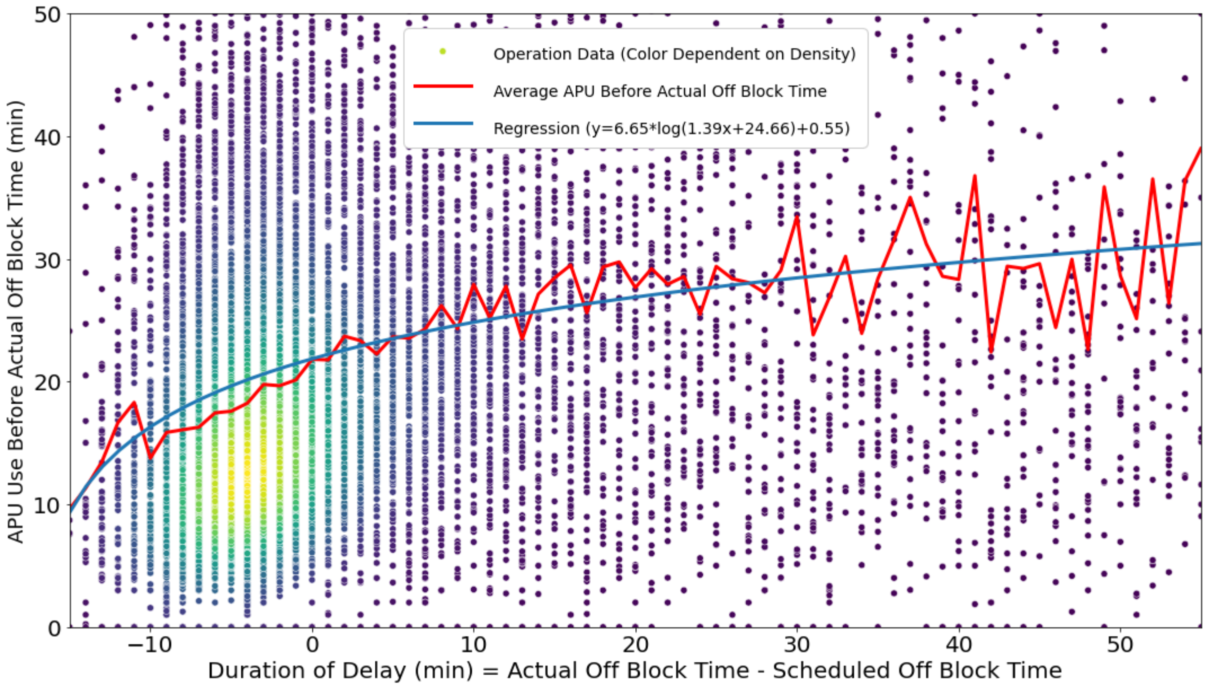


Figure 20: APU use time before off-block time versus off-block time delay

Analogously to how power consumption statistics were presented (Section 4.4), the metrics of GP utilization rate and total APU use time can be grouped by aircraft model and gate. Figures 21 to 24 illustrate the variability of these performance metrics, accompanied by their data shown in appendix Table A9, A10, A11, and A12. On a broad scale, Figures 21 and 22 show that most narrow-body aircraft have the highest GP utilization rates and the lowest APU use times. Some outliers, such as the low GP utilization rate of the Airbus A320 Neo or Airbus A330-200, raise concerns on what could be the cause of their inferior performance and warrant further investigation. Most wide-body and jumbo-wide body operations not only show a lower GP utilization rate, but they also have the longest APU use times and the highest emission rates. Smaller regional aircraft show some of the poorest GP utilization rates in the data set, although the APU use times are only a fraction of the wide-body aircraft use times and their emission rates are smaller.

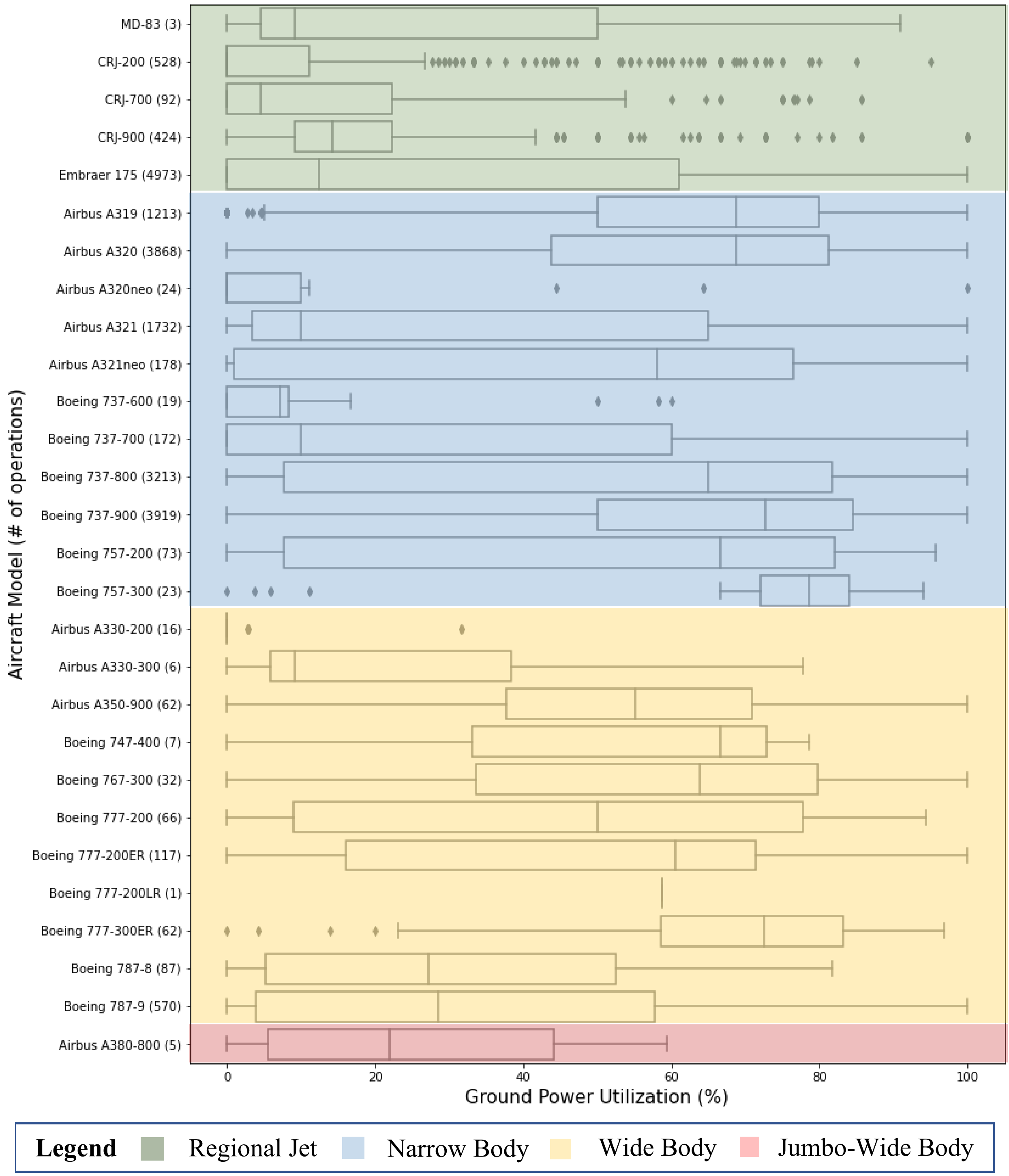


Figure 21: Ground power (GP) utilization rate of different aircraft models (Appendix Table A10)

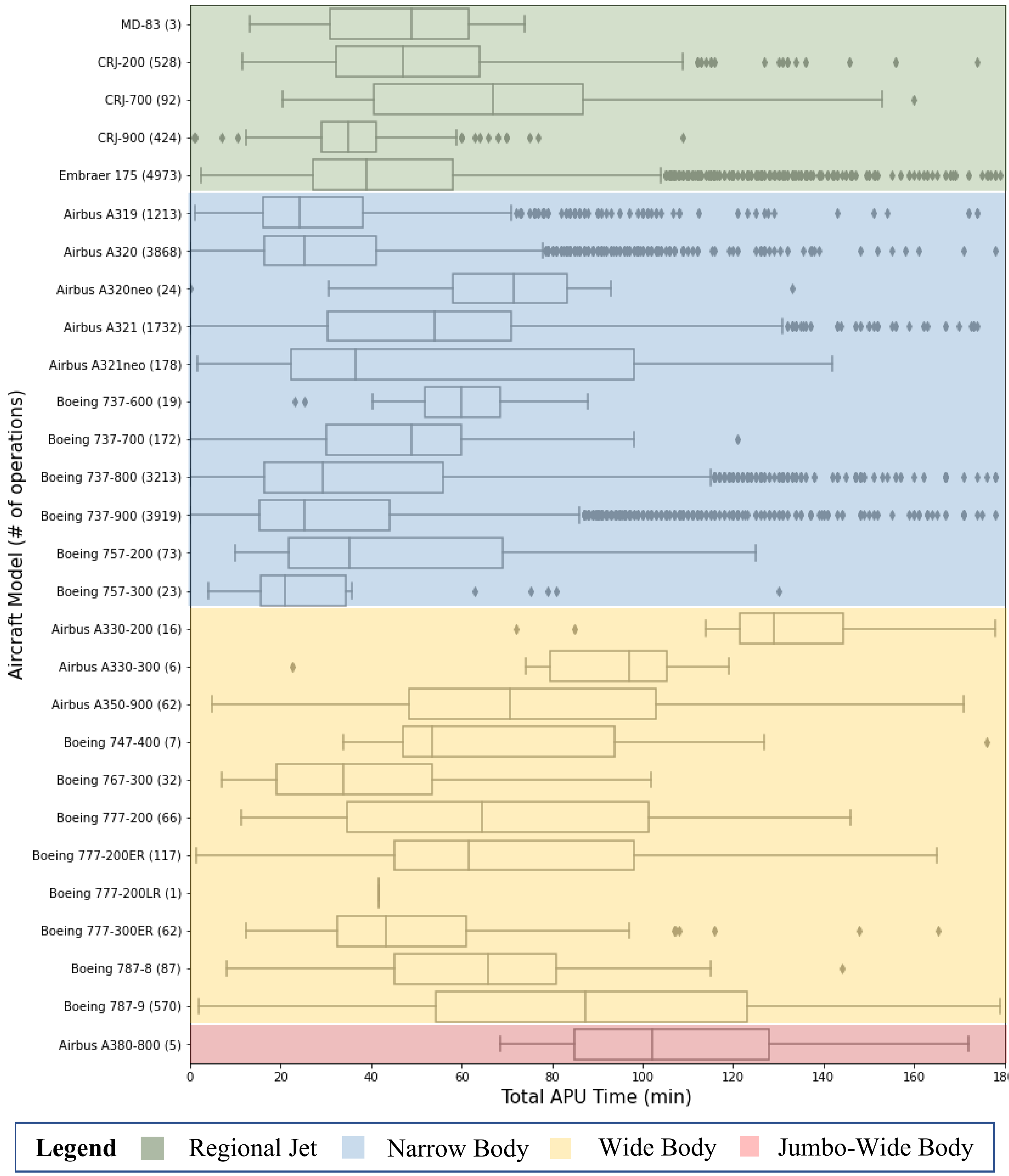


Figure 22: Total auxiliary power unit (APU) time of different aircraft models (Appendix Table A12)

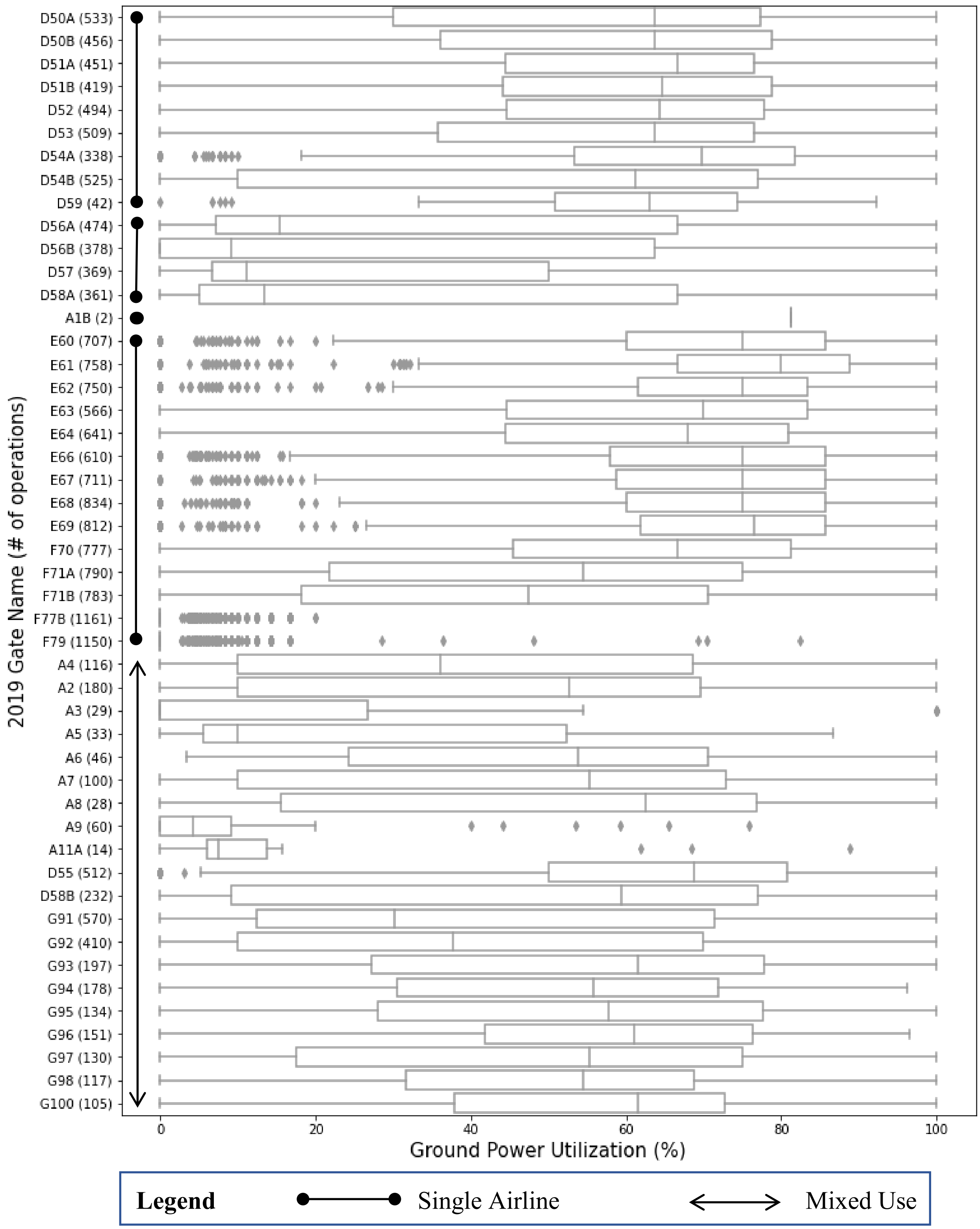


Figure 23: Ground power (GP) utilization rate for different gates (Appendix Table A11)

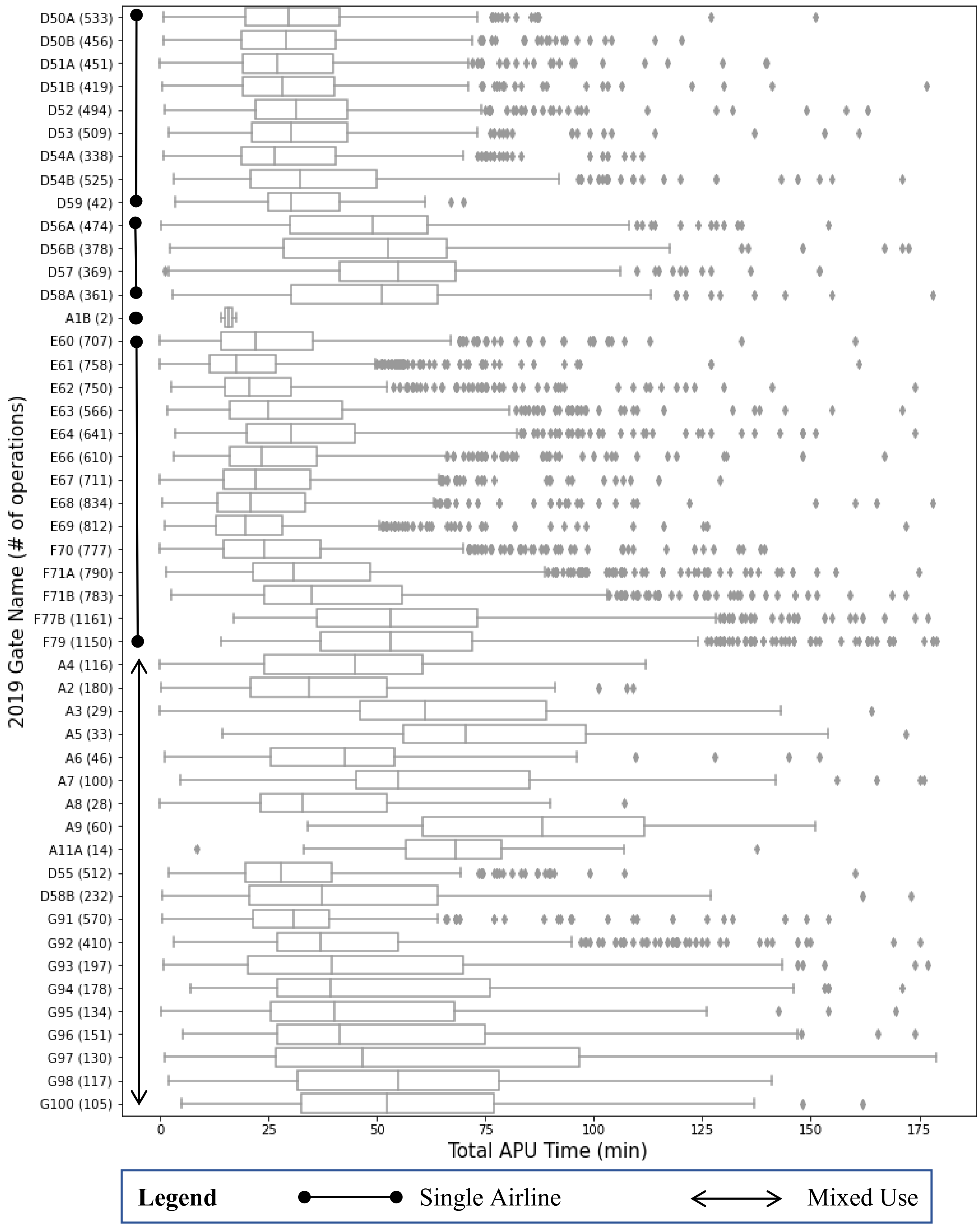


Figure 24: Total auxiliary power unit (APU) time of different gates (Appendix Table A12)

Figures 23 and 24 show that the gate also has an important impact on GP use. Very low GP utilization rates at specific gates such as F79 and A3 warrant further investigation into their cause, which may be attributed to a malfunction, maintenance, or measurement problem. Figure 24 groups single-use gates by airline to show how the GP utilization rate at gates is usually highly dependent on the airline that manages them. For shared-use gates, the GP utilization rate is highly variable, although typically lower than the best performing single-use gates. These results suggest that GP under-use is an issue rooted in inconsistent gate management rather than an intrinsic problem associated with every operation.

To evaluate this hypothesis, operations across the entire dataset were grouped by airline. Tables 7 and 8 summarize how different airlines show vastly different performances according to every metric. Airline B not only had the best overall GP utilization rates, but they also had the lowest rate of operations that failed to use any GP and the lowest average APU use time. Airline D shows almost no GP use, attributed not only to the fact that most of their operations fail to use any GP, but also to the fact that operations that do use GP have low GP use and long APU use times. Furthermore, different airlines show very different APU use times before off-block time (assuming at least some GP use), indicating very different procedures to manage the departure sequence. No clear pattern is evident when comparing these results to the airline's average delay. Since these results are indicative of very different standards and uses of sustainable infrastructure, the airline names had to be withheld. These results underline the importance of airport-airline accountability and the current discrepancy between expected and actual performance.

Table 7: Average GP utilization rate for different airlines
(Conditional formatting: green gradient for positive metrics, red gradient for negative metrics)

Airline	Number of Operations	Overall Average GP Utilization (%)	Overall Average GP Utilization of Operations With no GP Use (%)	Average GP Utilization for Operations that use GP (%)
A	1,076	36	41	61
B	4,356	50	18	61
C	1,732	28	54	60
D	330	1	97	30
E	284	11	78	53
F	508	14	80	68
G	372	15	72	53
H	61	47	20	59
I	111	39	30	56
J	12,656	43	33	64

Table 8: Average APU use times for different airlines
(Conditional formatting: red gradient for negative metrics)

Airline	Average APU Use Time (min)				Average Delay (min)
	All Operations	Operations with no GP Use	Operations that use some GP		
			Total Across Operation	Before Off-Block Time	
A	35	43	27	5	16
B	34	56	29	9	9
C	51	66	31	11	14
D	106	107	50	24	7
E	58	65	34	11	29
F	67	76	26	4	16
G	74	94	35	15	22
H	75	136	61	30	1
I	75	128	55	26	19
J	41	63	29	10	6

3.3.7 Aggregated Results

Although analyzing individual operations reveals the intricacies and variability of the GP use problem, the aggregation of all the results provides a way to estimate its size and represent it with average values. Table 9 provides the total results for APU fuel consumed and relative emissions released, whereas Table 10 provides the averages for a single operation.

Table 9: Total APU related fuel consumption and emissions across the entire dataset

Rate Source	Emission Type	Calculated from Operation Data			Scenario Totals	
		No Load (kg)	ECS (kg)	Totals (kg)	Worst (kg)	Best (kg)
Winther et al. (2015)	NO_x	643	11,959	12,602	21,810	3,572
	NO_2	219	4,090	4,309	7,457	1,221
	CO	5,134	7,779	12,913	13,162	5,242
	HC	3,341	1,152	4,493	2,164	2,287
	PM	48	488	536	870	162
	Fuel	155,527	1,585,984	1,741,512	2,827,649	523,161
ACRP (2012) (EI=Equivalent)	Fuel	123,202	1,654,361	1,777,562	3,037,148	528,956
	EI-CO_2	388,701	5,219,508	5,608,209	9,582,203	1,668,858
	EI-CO	3,200	8,508	11,708	15,811	11,708
	EI-HC	652	668	1,320	1,233	577
	EI-NO_x	707	11,808	12,515	21,698	3,540

Table 10: Average APU fuel consumption and emissions across the entire dataset

Rate Source	Emission Type	Calculated from Operation Data			Scenario Totals	
		No Load (kg)	ECS (kg)	Totals (kg)	Worst (kg)	Best (kg)
Winther et al. (2015)	NO_x	0.030	0.557	0.587	1.015	0.166
	NO_2	0.010	0.190	0.201	0.347	0.057
	CO	0.239	0.362	0.601	0.613	0.244
	HC	0.156	0.054	0.209	0.101	0.106
	PM	0.002	0.023	0.025	0.040	0.008
	Fuel	7.24	73.81	81.05	131.60	24.35
ACRP (2012) (EI=Emission Index)	Fuel	5.73	77.00	82.73	141.35	24.62
	EI-CO_2	18.09	242.93	261.02	445.97	77.67
	EI-CO	0.149	0.396	0.545	0.736	0.545
	EI-HC	0.030	0.031	0.061	0.057	0.027
	EI-NO_x	0.033	0.550	0.582	1.010	0.165

When comparing the current average scenario to the idealized scenario of 15 minutes of APU use per operation, the difference in average fuel consumed is 56.70 kg and 58.11 kg of fuel per operation, according to Winther et al. (2015) and ACRP rates, respectively. The relative EI-CO_2 savings would be 179 kg and 183 kg per operation, respectively.

The installation of GP systems with current use rates has enabled an estimated 40% reduction in both APU fuel and CO_2 emissions. Although a 100% GP utilization rate is technically impossible with current equipment and practices, ensuring that a realistic yet stringent policy like a 15-minute maximum APU time is consistently respected would lead to a further 70% reduction from current rates. If the gate electrification infrastructure is already installed, these are immediately realizable savings.

Considering the above figures as representative, they could be used to roughly estimate the magnitude of the problem across the entirety of the aviation sector. With a fuel price of $0.91/kg (IATA, 2023) and 38 million worldwide flights in 2019 (IATA, 2021), the approximate size of the potential yearly savings is $2 billion in direct APU fuel costs and 6.3 million mTons-CO_2, or 0.016% of 2019 global CO_2 emissions (IEA, 2021).

3.4 Discussion

The average missed savings of $50 in fuel per operation may seem infinitesimal for an airline whose costs for each flight are several orders of magnitude greater. High GP use is a non-critical aspect of turnaround operations, whereas most other turnaround processes are critical and highly consequential. Although pilots, ground crews, and airlines might be willing to use GP whenever it is possible, $50 in fuel savings might not be a great enough incentive to guarantee the equipment reliability, sufficient labor, tight schedule coordination, and trust between stakeholders that optimal GP use requires. However, not only do these preventable costs scale up quickly, they also do not include the environmental externality of global and local air pollution. To ensure that gate electrification infrastructure is used and to mitigate APU use as much as possible, pilots, ground crews, and airlines need to have additional incentives or oversight.

A fundamental characteristic of this method is that it is airport-centric. Although airline self-management can directly increase GP use, there is no system to ensure transparency and accountability. In an ideal world, data-sharing agreements among airports, airlines, and governments would provide an integrated solution to monitor, predict, and manage individual gate operations. However, the current technology and fragmentation of interests and responsibilities between the stakeholders means that GP use data is either confidential or absent. The analysis presented in this chapter shows how an airport can independently and immediately overhaul its GP monitoring, policy, and enforcement strategy. With a high-resolution comprehensive monitoring system, they can customize their gate lease agreements to provide the financial and legal structures to influence gate emissions. Governments and institutions like Airport Carbon Accreditation should guide and support airports in their drive to establish gate infrastructure monitoring systems, as they provide the essential line of contact between the regulatory frameworks and actual industry practice.

This analysis did not include PCA in the scope since the data was unavailable. However, PCA use is highly intertwined with GP use. Typically, PCA is plugged in right after GP for the arrival sequence and removed right before GP is unplugged for the departure sequence. Since APUs supply both power and bleed air, they are often kept on until both GP and PCA are ready to be used during the arrival sequence or switched on before either GP is disconnected. Additionally, in elevated temperature conditions, PCA systems might not have sufficient capacity, prompting pilots to turn on the APU much earlier than off-block time to provide a comfortable passenger experience. For example, at ZRH such conditions occur for up to 30% of the year (Fleuti, 2018). These PCA use cases imply that APUs could be turned on for even greater durations than those calculated in this GP-focused method. Only detailed monitoring, modeling, and management of PCA will provide further airport-centric insights into the energy efficiency of turnaround operations.

The drive to increase gate electrification infrastructure comes with the need to ensure the reliability of the airport's energy systems. The use of GP and pre-conditioned air can demand more than half of the peak energy use for an airport. This highly variable load is not being centrally predicted or managed, as the gate equipment is always ready to be used by the airlines according to their everchanging needs. There is a significant variability in GP demand magnitude down to individual operations. One part of the variability is caused by the fluctuating demand for power from the aircraft. The other part of the variability is caused by the use times of GP. The analysis presented in this chapter demonstrates that both the fluctuations in energy demand and the behavior of the ground crews and pilots can be monitored for trends.

Regarding other publications on the subject, the analysis supports certain conclusions, offers further insight, and clarifies some inconsistencies within the industry. In reference to Sadati & Cetin (2020), this research provides evidence that the use times of GP have a considerable influence on the power consumed at the gate. The lower utilization rates of larger aircraft could have been the cause of this result, indicating that larger aircraft consumed less power. To predict overall loads on the airport's grid precisely, more complex and granular models need to incorporate a model for human behavior. Regarding Padhra (2018), this study provides insights for how power consumption and behavior are dependent on the gate, airline, and model type. Although similar results for APU use times and GP utilization rates are observed across large samples of operations, these metrics vary considerably depending on the features of single operations. Regarding ACRP (2012) and ACRP (2019), this work offers a tested, detailed approach toward performing the monitoring and cost analysis that they suggest as a long-term strategy towards optimizing the use of gate electrification infrastructure.

3.5 Conclusions

Despite the apparent incentive to use less expensive power, gate turnaround operations appear to use GP at a fraction of its potential. 64% of operations use GP for an average of 62.5% of their turnaround time, and 36% do not use any GP at all. The assumption that an airline will independently optimize the use of GP to save on fuel is false, and actual performance is heterogenous; different aircraft models, gates, and airlines show vastly different GP utilization rates and total APU use times. Although approximately 40% of APU fuel and CO_2 emissions are already being achieved with the current use of GP, a further 70% reduction from current rates can be feasibly achieved through more aggressive regulation and enforcement. The APU was turned on an average of 21 minutes before off-block time, although this quantity was positively related to the delay of each operation, showing the lack of resilience of GP with dynamic airport schedules.

One step towards reducing APU use at gates is implementing an airport-centric monitoring system capable of modelling operation behavior and evaluating it. This can be achieved by diving into the circumstances of single operations and identifying trends across many operations. Having such a detailed analysis enables airports to discern the causes of inefficiency in the use of GP rather than solely understanding the average or total impact of the problem across the airport. This is fundamental as it provides insight into the efficacy of ground handling practices, allowing for actionable changes. An increase in accountability between airlines, ground crews, and infrastructure providers would help in understanding and reducing the large variability in energy efficiency at airport gates. With an improved understanding of the technical issues, behavioral drivers, and overall consumption patterns, clear challenges can be defined and subsequently mitigated. In future developments of a monitoring system, it is fundamental that monitoring, policy, and enforcement work in unison to progressively restrict APU use. The monitoring system should inform how to set a realistic but ambitious goal and provide the information required to enforce it. As airport-wide performance improves and becomes consistently ingrained, policy can be pushed towards more ambitious targets.

4. Operation Assessment

This section of the report expands its focus on APU, GP, and PCA systems and performs a more rigorous assessment for each operation. The analysis of GP use in Section 3 enabled a detailed yet narrow insight into turnaround operations. It underlined the importance of monitoring operations individually, and it generated detailed estimates for fuel cost and tailpipe emissions associated with APU use. However, the estimates were only one component within the larger scope of evaluating turnaround operations, both monetarily and environmentally. This section complements the previous one by constructing a more comprehensive assessment methodology.

4.1 Introduction

Monitoring turnaround operations provides the detailed data required to assess their performance. The use of GP and APU must be contextualized before making quantitative comparisons and holistic conclusions. That requires a systematic accounting methodology that leverages both the available data and estimates on the absent data.

ACRP (2012) proposed a systematic accounting methodology to estimate the costs associated with APU, GP, and PCA systems. The report compiled estimates for the installation, operation, and maintenance of the systems, along with the associated monetary and environmental APU savings. These estimates are broad averages across many airports in the world; although they provide data, they lack precision. The report explicitly recommended using more precise data when available; however, it did not elaborate on how the methodology can be strengthened. On a broad level, ACRP (2012) developed a methodology that estimates the benefits of installing gate electrification equipment, making it an excellent tool for airports that are considering such large capital investments. However, to accurately assess the actual operation of the equipment once it is in place, a more fine-grained methodology is necessary, especially when considering the high variabilities outlined in Section 3.

Life Cycle Assessment (LCA) is a standardized methodology that helps uncover the true costs of systems and products for holistic decision making. The International Organization for Standardization (ISO) 14040 outlines how to estimate the environmental impacts throughout a product, project, or service's life-cycle phases (i.e., raw material extraction, processing and manufacturing, transportation and logistics, operations, maintenance, and end-of-life) (ISO, 2006). The structure of a LCA typically includes: (i) system boundaries, (ii) data collection, (iii) life cycle inventory, (iv) impact assessment, and (v) interpretation. Chester & Horvath (2009) used the LCA method to determine the footprint of aviation travel on a broad level and included the operation of the APU, airport infrastructure, aircraft manufacturing, and maintenance in its scope. Altuntas et al. (2014) applied LCA methodology to compare the operation of APU engines and mobile GPUs to provide GP to aircraft. Greer et al. (2021) focused the LCA methodology on turnaround operations across commercial airports while considering different gate infrastructure use scenarios and equipment. Greer et al. (2023) applied a holistic LCA methodology to airport terminal buildings, demonstrating how it is the first step towards helping stakeholders make decisions that lead to healthier and more sustainable airports.

To feasibly apply LCA to a specific scope, the method must balance the ideal of reaching accurate, precise, and comprehensive conclusions with the practical constraints of doing so (e.g., assumptions, data availability, complexity). As more circumstantial data become accessible to airports with developing equipment and technologies, they gain the ability to evaluate individual gate operations for their monetary, environmental, and health costs. A granular analysis of costs not only provides a more detailed estimate for the costs of the entire system, but it also reveals the variability associated with each circumstance. Furthermore, detailed life cycle cost assessments are useful in setting performance targets, establishing clear-cut pricing strategies in leasing agreements, and enabling the sharing of costs and resources among different stakeholders and companies.

This section of the report contributes to the topic of gate electrification infrastructure by constructing an LCA analysis focusing on single operations. The analysis methodology is showcased through the SFO data used in Section 3 combined with estimates available in the literature. Since exact circumstantial data was not available, different scenarios were used to showcase variability and estimate monetary and GHG costs.

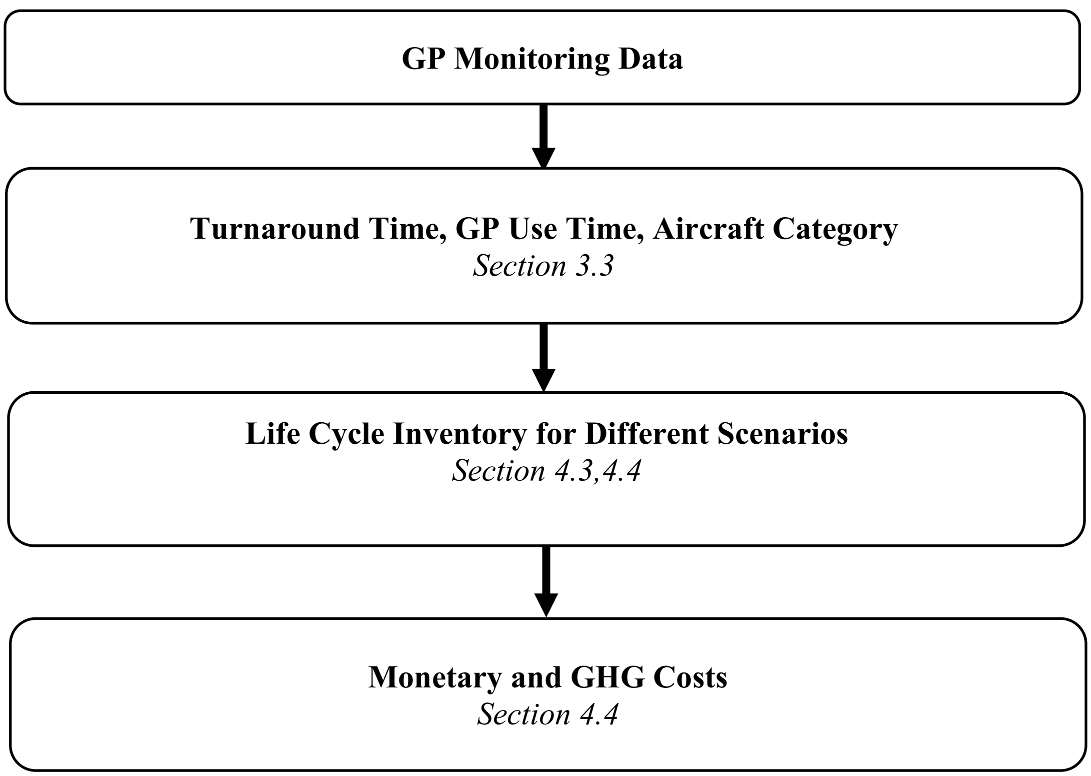


Figure 25: Structure of operation assessment section

4.2 Scope and Assumptions

Since the use of electrification infrastructure for turnaround operations is highly interdependent with many other airport processes, it is fundamental to establish clear and consistent boundaries for a life cycle assessment. The objective of this section is to provide a comparison of different use cases for GP, PCA, and APU. The variability associated with different equipment types available in the industry and the relationship to other turnaround processes are not within the scope.

The LCA presented here assumes that PCA systems are never used more than GP systems. Although it is technically possible to run the APU on power-only mode while using external PCA, this case rarely occurs for several reasons. First, ground crews prioritize GP use by plugging in PCA hoses after GP cables during arrival cycles and vice-versa for departure cycles. Second, some airlines have internal policies to prevent this mode from occurring (Delta, 2020).

This LCA will consider only the fixed GP and PCA systems that are available at SFO gates to reflect the input data. The passenger boarding bridge is excluded. GP and PCA systems are all decentralized and powered by electricity, not natural gas. The electricity transmission efficiency from the grid to the equipment will be assumed to be 100%; further research is necessary to derive an accurate efficiency multiplier.

The costs associated with local air pollutants consumed will be omitted. Section 3 shows how tailpipe emissions for NO_x, CO, PM, and HC can be calculated for the APU. Calculating these emissions relative to other elements would require data that are not available, so they were not included in the LCA. However, Sections 4.2.4 and 4.2.5 investigate the impact of local air pollutants.

The LCA will omit end-of-life costs. The use period will be assumed to be 15 years following the example of ACRP (2012), although the systems can have longer lifespans. The changes in costs due to inflation will not be reflected since they constitute a very minor component of variability. The environmental costs associated with the production and installation of GP, PCA, and APU systems will be omitted.

This analysis will only consider fast turnaround operations with a maximum duration of 3 hours. This assumption removes the confounding circumstances of standby times, overnight operations, and complete aircraft shutoffs.

Although turnaround delay and opportunity cost are highly related to GP, PCA, and APU use (described in Section 5), they will be omitted in this LCA. The available data were insufficient to determine if the processes involving GP, PCA, and APU are the direct cause for a delay.

The fuel flow to the APU and the relative emissions are highly variable (Kinsey et al., 2012; Padhra, 2018). It is challenging to establish what the instantaneous fuel flow is at any moment in time unless it is being measured directly from the aircraft. It is even more challenging to measure instantaneous emissions, which are not proportional to the fuel flow and require an experimental setup. Although it is desirable to have as much granularity as possible on fuel flow and emissions, assumptions must be made to make a calculable estimate. For fuel flow, the APU's ECS loading condition (ACRP et al., 2012) represents a blend of different loading conditions that are better distinguished in Padhra (2018). Whereas ACRP (2012) effectively provides an estimate for fuel flow and emissions for different categories of aircraft, Padhra (2018) provides an estimate of the different fuel flow rates for each loading condition specific to A320 aircraft. Table 11 was constructed by applying the proportions of fuel flow from Padhra's (2018) loading conditions to ACRP (2012) fuel estimates for each aircraft category. For the no-load condition fuel flow and for all emission rates, the values from ACRP (2012) will be used (Appendix A1, A3, A4). If the APU starts up at the gate, a 3-minute no-load condition will be assumed, following the example of ACRP (2012).

Table 11: Fuel flow estimates for different aircraft categories and loading conditions

Aircraft Category	ACRP (2012) Values (kg/s)	Electrical Power Only (kg/s)	Bleed Air for AC Only (kg/s)	Electrical Power and Bleed Air for AC (kg/s)
A320 Padhra (2018)	n/a	0.025	0.028	0.030
Narrow Body	0.033	0.028	0.031	0.033
Wide Body	0.052	0.043	0.049	0.052
Jumbo Wide	0.061	0.051	0.057	0.061
Regional Jet	0.019	0.016	0.018	0.019
Turbo Prop	0.019	0.016	0.018	0.019

In the dispersion analysis for local air pollutants, the measured point-source emissions were assumed to be released at a constant rate throughout the data's date range. Since not all operations and gates were included in the analysis, and since the actual emissions are not uniformly distributed, the true values for pollutant concentrations may be systematically greater than those estimated.

4.3 Scenarios

With the data available in this report, the use times of PCA are uncertain. In Section 3, the estimation of APU use times hinged on the assumption that if GP was not being used, then the power was being supplied from the APU. Although this is largely true, it does not imply that the inverse is true (if GP is being used, then the APU is off). In fact, there are many situations in which this may happen. The pilot could leave the APU in idle mode for an extended period even while the aircraft sources its power from GP. If conditioned air is needed, and the PCA is not available or insufficient, the APU may be used even if electrical power is being sourced through GP system. To eliminate this uncertainty, further monitoring data would be necessary. To perform an assessment with the uncertainty in APU and PCA use times, eight scenarios will be applied to each operation's original data as presented in Section 3. The following section provides the qualitative rationale for each scenario.

Scenario 1
The APU was kept on throughout the whole operation to supply both power and bleed air. GP and PCA were never plugged in because they were not available. No labor costs were incurred. The purpose of this scenario is to represent the theoretical case in which neither the airport nor the airline invested in gate electrification equipment (including mobile units).

Scenario 2
The APU was kept on throughout the whole operation to supply both power and bleed air. GP and PCA were never plugged in, despite their availability. Labor costs were omitted. The purpose of this scenario is to represent the case in which the gate electrification infrastructure is never successfully connected to the aircraft. This scenario occurs often (Section 3), e.g., when no ground crew is present to perform the connection on time in coordination with the pilot. An airline that might not invest in maintaining a responsive ground crew is likely to run into this problem.

Scenario 3
GP was used as measured; however, the PCA was not available. The APU was kept on bleed-air-only mode whenever it was not on electrical power and bleed-air mode to enable comfortable passenger boarding, deboarding, and servicing. The purpose of this scenario is to represent the case in which only GP is installed. Although PCA is not necessarily required with ideal ambient conditions, any time air conditioning is needed, the APU must be used.

Scenario 4
GP was used as measured; however, the PCA was not sufficient or was not used despite being available. The APU was kept on bleed-air-only mode whenever it was not on electrical power and bleed-air mode to enable comfortable passenger boarding, deboarding, and servicing. The purpose of this scenario is to represent operations in which the PCA systems were insufficient to maintain a comfortable cabin temperature, forcing the pilot to use the APU. This is a common occurrence on hot days.

Scenario 5
GP was used as measured. The PCA was used for 10 minutes less than GP (with a minimum of 0 minutes). The APU was on bleed-air-only mode whenever GP was used. The APU was on electrical power and bleed-air mode whenever both GP and PCA were not used. The APU was idle for 3 minutes on startup and on electrical power and bleed-air mode for the remaining time. The purpose of this scenario is to represent a realistic and conservative use of gate electrification equipment when the PCA system is barely sufficient. Although GP can still be used during passenger boarding, the additional passenger heat can exceed the cooling power of the PCA, forcing the pilot to turn on the APU early to maintain comfortable boarding conditions.

Scenario 6
GP and PCA systems were used for the same amount of time, as measured by GP data. The APU was idle for 3 minutes on startup and on electrical power and bleed-air mode for the remaining time. The purpose of this scenario is to represent a typical case in which the switch from APU to GP and PCA and vice versa occurs (almost) simultaneously. This would be the best-case scenario, according to the measured data.

Scenario 7
GP and PCA systems were used for the same amount of time, as measured by GP data. The APU was idle for 3 minutes on startup and on power and bleed-air mode for the remaining time. GP and PCA systems are shut down when there is no aircraft at the gate to avoid non-operational costs instead of being kept continuously on and ready. The purpose of this scenario is to represent a theoretical yet realistic case in which the operation flows exactly like in scenario 6, but GP and PCA systems are shut off when there is no aircraft at the gate to save on idle costs.

Scenario 8
GP and PCA systems were used for the same amount of time, for the entire duration of the turnaround time minus 15 minutes. The APU was idle for 3 minutes on startup and on power and bleed-air mode for 12 minutes. GP and PCA systems are shut down when there is no aircraft at the gate to avoid non-operational costs. The purpose of this scenario is to represent an idealized yet achievable use case for gate electrification equipment. Not only are the APU use times in line with the most stringent APU airport policies in Europe, but the gate equipment is shut off when there is no aircraft at the gate to save on idle costs.

4.4 Life Cycle Inventory

The Life Cycle Inventory (LCI) involves estimating the input and output processes included in the life cycle analysis according to each scenario. Figure 26 shows the categorized costs included within the scope of the LCI. Table 12 shows whether each cost element is included for each scenario.

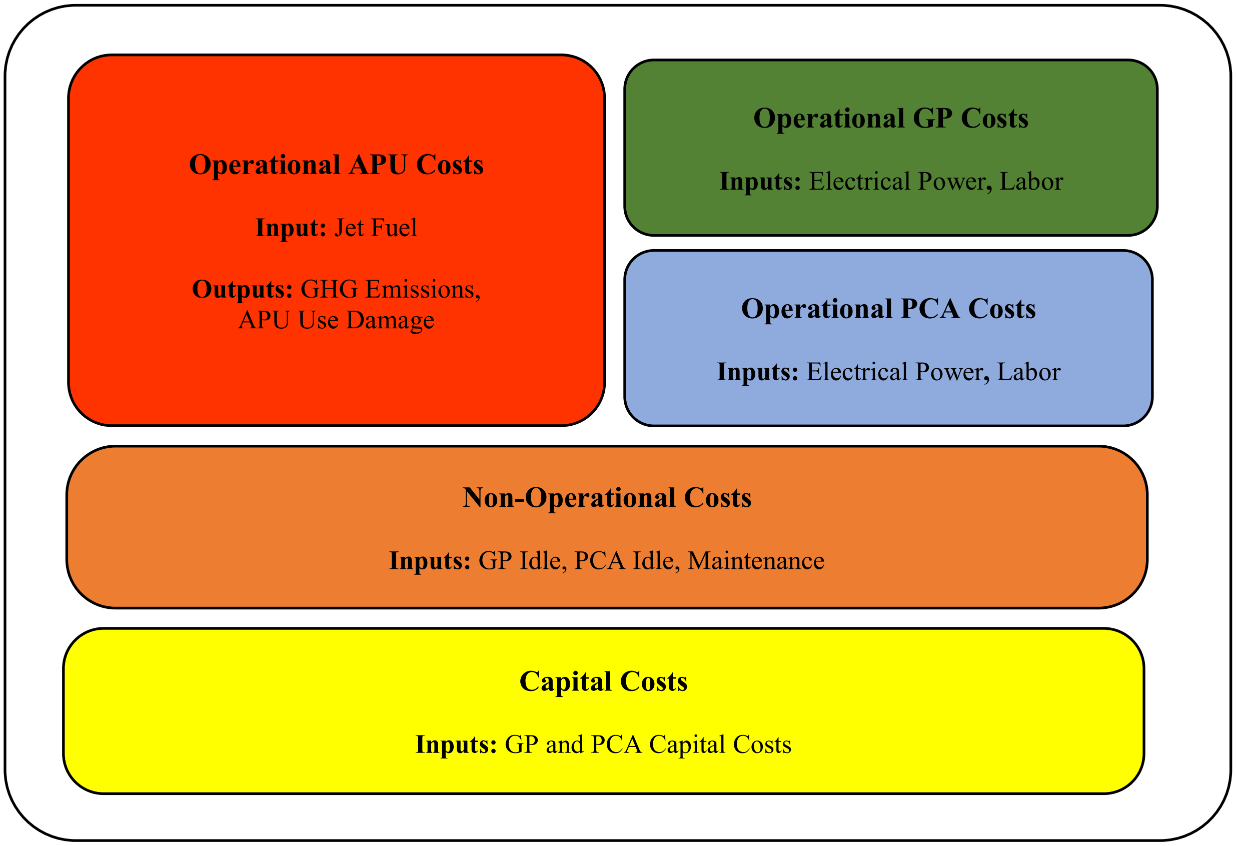


Figure 26: LCI scope for individual turnaround operations

Table 12: LCI cost elements included for each scenario

LCI Element	Scenario							
	1	2	3	4	5	6	7	8
APU Fuel	X	X	X	X	X	X	X	X
APU Emissions	X	X	X	X	X	X	X	X
APU Damage	X	X	X	X	X	X	X	X
GP Electrical Power			X	X	X	X	X	X
PCA Electrical Power					X	X	X	X
Labor (GP or PCA)			X	X	X	X	X	X
GP Idle		X	X	X	X	X		
PCA Idle		X		X	X	X		
Maintenance		X	X	X	X	X	X	X
GP Capital		X	X	X	X	X	X	X
PCA Capital		X		X	X	X	X	X

4.4.1 Operational Costs

This section describes a method for estimating each cost element from the available operational data.

APU Fuel

First, the time of APU use $(\Delta t)_{mode}$ in each mode must be determined. Table 13 provides a method for each scenario that uses results for turnaround time and GP use time from Section 3.

Table 13: Time for each APU loading condition

Scenario	APU Time for Loading Condition (min)		
	Idle / Startup	**Bleed Air for AC Only**	**Electrical Power and Bleed Air for AC**
1	0	0	Turnaround Time
2	0	0	Turnaround Time
3	0	GP Use time	Turnaround Time – GP Use Time
4	0	GP Use time	Turnaround Time – GP Use Time
5	3	10	Turnaround Time – GP Use Time
6	3	0	Turnaround Time – GP Use Time
7	3	0	Turnaround Time – GP Use Time
8	3	0	7

The amount of fuel was estimated using equation 9 and $FuelRate_{category,mode}$ values from Table 13.

$$APU_{fuel,kg} = \sum_{t=in\ block}^{t=off\ block} FuelRate_{category,mode} * (\Delta t)_{mode} \qquad \text{(Eq. 9)}$$

The current price of jet fuel is \$0.91/kg (IATA, 2023). The price of fuel $APU_{fuel,\$}$ was estimated using equation 10:

$$APU_{fuel,\$} = APU_{fuel,kg} * FuelPrice \qquad \text{(Eq. 10)}$$

The energy density of jet fuel is 43.5 MJ/kg (SMU, 2009). The well-to-pump (WTP) emissions for jet fuel in the U.S. are 19 gCO_2e/MJ (Speth et al., 2016). The total WTP emissions $APU_{fuel,WTP\ CO_2eq}$ were estimated using equation 11:

$$APU_{fuel,WTP\ CO_2eq} = APU_{fuel,kg} * 43.5\,\frac{\text{MJ}}{\text{kg}} * 0.019\,\frac{\text{kgCO}_2\text{e}}{\text{MJ}} \qquad \text{(Eq. 11)}$$

APU Emissions

The tailpipe GHG emissions and the local criteria emissions were computed using separate methodologies. The tailpipe GHG emission estimate was obtained using equation 12:

$$APU_{fuel,CO_2eq} = APU_{fuel,kg} * 3.155 \frac{kgCO_2}{kgFuel} \qquad \text{(Eq. 12)}$$

APU Use Damage

When APUs are used, they accumulate wear and tear, eventually requiring maintenance. Unexpected breakages could incur large costs for airlines, but regular maintenance is expensive as well. According to Ahmed et al. (2021), “An aircraft APU that requires maintenance after 7,000 flight hours, would require a maintenance cost of nearly $0.4 Million. (...) Aircraft APUs are found to be replaced more than 50% of the time whenever a fault is reported.” That implies an approximate use cost of $57/hr of APU use. In this LCI, the use of APU at the gate $(\Delta t)_{APU\ ON}$ was considered a part of the flight hours that contribute to APU maintenance expenses. Equation 13 was used to estimate the APU damage cost $APU_{damage,\$}$.

$$APU_{damage,\$} = \frac{\$57}{hr} * \sum_{t=block\ in}^{t=block\ out} (\Delta t)_{APU\ ON} \qquad \text{(Eq. 13)}$$

GP Electricity

To calculate the total GP energy relative to each operation, the measured and predicted kWh derived in Section 3 were used. Depending on the scenario, GP energy quantities according to Table 14 were applied.

Table 14: GP energy for each scenario

Scenario	GP Energy (kWh)
1	0
2	0
3	Measured GP Energy
4	Measured GP Energy
5	Measured GP Energy
6	Measured GP Energy
7	Measured GP Energy
8	Predicted GP Energy

The pricing strategy for GP use depends on the lease agreements between the airport and airline. In the case of SFO, the electrical power from the Public Utilities Commission (PUC) is resold to airport tenants according to Pacific Gas and Electric (SFO, 2020). The average PG&E rate for industrial customers in 2019 was \$0.16/kWh (PG&E, 2019). This estimate does not consider the variable pricing dependent on total power demand. Equation 14 was used to estimate the monetary cost of GP electricity $GP_{\$}$ from the total energy $\mathrm{GP}_{\mathrm{total}}$.

$$GP_{\$} = \frac{\$0.16}{\mathrm{kWh}} * \mathrm{GP}_{\mathrm{total}} \quad \text{(Eq. 14)}$$

The total energy consumption from GP must be multiplied by the life-cycle emission index for the grid's electricity to obtain an environmental cost. In the case of SFO airport, the sources of the electricity are 99% hydroelectric and 1% solar (CEC, 2020). The life cycle emission factor for hydroelectric and solar energy are 0.055 $kgCO_2eq$/kWh and 0.064 $kgCO_2eq$/kWh, respectively (Horvath & Stokes, 2011). Therefore, the weighted footprint of SFO's electricity is 0.055 $kgCO_2eq$/kWh. Equation 15 was used to calculate the total GHG footprint associated with GP energy usage GP_{CO_2eq}.

$$GP_{CO_2eq} = \frac{0.055 \text{ kg } \mathrm{CO}_2 eq}{\mathrm{kWh}} * \mathrm{GP}_{\mathrm{total}} \quad \text{(Eq. 15)}$$

PCA Electricity

Each scenario has a PCA use time $(\Delta t)_{PCA,mode}$ according to Table 15.

Table 15: PCA use time for each scenario

Scenario	PCA Use Time (min)
1	0
2	0
3	0
4	0
5	Max (GP Use Time – 10, 0)
6	GP Use Time
7	GP Use Time
8	Turnaround Time – 7

PCA systems require variable power, primarily depending on the size of the aircraft that is being serviced, the ambient temperature, and the humidity (ACRP et al., 2012). Below approximately 10°C, the PCA will be used to heat the aircraft; above approximately 12°C, the PCA will be used for cooling (Greer et al., 2021; Sadati & Cetin, 2020). The exact demand from these systems depends on the temperature gradient; however, that data is not available. Table 16 was used as a source for PCA requirement $Power_{PCA,mode}$. Since SFO ambient temperature is mostly over 12°C, the cooling rates are applied (highlighted in blue).

Table 16: Point-of-use electricity requirements for different aircraft categories (ACRP, 2012)

Category	Ground Power (kW)	Cooling PCA (kW)	Heating (kW)
Narrow Body	23.88	68.64	46.71
Wide Body	37.12	174.04	96.71
Jumbo Wide	53.21	189.95	113.73
Regional Jet	13.30	39.33	16.68
Turbo Prop	26.60	31.16	12.72

With this information, Equation 16 was used to calculate the total PCA energy demand PCA_{total}.

$$PCA_{total} = \sum_{t=in\ block}^{t=off\ block} Power_{PCA,mode} * (\Delta t)_{PCA,mode} \tag{Eq. 16}$$

Similar to the GP calculation, PCA monetary costs $PCA_{\$}$ and CO_2eq footprint PCA_{CO_2eq} were calculated with equations 17 and 18.

$$PCA_{\$} = \frac{\$0.16}{\mathrm{kWh}} * PCA_{\mathrm{total}} \tag{Eq. 17}$$

$$PCA_{CO_2eq} = \frac{0.055\ \mathrm{kgCO_2}eq}{\mathrm{kWh}} * PCA_{\mathrm{total}} \tag{Eq. 18}$$

Labor

To use GP and PCA systems, a worker must physically connect and disconnect the hoses and cables at the beginning and end of each operation. Although the actual tasks do not take more than a couple of minutes, the responsible ground crew worker needs to travel to the gate and be available to perform the task. Often, workers are responsible for other tasks in the turnaround operation outside the scope of this LCI. In this LCI, a 30-minute shift is assumed for any turnaround operation that uses GP, PCA, or both. The wage for an airport ground staff in San Francisco is $42/hr (ZipRecruiter, 2023). That implies an estimated $21 labor cost per turnaround operation. The carbon footprint for the labor was omitted.

4.4.2 Non-Operational Costs

Non-operational costs refer to costs that accumulate continuously, whether the gate equipment is being used or not, or whether an aircraft is present at the gate or not. These costs are intrinsic to maintaining functioning GP and PCA systems, so they must be appropriately distributed to each turnaround operation. The distribution can be done based on the time of use or the energy consumed, depending on the data available.

In this LCI, the non-operational costs were distributed proportionally to the ratio between the turnaround time $Turnaround\ Time_{operation}$ and the total turnaround time across the expected lifetime of the equipment. To estimate the expected lifetime use of gate equipment $Turnaround\ Time_{total}$, equation 19 was used. A gate utilization rate of 60% was assumed across the expected lifetime using the data from Section 3.

$$Turnaround\ Time_{total} = (15\ years) * \left(525600 \frac{min}{year}\right) * \left(0.6 \frac{turnaround\ time}{total\ time}\right)$$

$$= 4{,}730{,}400\ min \qquad \text{(Eq. 19)}$$

GP Electricity Idle

As discussed in Section 3, a continuous phantom electrical load is measured on GP systems even if there is no aircraft at the gate. This power is consumed to keep GP systems up and running, ready to use on demand. Table A14 shows the phantom power $Power_{GP,idle}$ associated with each gate in the analysis. With this information, equations 20, 21, and 22 were used to estimate GP phantom energy $GP_{idle,total}$, monetary cost $GP_{idle,\$}$, and GHG cost GP_{idle,CO_2eq} for each turnaround operation, respectively.

$$GP_{idle,total} = \frac{Turnaround\ Time_{operation}}{Turnaround\ Time_{total}} * Power_{GP,idle} * (15\ yr) * \left(8760 \frac{h}{yr}\right) \qquad \text{(Eq. 20)}$$

$$GP_{idle,\$} = \frac{\$0.16}{\text{kWh}} * GP_{idle,total} \qquad \text{(Eq. 21)}$$

$$GP_{idle,CO_2eq} = \frac{0.055\ \text{kgCO}_2 eq}{\text{kWh}} * GP_{idle,total} \qquad \text{(Eq. 22)}$$

PCA Electricity Idle

Decentralized PCA systems also have a significant idle cost because they need to maintain a temperature so that they can be used on demand. As (Sadati & Cetin, 2020) shows, even when no aircraft is at the gate, the PCA system intermittently turns on and off to maintain the desired output temperature. Without direct PC metering data and further research, this highly variable load can only be assumed. This LCI assumes that the continuous idle load $Power_{PCA,idle}$ is equivalent to 10% of the in-use power load indicated in Table 16.

Similar to GP idle cost, PCA idle cost must be distributed for individual turnaround operations. The energy cost $PCA_{idle,total}$, monetary cost $PCA_{idle,\$}$, and GHG cost PCA_{idle,CO_2eq} for idle PCA were calculated with equations 23, 24, and 25, respectively.

$$PCA_{idle,total} = \frac{Turnaround\ Time_{operation}}{Turnaround\ Time_{total}} * Power_{PCA,idle} * (15\ yr) * \left(8760 \frac{h}{yr}\right) \qquad \text{(Eq. 23)}$$

$$PCA_{idle,\$} = \frac{\$0.16}{\text{kWh}} * PCA_{idle,total} \quad \text{(Eq. 24)}$$

$$PCA_{idle,CO_2eq} = \frac{0.055\ \text{kgCO}_2eq}{\text{kWh}} * PCA_{idle,total} \quad \text{(Eq. 25)}$$

GP and PCA Maintenance

GP and PCA require proper maintenance to function. ACRP (2012) estimated a maintenance cost of \$5,698 per gate. The true cost is highly variable and dependent on factors such as the provider, the location, the number of units, and inflation, which will not be considered in this estimate. Similar to idle costs, the maintenance cost needs to be distributed to each turnaround operation. Equation 26 was used to calculate the monetary cost of maintenance $Maintenance_{\$}$ for either GP, PCA, or both.

$$Maintenance_{\$} = \frac{Turnaround\ Time_{operation}}{Turnaround\ Time_{total}} * \frac{\$5{,}698}{1\ yr} * (15\ yr) \quad \text{(Eq. 26)}$$

4.4.3 Installation Costs

Similar to non-operational costs, capital costs for the installation of GP and PCA systems, $Capital_{GP,\$}$ and $Capital_{APU,\$}$ respectively, need to be distributed to each turnaround operation. The true capital costs depend on each specific project and airport. In this LCI, ACRP's (2012) estimates were used, shown in Tables 17 and 18. Both basic installation costs and the two levels of electric installation costs were included. In both tables, the category refers to the largest aircraft category that the gate can accommodate, not the category of the aircraft being serviced, as listed in appendix Table A15.

Table 17: Point-of-use capital costs for GP per gate (ACRP, 2012)

Max Category	Equipment and Basic Install ($)	Level 1 Electric ($)	Level 2 Electric ($)	Total ($)
Narrow Body	49,000	15,000	15,000	79,000
Wide Body	74,000	30,000	30,000	134,000
Jumbo Wide	134,000	60,000	60,000	254,000
Regional Jet	42,000	15,000	15,000	72,000
Turbo Prop	42,000	15,000	15,000	72,000

Table 18: Point-of-use capital costs for PCA per gate (ACRP, 2012)

Max Category	Equipment and Basic Install ($)	Level 1 Electric ($)	Level 2 Electric ($)	Total ($)
Narrow Body	87,000	15,000	15,000	117,000
Wide Body	108,833	43,333	43,333	195,499
Jumbo Wide	293,900	103,500	103,500	500,900
Regional Jet	70,500	15,000	15,000	100,500
Turbo Prop	70,500	15,000	15,000	100,500

The installation cost is highly variable and dependent on factors such as the provider, the location, the number of units, and inflation, which will not be considered in this estimate. With these quantities, equations 27 and 28 were applied to derive the capital costs distributed to each operation.

$$Capital_{GP,\$} = \frac{Turnaround\ Time_{operation}}{Turnaround\ Time_{total}} * Capital_{GP,\ \max category,\$} \quad \text{(Eq. 27)}$$

$$Capital_{PCA,\$} = \frac{Turnaround\ Time_{operation}}{Turnaround\ Time_{total}} * Capital_{PCA,\ \max category,\$} \quad \text{(Eq. 28)}$$

Each scenario was applied to every operation in the dataset presented in Section 3. Each operation can receive its own LCI applied to each scenario. The results were aggregated to produce average cost estimates for each operation. Table 19 shows the average LCI cost elements according to each scenario.

Table 19: Average LCI cost elements for different scenarios from the dataset

Cost Element	Scenario							
	1	2	3	4	5	6	7	8
APU (kg)	141.35	141.35	137.10	137.10	97.82	81.03	81.03	25.04
APU ($)	128.63	128.63	124.76	124.76	89.02	73.73	73.73	22.79
APU WTP (kgCO_2eq)	116.83	116.83	113.32	113.32	80.85	66.97	66.97	20.70
APU Tailpipe (kgCO_2)	445.97	445.97	432.56	432.56	308.63	255.64	255.64	79.01
Damage ($)	71.30	71.30	71.30	71.30	52.47	42.97	42.97	14.25
GP (kWh)	0.00	0.00	13.18	13.18	13.18	13.18	13.18	28.67
GP ($)	0.00	0.00	2.11	2.11	2.11	2.11	2.11	4.59
GP (kgCO_2eq)	0.00	0.00	0.73	0.73	0.73	0.73	0.73	0.73
PCA (kWh)	0.00	0.00	0.00	0.00	31.90	39.10	39.10	75.21
PCA ($)	0.00	0.00	0.00	0.00	5.10	6.26	6.26	12.03
PCA (kgCO_2eq)	0.00	0.00	0.00	0.00	1.75	2.15	2.15	4.14
Labor ($)	0.00	0.00	21.00	21.00	21.00	21.00	21.00	21.00
GP Idle (kWh)	0.00	1.10	1.10	1.10	1.10	1.10	0.00	0.00
GP Idle ($)	0.00	0.18	0.18	0.18	0.18	0.18	0.00	0.00
GP Idle (kgCO_2eq)	0.00	0.06	0.06	0.06	0.06	0.06	0.00	0.00
PCA Idle (kWh)	0.00	14.72	0.00	14.72	14.72	14.72	0.00	0.00
PCA Idle ($)	0.00	2.35	0.00	2.35	2.35	2.35	0.00	0.00
PCA Idle (kgCO_2eq)	0.00	0.81	0.00	0.81	0.81	0.81	0.00	0.00
Maintenance ($)	0.00	1.36	1.36	1.36	1.36	1.36	1.36	1.36
GP Capital ($)	0.00	1.50	1.50	1.50	1.50	1.50	1.50	1.50
PCA Capital ($)	0.00	2.22	2.22	2.22	2.22	2.22	2.22	2.22

Figure 27 shows the aggregated monetary costs from Table 19. Although APU fuel cost and damage account for the majority of the cost, the other elements are non-negligible. An airline is usually directly responsible for APU and labor costs. The airline may be responsible for other costs depending on their gate lease agreement, although these costs are typically not dependent on circumstantial use (ACRP et al., 2012; ACRP et al., 2019).

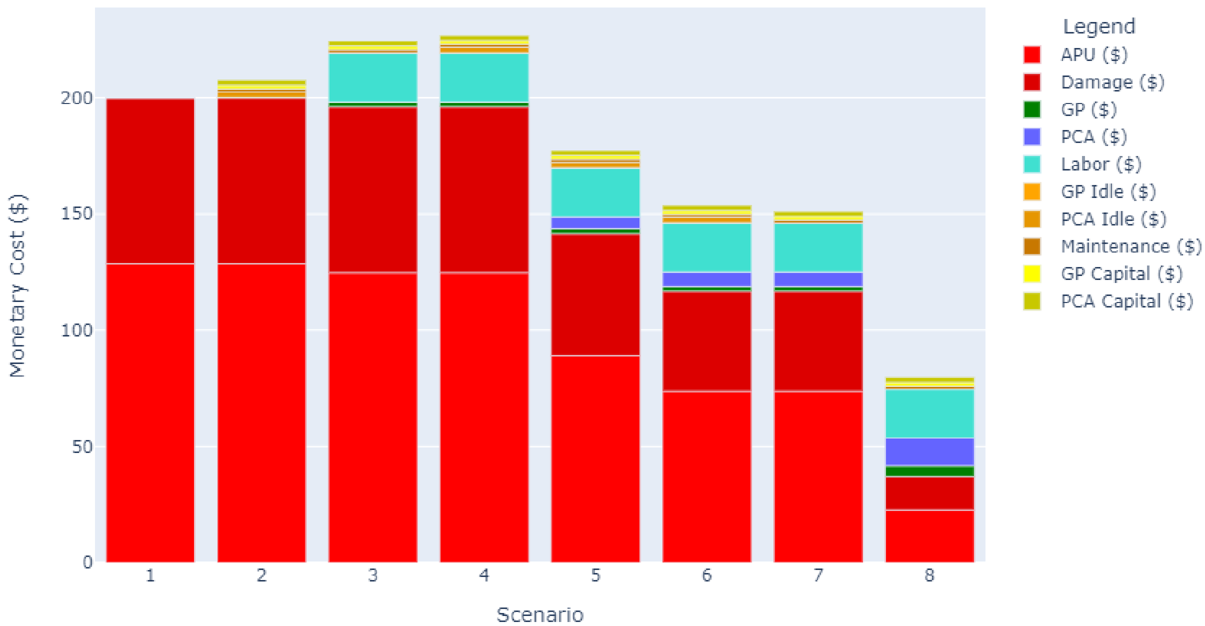


Figure 27: Average monetary cost LCI for different scenarios

Figure 28 shows the aggregated GHG costs from Table 19. The GHG costs from gate equipment operations are neglegible in comparion to the APU tailpipe and well-to-pump GHG costs.

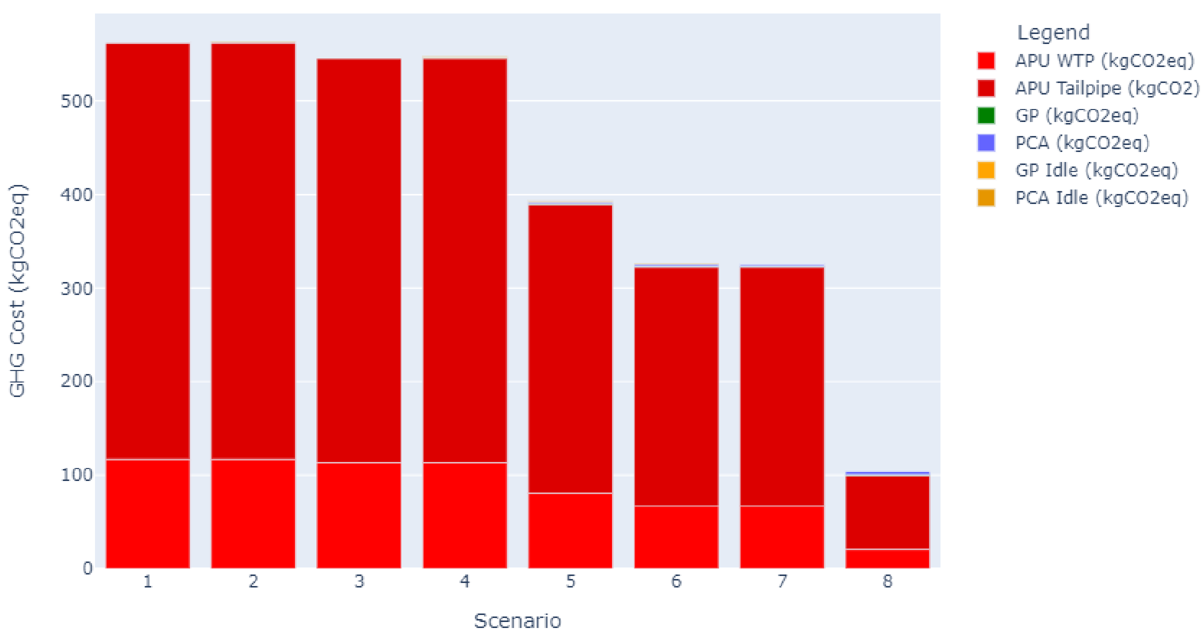


Figure 28: Average GHG cost LCI for different scenarios

To make a holistic comparison between scenarios that considers both monetary and environmental costs, the social cost of carbon emissions (SCC) needs to be calculated. According to (Greer et al., 2021), the approximate SCC in 2019 with a 3% discount rate was \$52/mTCO_2eq. This rate was multiplied by the LCI GHG emissions shown in Table 19. Figure 29 shows the addition of the total SCC and the monetary cost of each scenario.

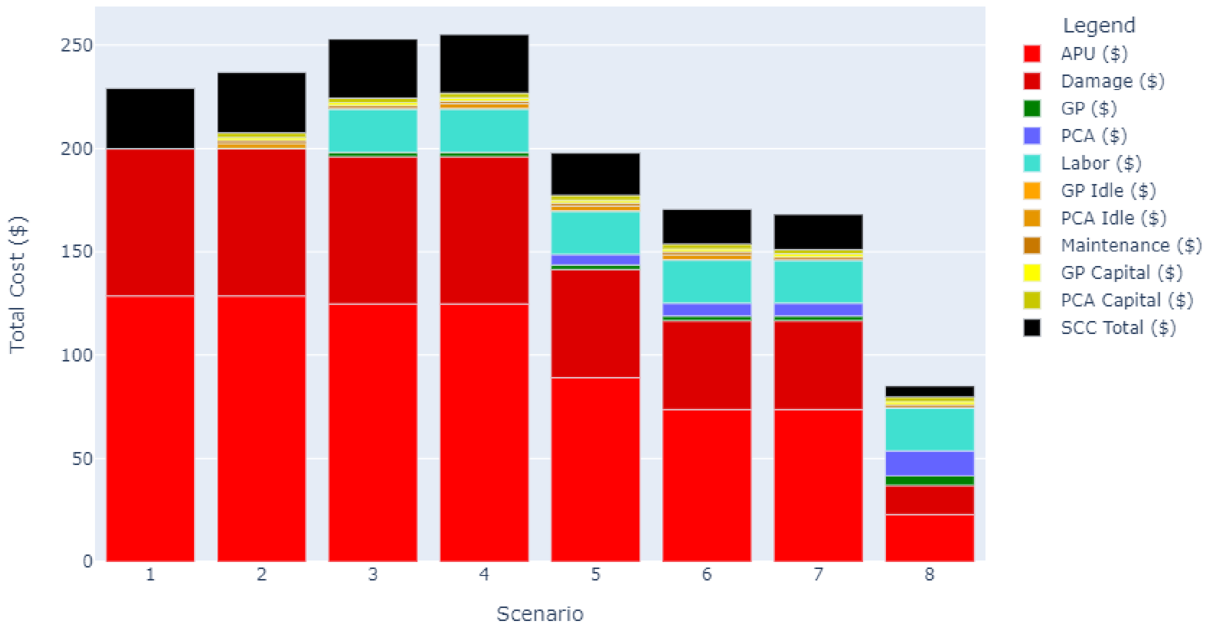


Figure 29: Average monetary cost LCI for different scenarios including SCC cost

4.7 Discussion

Without direct data on PCA use, the LCI of possible scenarios (2-6) shows large variability in cost, especially when pertaining to APU fuel and damage costs. This highlights the importance of integrating PCA monitoring with GP monitoring before making any strong inferences about APU use and costs. Airlines may have access to direct information on APU fuel costs, but they account for less than 50% of overall LCI costs.

Whereas all LCI components are significant in a monetary cost evaluation, only the APU tailpipe and WTP emissions are significant from a GHG perspective. This might not be true of airports other than SFO, which do not source 99% of their electrical power from hydroelectric sources.

Comparing the saving potential of each scenario reveals that improved gate electrification use brings relatively higher environmental savings than monetary savings. Although reducing APU costs is the cardinal strategy towards reducing overall costs, the monetary costs of installing and using gate infrastructure are relatively important concerns with well-performing operations. Pricing strategies in airport-airline lease agreements should reflect the operational costs proportionally to provide transparency and incentives for using the equipment. This is particularly true of shared equipment and gates where multiple airlines should have detailed accounting of costs.

The LCI analysis predictably concludes that turnaround operations ineffectively using GP and PCA have a higher monetary and environmental cost when compared to operations where there is no gate electrification present at all. This conclusion does not suggest that these systems should not be installed, but rather that there is a further incentive to monitor and enforce the use of this infrastructure.

4.8 Conclusions

Although the operation assessment performed in this report makes broad assumptions, it reveals that a detailed airport-centric life cycle analysis for APU, GP, and PCA that outlines costs and impacts is both possible and warranted. This report suggests how such an analysis could be accomplished, though further detailed data and research are required to truly perform a holistic life cycle assessment.

LCA methodologies reveal and detail those external costs; they are a way to introduce supervision and incentive structures that promote positive social, environmental, and health outcomes. Furthermore, these methodologies provide the foundation for the responsible sharing of resources between stakeholders and the basis for holistic decision making.

The use of APU is a classic example of a negative economic externality, where the costs carried by the users of the system are lower than the overall global costs. In a free and unsupervised market, the equilibrium between supply and demand equates to a greater volume of APU use than if the equilibrium accounted for its negative externality costs. In contrast, the use of GP and PCA systems (including the labor and processes required to use them) is a positive economic externality that is used less than it should when global costs are accounted for.

5. Adaptive Scheduling

This section of the report proposes an active solution towards improved gate electrification use. Sections 3 and 4 described fundamental techniques for measuring and evaluating ground power operations, but these operations are reactive in nature. Improved supervision and accountability might add pressure to pilots, ground crews, and airlines to implement better practices and prioritize energy efficiency. However, improved supervision and accountability do not directly help improve efficiency. Retrospective reports on performance, no matter how detailed, are not going to improve the efficiency of the reported operations. Furthermore, stringent oversight and an aggressive regulatory approach might be antagonizing in airport-airline relationships and poorly welcomed in the overall aviation industry. In contrast, solutions that propose increased sustainability and profits while also making airport workers' lives easier and safer may be more likely to gain traction. This section reframes monitoring, prediction modelling, and cost evaluation as processes that can be centralized, automated, and streamlined to provide immediate value to turnaround operation stakeholders.

5.1 Introduction

In essence, turnaround operations are a project delivery system. An ensemble of interdependent resources and activities interact with each other to provide a final service or product while incurring a certain cost. A project manager needs to understand the constraints of the project, formulate possible scenarios and schedules, estimate the associated costs, and decide how to proceed in a way to best balance the desires to maximize the expected value and minimize the expected costs.

Turnaround operations are characterized by both high variability and a fast pace. On one end of the spectrum, industrial manufacturing systems often rely on standardization and low variability to achieve a fast pace without much managerial intervention (e.g., a soda manufacturing plant). On the opposite end of the spectrum, highly unique projects rely on continuous managerial intervention to deal with the ever-changing uncertainties of the project (e.g., a skyscraper's construction). A human manager needs time to observe a project, assess the risks, and make decisions. For a construction project, reaching a holistic managerial conclusion takes several hours, days, or weeks, but, comparatively, the duration of the project is much greater than the time lag in intervention. In contrast, turnaround operations, many of which last less than an hour, are too short to apply the same holistic decision-making process. However, there are benefits to real-time oversight. The human delay in observing, estimating, and reacting may constitute a large fraction of the overall time, making the project delivery system less reactive to variability, especially regarding processes that are not critical to the overall gate turnaround operation.

Sections 3 and 4 of the report showed the variable performance and impact of the use of gate electrification infrastructure. To maximize energy savings, GP and PCA need to be used as long as possible instead of the APU; they need to be connected as early as possible and disconnected as late as possible. Padhra's (2018) analysis of airline data determined that excessive, non-compliant use of APU is widespread, especially in the longer pre-departure phase as opposed to post-arrival, where its emissions are disproportionately greater. In its conclusion (p. 443), the article "hypothesizes that more accurate estimates of departure time, efficiently communicated between air traffic controllers and flight crew would enable APU fuel and emissions savings." Figure 20 in Section 3.3.6 supports this conclusion, showing how, during turnaround operations, there is a strong positive relationship between delay and APU use time prior to departure. Padhra's article provided a rigorous way to measure the ground power use problem, and it points to the conclusion that actively improving the situation requires a logistical, practical solution that alters the schedules and behaviors of pilots and ground crews.

The field of lean management provides a suite of principles that can be used to improve the management of turnaround operations. Taiichi Ohno, a Toyota industrial engineer and executive, laid the foundations for the field of lean management to improve efficiency and cut waste in the car manufacturing processes (Womack & Jones, 1996). Ohno classified seven categories of waste in production delivery systems, and Womack & Jones (1996) added an eighth waste: goods and services that do not meet the customer's needs. Table 20 lists the eight wastes and presents a specific example of each within the scope of this report. Lean philosophy presents the antidote to such waste with five main principles (Womack & Jones, 1996): (i) specify customer value, (ii) identify the value stream, (iii) improve value-creating flow, (iv) implement pull management systems to deliver the right amount of work just in time, (v) record performance and continuously pursue perfection. All these principles are integrated in this section of the report as guiding principles for a computerized management system.

Table 20: Lean management waste categories and examples

#	**Category of Waste** Womack & Jones (1996)	**Examples of Waste in APU, GP, and PCA Operations**
1	Defects in products	Unexpected breakages; Unreliable GP
2	Overproduction of goods not needed	Idle GP and PCA when an aircraft is not present at the gate; keeping APU on when using GP
3	Inventories of goods awaiting further processing or consumption	Passengers waiting inside the aircraft for other processes to complete; parked ground handling equipment awaiting future use
4	Unnecessary processing	Turning the APU on early when GP and PCA are available
5	Unnecessary movement of people	Ground crew member moving between aircraft and passenger bridge to move equipment and connect each cable individually
6	Unnecessary transport of goods	Contingency fuel being added to aircraft for uncertain APU consumption
7	Waiting by employees for process equipment to finish its work or for an upstream activity to complete	Waiting on jet bridge movement before GP and PCA can be operated or before the aircraft can leave
8	Design of goods and services that fail to meet user's needs	GP or PCA is incompatible or insufficient for the parked aircraft

A pull system is a lean management principle that involves drawing resources when they are needed rather than processing them as soon as possible (e.g., Tommelein, 1997). The concept of pull-driven management systems is especially relevant to turnaround operations. Since the schedules of ground operations are dynamic and full of uncertainty, the lack of tight management might lead individual stakeholders to have a "just-in-case" approach rather than a "just-in-time" approach. If there is no clear indication of when to perform an activity, it might seem safer to act as soon as possible rather than too late. Such performance might safeguard individual workers from being the cause of large mistakes or delays, but overall, it leads to suboptimal performance. Pull systems that work within an uncertain schedule are critical for cutting waste, but they require a reliable and swift flow of information.

Digital twins are computerized models of physical systems that enable integrated decision making and effective transmission of information. Data acquisition processes provide the inputs required to keep the model updated, while the model can be used to record, analyze, predict, or simulate scenarios that provide actionable conclusions with which the physical system can be managed. Conde et al. (2022) showed how digital twins of turnaround operations can be generated and used for improved turnaround operations management.

Most literature about turnaround operations management focuses on optimizing the overall completion of the turnaround operation because that is where the greatest value lies. There are plenty of savings from effectively managing the fleet of ground equipment and workers so that fewer resources are required to achieve the same turnaround operations performance. For example, integer linear programming and simulation optimization are effective and tested numerical methods for equipment scheduling (see Section 2.6). However, once the equipment is at the gate, the rule is to perform an activity as soon as possible, and it is normal to model the system as a "push" system. This makes sense for most activities in a turnaround operation, where there is barely any loss in value by performing a task too early (e.g., refueling, cleaning) but a substantial risk in performing them too late. GP, PCA, and APU management are the exception to this rule, which is likely why they are excluded from most of the relevant literature.

This section of the report shows that it is possible to include a pull management system for GP, PCA, and APU that produces energy savings without compromising the rest of the turnaround operation. A computerized adaptive scheduling system is first described in theory, and then a prototype is presented to deliver proof of concept.

5.2 Detailed Process Description

To showcase the use of gate electrification equipment as a project-production management problem, this section maps out turnaround operations in further detail and expands the scope. Luggage handling, passenger movement, and refueling are some of the numerous processes that happen promptly and concurrently so that aircraft can get back to flying and generating value. These processes are part of the same system that involves the use of GP, PCA, and APU.

Turnaround operations at gates have similar activities, but there can be significant variation in the procedures, resources, infrastructure, and standards. To showcase the concept of adaptive scheduling and to isolate confounding variables, this section of the report makes the following assumptions:

1. Operations occur at a fully functional gate where the stationary PCA hose and the GP cables are connected to the passenger jet bridge and source their power from the airport's electrical grid (Figure 30).
2. As a safety precaution, the jet bridge is allowed to move only when the PCA hose and the GP cable have been fully stowed.
3. The narrow-body aircraft that are serviced at this gate have an APU at their tail end.
4. The ambient temperature is such that the aircraft requires air conditioning when passengers are boarding, aboard, or deboarding.
5. Although it is practically possible, the external ground power cannot be used if the APU is being used to generate bleed air for air conditioning. No testing or maintenance procedures are performed.

Figure 30: Jet bridge with GP cable connected to a pulley system at SFO international airport (Achatz Antonelli, 2019)

Before the aircraft arrives at the gate, all relevant parties (Air Traffic Control (ATC), airline, ground crew, pilots) are informed of the gate assignment and expected duration of the turnaround operation. This information is tentative, but it enables everyone to better schedule their tasks while having a set completion time to strive for. When the aircraft arrives at the gate, the ground crew and apron managers are assumed to be present and ready to assist the pilots in parking the aircraft in the right spot and placing blocks behind the wheels. The block-in action signals the beginning of the turnaround operation. Subsequently, a ground crew worker can slowly move the jet bridge towards the cabin door and lock it in position. Then, they lower the GP cable from the jet bridge, drag it to the bottom of the aircraft, and connect it to the GP receptacle (Figure 31). The aircraft automatically runs a series of tests on the supplied GP, and if every test is successful, a signal light appears in the pilot's cabin. The pilot can then switch over the aircraft power supply from the APU to GP. Depending on ambient conditions, the pilot sometimes needs to keep the APU on to generate the pressurized air needed to produce conditioned air to ensure a pleasant passenger experience. Meanwhile, the ground crew member who connected GP returned to the jet bridge to lower the PCA hose, drag it into place, connect it to the aircraft, and turn on the PCA. As soon as this happens, the pilot can turn off the APU, which slowly spins down to rest.

Figure 31: GP connector and receptacle at SFO international airport (Achatz Antonelli, 2019)

When the turnaround operation has started, the other tasks are initiated as soon as possible: passenger deboarding and boarding, crew switch, luggage handling, cabin cleaning, refueling, catering service, water, and wastewater servicing. These tasks need to be completed as quickly as possible so the aircraft can return to its flight route and make revenue. Although there may be some dependencies between these processes (e.g., boarding usually starts after cabin cleaning is complete), they can happen mostly independently until the finalization of the turnaround. The completion will be determined by the longest processes. All parties are directed to punctually execute and complete their tasks so that ATC can schedule the aircraft's taxiway and runway use times appropriately.

Before the scheduled off-block time interval, the aircraft needs to disconnect from GP and PCA, ideally at the last responsible moment. To do so, the pilot first needs to start the APU, which takes a few minutes to spin up to an rpm capable of generating power and conditioned air. Once this is achieved, the pilot can switch over to APU power and conditioned air. Only at this point can the ground crew disconnect the GP cable and PCA hose, drag them towards the jet bridge, and stow them appropriately (Figure 32). With everything safely secured, the jet bridge can be moved away from the airplane, and the blocks behind the wheels can be removed. Finally, with approval from ATC and apron managers, the tow truck can push the aircraft back away from the gate so that it can proceed towards the runways.

Figure 32: Ground crew worker disconnects a GP cable from a 787-900 which requires 2 GP cables for higher current supply (Achatz Antonelli, 2019)

5.3 Problem Statement

It is in the interest of all aviation stakeholders to maximize the fraction of time that ground power is used, and this has been a clear objective for decades. ACRP (2019) identified numerous challenges with the process described earlier and suggests several solutions to address them. The report described how insufficient resources, inconsistent practices, lack of oversight, and maintenance issues can lead to ground power being underused, and proposes a standardized method for tracking airport-wide utilization rates. The focus of this ACRP report was to understand why some operations fail to use any ground power or PCA at all. It did not focus on understanding how GP-use for partially successful operations can be improved.

The ACRP report acknowledged that "pilots make the decision whether, when, and how long to use electric PCA and ground power and when to use the APU." However, the report did not dive into the critical decision-making process of the pilots, and did not advise them when precisely the decision must be made. Since pilots are the ultimate decision makers, they are responsible for assessing the state of the turnaround operation, predicting the consequences of their decisions and actions, and then taking responsibility for them. This can be a challenging and stressful task, and it is even more challenging when considering the other duties that the pilot is executing simultaneously.

The pilot's decision to switch off the APU to increase ground power use is straightforward. As soon as the APU can be substituted with the GP and PCA, that action should be executed. In contrast, the decision of when to turn the APU on before departure is not so simple. Turning on the APU has no prerequisite, and the pilot can do it anytime. If they turn it on early, they will cause the APU to burn expensive and polluting fuel beyond the necessary time. If they turn it on late, they risk causing a delay to the whole operation, perhaps losing their departure slot time. In addition to this tradeoff between energy inefficiency and delay risk, turnaround operations processes are unpredictable (due to delays, maintenance issues) and depend on other stakeholders (ground crews) and external decision makers (ATC, ACDM). In addition, the pilot experiences new combinations of equipment and ground crews at each airport, some of which can be faulty, late, or absent. With all this risk, variability, and sometimes unreliability, a pilot will likely make conservative decisions. In practice, if the pilot does not know with certainty when the aircraft can be pushed back, and the task of disconnecting from the jet bridge both takes some time and is dependent on ground workers they do not know, they may choose to turn on the APU early. On a systematic level, such behavior decreases the potential use of GP and PCA, increasing costs and emissions that could otherwise be saved. If instead pilots were assisted in predicting the ever-changing schedule of turnaround operations and weighing the risks associated with turning the APU on, they would be enabled to make this crucial decision at the last responsible moment.

The root of this problem lies in optimizing a turnaround operations schedule that mitigates the inefficiencies created by unexpected variability in the completion of its component tasks. On one side, the standardization that comes with preplanning and choreographing is instrumental in minimizing costs and wait times *a priori*. On the other side, a detailed preset schedule makes it vulnerable to unforeseen challenges and delays. That is why turnaround operations managers with years of experience navigate the variable circumstances of each operation and adapt their team's schedules in real time. They use experience-based heuristics based on a limited set of data available to make their decisions. The turnaround operations managers are not the pilots who make the ultimate decision about turning the APU off or on. Everyone is restricted by their limited ability to perceive the many parallel operations they manage, predict changing schedules and outcomes according to their experience, and communicate instantly to all relevant parties. Nevertheless, they perform the real-time management role that is critical toward mitigating unexpected variability, one that can be used as a blueprint for a computerized monitoring and management system.

How can the best time to turn the APU on before departure be determined with an implementable, data-driven, and scalable method? This section proposes a framework for a computerized intelligent agent system that can monitor, predict, and optimally schedule ground operations at every step of the evolving operation. To do so, the **percepts** (inputs), the agent-based architecture (algorithm), and the **actuators** (outputs) of a real-time AI system that would assist turnaround operations stakeholders need to be defined. Figure 33 shows a conceptual blueprint for such a system with the following components:

- A **process model** is needed to make sense of the dependencies in activities.
- An **integrated sensing** must fuse the precept data with the model to interpret the circumstances of the problem.
- A **long-term memory** must accumulate historical data for future analysis.
- Multiple **prediction models** trained on historical data must make predictions on potential turns of events.
- A **simulation optimization** must fuse the dependencies of the process model, the circumstances of present state, and the stochastic predictions of future states to determine which actuator minimizes the expected cost.

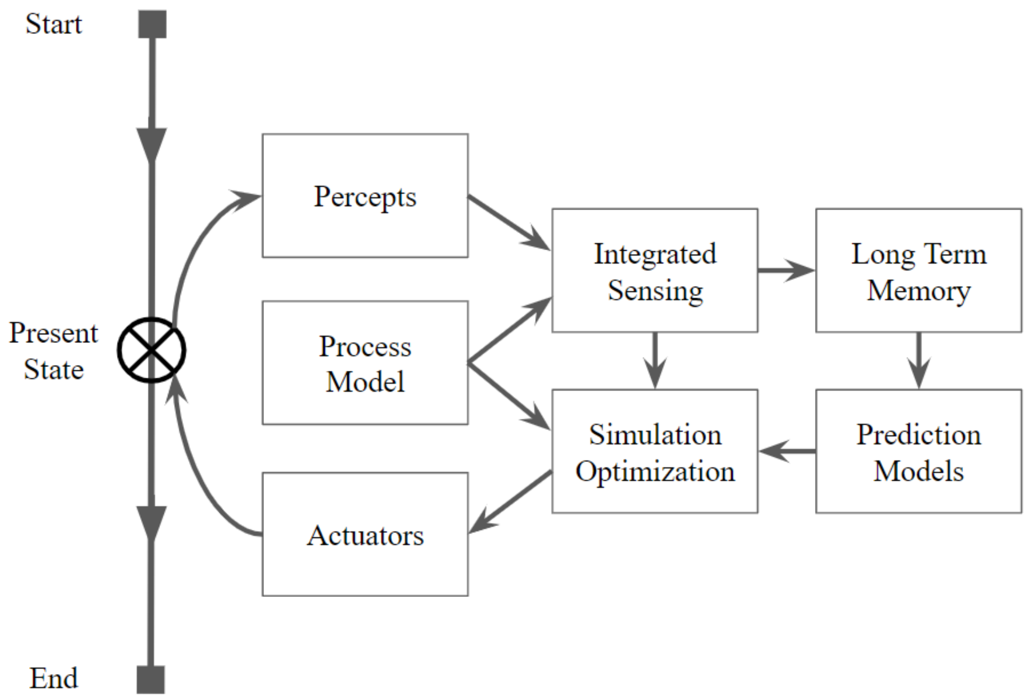


Figure 33: Blueprint for adaptive scheduling management system

5.4 Percepts

The first step towards developing an automatic and computerized management of turnaround processes is understanding what data inputs (percepts) such a system can leverage to collect data in real time and use to monitor the operation. Percepts that can be used include, but are not limited to:

1. Energy Monitoring
2. Position Tracking
3. Visual Monitoring
4. Acoustic Monitoring
5. Weather Monitoring
6. Thermal Imaging
7. Air Quality Monitoring
8. Human Signaling
9. External Information Systems

The wider the scope of the monitoring system's percepts is, the more the data will allow for integrated and comprehensive conclusions. The more frequently the percepts feed data to the system, the more detailed and precise the conclusions can be. The following section will discuss potential methods by which data collection for gate operations can happen systematically and automatically. Many of these percepts are redundant or not critical toward the functioning of a monitoring system; nevertheless, all will be listed and described as potential inputs.

5.4.1 Energy Monitoring

Turnaround operations have many energy sources and loads, from that of the aircraft to that of the ground support equipment. Where and how that energy is consumed may not be tracked in detail by a central system. Each source of energy has its own cost and emission rate. For each operation, the different sources are used at variable rates, and their use rates are dependent on each other. If a supposed computerized system must make nuanced conclusions that minimize the expected aggregate cost, it needs to know precisely what the use rates and costs are for each source. Looking at average rates or average consumption over extended intervals of time would not provide actionable data for individual operations.

Information on energy use can be used for two purposes: accounting and prediction. Accounting refers to the systematic recording and addition of all energy costs once all the data is recorded. Prediction refers to leveraging previous data and trends to estimate probable energy uses and costs rates before any real data is available.

5.4.1.1 Source Use & Magnitude

In this section we discuss various power sources an aircraft uses during the turnaround time such as: aircraft power, gate GP, GPU, PCA, PCU, jet bridge, and Ground Service Equipment (GSE).

5.4.1.1.1 Aircraft Power

An aircraft has several engines at its disposal to generate its electrical power. It is most common to use the APU as the power source during idle times at the gate. The main engines can be used at the gate but are usually turned off. Most aircraft models are already fully equipped to record all fuel consumption and energy consumption in detail. This data is being used by several airline-facing companies that leverage AI analytics for evaluation, prediction, and optimization to the airlines. In this case, the aircraft data is envisioned as a potential real-time percept of the centralized monitoring system. It would need to be transmitted from the airline to the monitoring system in real time.

5.4.1.1.2 Gate GP Power

The software and manual described in Achatz Antonelli et al. (2020b; 2020c) showed how power consumed through metered ground power cables can be leveraged to predict future energy demand. Assuming no other source of energy was used to continuously power aircraft during short turnaround operations, the system infers when and how many APUs were being used at the gate without any direct data from the aircraft or airline (Section 3). The data collected by the gate meters describe the amount of cumulative energy consumed at every gate at 5-minute intervals. This data was collected and analyzed retrospectively, but in theory, it could have been collected in real time as a component of a central monitoring system.

There is no standard for the collection of energy data from ground power systems; the airports that meter their ground power often do so with proprietary software. Whereas some airports have installed electrical meters that exclusively measure the consumption of ground power from individual gates (SFO and CDG, for example), not all airports have gate-level meters (SEA, for example). Ideally, all gates would be metered independently, but it is understandable that changing or upgrading existing infrastructure comes at a large, sometimes unreasonable, cost that outweighs the benefits it could provide.

5.4.1.1.3 GPU Power

Many operations use mobile ground power units that provide power with a diesel generator (ACRP, 2019). Although their cost and emission rates are not as low as those of ground power cables from the terminal, they are still an excellent alternative to APU use during idle times (Greer et al., 2021). They are mobile and can be relocated where they are most needed.

In Achatz Antonelli et al. (2020b), GPUs were excluded from the analysis, as they are not common for gate operations at SFO and GP is provided at all gates. However, this exclusion would be invalid for many other airports. In a comprehensive monitoring system, it would be important to understand the supply of power from GPUs just as well as GP. To do so, GPUs need to meter their fuel consumption and supply of electrical energy at regular intervals and transmit it in real time through an IoT architecture. Once again, upgrading existing GPUs to perform these tasks might prove expensive and challenging, but this should be considered in the design of future mobile GPUs.

5.4.1.1.4 PCA Power

Pre-conditioned air systems are often paired with ground power systems because their use is correlated. For example, an APU can be turned off if both functions it provides, power and air conditioning, can be substituted by external sources. Gate-installed air systems can either have their heating and cooling units installed at each gate independently or centralized within the terminal and then distributed to each gate. For independent units, the power consumption of the unit should be measured at regular intervals and shared in real time to a centralized data acquisition platform, just like for GP. For centralized systems, it is more challenging to dissect PCA power use by gate, but it is at least possible to identify the times when air is flowing. Independently of the configuration and sensory capabilities, the objective of a PCA system is to monitor when and how much PCA is used.

5.4.1.1.5 PCU Power

Just like for ground power, preconditioned air can be supplied through stationary gate infrastructure or mobile PCUs. Similar to GPUs, the power consumption and air flow from these units would need to be collected at regular intervals and shared in real time.

5.4.1.1.6 Jet bridge

The jet bridge that connects the terminal to the aircraft consumes power. During its movements at the beginning and end of gate operations, it requires more power. Some jet bridges consume an amount of base power for the internal electrical equipment, even while stationary. The energy used should be collected at regular intervals and shared in real time.

5.4.1.1.7 Ground Service Equipment (GSE)

Ground service equipment (GSE) encompasses a vast number of vehicles that can be used for turnaround operations. The most noteworthy are the tow, luggage trolleys, luggage loading equipment, catering trucks, refueling trucks, water servicing vehicles, and wastewater servicing vehicles. This equipment uses energy. The ability to collect and analyze energy consumption would be crucial for having a comprehensive understanding of energy uses at the gate. These vehicles are often diesel-powered and do not have sophisticated data collection and sharing as part of their design, making it challenging to know how much power they are using at any point. Many of these vehicles are being modernized and electrified, making such a data collection more feasible. Ideally, the centralized monitoring system would receive data on energy consumption for each vehicle, but recognizing which vehicle is on, idle, or off would provide a foundation for insightful decision making.

To exemplify the relevance of GSE energy monitoring, consider a tow truck at a gate. A typical tow with no sensors could not share information on instantaneous fuel consumption with the IoT system. However, if such a tow were able to communicate when it is ON or OFF, it would provide a percept crucial for understanding if the tow is in use or idle with its engine on. One might say that this is a negligible detail in the overall picture of gate power consumption, but such detail sets the foundation for a comprehensive life-cycle assessment, energy prediction, and new management possibilities. Being able to estimate how much power the tow truck consumes per operation can help predict and optimize charging and usage times to lower energy costs and energy loads on airport infrastructure.

5.4.1.1.8 Estimation of Unknown Quantities

Many of the precepts for energy monitoring described are not always attainable for all operations and all airports. However, there are two ways that can be used to bridge that gap in information: by leveraging historical data or literature data.

If monitoring systems were implemented at numerous airports, the data from some airports with the necessary precepts can be used to estimate the energy consumption at airports without those same precepts. For example, SEA airport does not have independent electrical energy meters at each gate. However, they are landing mostly the same aircraft models as SFO, which instead does have the capacity to measure energy consumption for each operation. Within a reasonable margin of error, it would not be inappropriate to expect similar levels of energy consumption rates for similar conditions and therefore work with a reasonable estimate.

When there is a complete absence of historical data, the system can use values from the literature or those provided by the manufacturer of the equipment. This data will lack precision but can function as a placeholder for a missing percept.

5.4.1.1.9 Switch Time Estimation from Metering

A fundamental precept of the monitoring system is understanding when a certain power usage is ON versus OFF. In some cases, the switch can be instantly detected and transmitted to a centralized system as a precise timestamp. Sometimes, that information is not available. In most energy meters, cumulative power is only recorded at consistent, predefined intervals that do not necessarily match the time at which the switch occurs. However, even in such a scenario, if the data is granular enough, it is possible to estimate the switch time. If enough data has been accumulated on the power usage trends of certain equipment, it is possible to formulate prediction models that can estimate the power rate of that equipment within the interval of time at which the switch occurred. By comparing how much energy was consumed versus how much was expected to be consumed, it is possible to estimate the proportion of time that the power was used within the interval, and consequently infer the switch time. This is a valid estimation process for any power use that does not have a delay between the time of use and the time of energy consumption (i.e., PCA has a delay). It can be used as an artificial percept of the centralized monitoring system.

5.4.1.2 Source Cost Rates

Each energy use is associated with a monetary cost and emission cost that is variable depending on the source and time of use. The clearest example is that of APU versus GP. When providing the same electrical power needs to the aircraft, the APU is clearly more expensive and polluting. All uses of energy abide by equation 32 to find the overall cost:

$$Cost = \sum_t (Duration_t * Utilization_t * Power_t * EnergyCostRate_t) \qquad \text{(Eq. 32)}$$

Where:

$Duration_t$ is the duration of time interval t
$Utilization_t$ is the fraction of time power was consumed during interval t
$Power_t$ is the instantaneous non-zero power consumed for interval t
$EnergyCostRate_t$ is the average cost per unit energy during interval t

Understanding the detailed costs of all energy uses is an ambiguous task, which requires a clear definition of the problem's boundaries. In a comprehensive life-cycle cost assessment, the cost rate of power would have to include the varying monetary and environmental costs of the electricity mix and fuel, along with the costs of the processes and infrastructure built to provide it. However, this report suggests limiting the scope to the operational monetary and emissions costs. Of the emissions costs, the most relevant pollutants influencing airport air quality and emissions are CO_2, CO, NO_x, SO_x, HC, and PM.

The monetary and environmental costs of electricity and fuel are variable data, so they need their own percept. This is a realistic implementation, as most airports detail their energy consumption mix, and some even have APIs that update the variable rates in real time. Similarly, there is public information on jet fuel and diesel monetary and environmental costs by airport and region, and some of this information is available through APIs.

5.4.2 Position Tracking

Another fundamental percept is understanding where any event or resource consumption is occurring.

For stationary equipment and sources, the position is predefined and does not change. This is true for stationary GPs, PCAs, and jet bridges. Their location can simply be manually input into the central monitoring system.

For mobile equipment, personnel, and resources, it is fundamental that their location is tracked frequently. This information needs to be shared in real time with the central monitoring system. For example, if a GPU is producing power for an aircraft, it will be challenging to attribute that power consumption to the operation it is servicing unless that GPU is geolocated next to the operation it is servicing.

There are several methods to keep track of the position. The first one is to have a geotag on the equipment that constantly sends updates on its new coordinates. Based on the proximity of those coordinates to any specific gate, it is possible to connect the resource use to that gate. Another method is to use image recognition systems to track the movement of equipment through the apron area, which is already being done for the aircraft and GSE in the apron. Another option is to use IoT capabilities to infer the location. If a particular IoT-connected resource (e.g., GSE, personnel) is connected to a specific set of neighboring devices, the location can be inferred.

5.4.3 Visual Monitoring

The last decade has seen leaps in the capabilities of image recognition technologies that are being used to monitor airport operations. Aircraft are already being visually tracked by integrated camera systems at many large airports around the world. The AODB, which was a major data set used in the software of the Phase 1 report, was largely generated using Aerobahn's visual monitoring software. The uses of image recognition are still improving and expanding, and they have terrific potential in assessing ground operations.

An excellent example of how visual monitoring is an outstanding percept for gate operations is the system created by the startup Assaia. They developed their Apron AI product, an information system that allows visual data collected from apron cameras to be translated into a set of timestamps for each event observed. Assaia went a step further and understood the value of being able to digitally monitor and model gate operations to inform decision-making processes. In addition to the timestamps collected from their cameras, they built a supervised machine learning model that predicts the push-back time of aircraft as operations are being completed. Their product directly interfaces with CDM systems, informing this prediction and allowing them to optimize schedule ramp movements, predict gate availability, and avoid queuing. Their work is already recognized and applied in the industry, with major sponsors such as EuroControl, International Air Transport Association (IATA), and Airport Council International (ACI); many clients such as Seattle Tacoma Airport, Gatwick, and Toronto International Airport; and pilot projects in a multitude of other locations, including SFO.

In the scope of this report, visual monitoring provides two fundamental pieces of information: the timestamps of visually recognizable operational milestones (e.g., block-in time, cable connected, doors open) and the recognition of which resources are being used (e.g., GP or GPU? Jet bridge or mobile staircase?).

5.4.4 Acoustic Monitoring

Sound is a relatively unexplored percept that can be used for ground operations. Several events in ground operations are better recognized by sound than by visual feedback. For example, sound can be a way to recognize the states of the main engines and the APU engine, which produce recognizable frequencies dependent on their spin rates. A directional microphone installed at a gate in combination with a trained machine learning system can recognize the moment at which an APU initially starts to spin up, the moment the APU has reached the rpm it requires to generate power, and the moment the APU is generating power. A well-positioned array of microphones would be able to distinguish where the sound is coming from. As a percept, it would essentially provide states and timestamps for the shutdown and startup sequence of aircraft engines at single gates.

5.4.5 Weather Monitoring

Weather can have significant impacts on ground operations and therefore should be monitored as a percept of the system. Extreme weather events, despite being rare, can hinder certain activities, cause delays, and affect the performance of the overall operation. Temperature also has a major impact on operations, especially on the use of pre-conditioned air systems. For example, in high-heat environments, some preconditioned air systems might be insufficient for cooling down the aircraft, forcing pilots to turn on APUs earlier than planned. Considering a human manager would take weather into account in the management of the operation, it should also be a percept of the computerized monitoring system.

This is a simple percept to implement. Weather APIs are commonplace and can be connected to the monitoring system. At regular time intervals, data should be collected on wind speed, precipitation, and temperature.

5.4.6 Thermal Imaging

Thermal imaging is a potential percept that can be used to identify which engines are in use. The fumes released by combustion engines can be recognized by image recognition software. This percept would provide the times of use of the engines. This is a challenging and expensive percept to implement, and this report speculates that it would also be inaccurate, as there is a delay between the heating and cooling of engines and the times that they switch on and off.

5.4.7 Air Quality Monitoring

One of the primary drives for this project is the reduction of pollutants at airport gates, which would have a measurable impact on air quality. A potential percept of gate operations would be the continuous measurement of criteria air pollutant concentrations at the airport. Some airports already perform this data collection to assess their environmental impact. However, for the purposes of ground handling management, such a percept would not provide much actionable information.

5.4.8 Human Signaling

A potential percept for a computerized monitoring system is that of signals and data provided directly by the human workers in the operation. In theory, a human can deliver any valuable data to a system by using a button, a smartphone, or any device that can be connected. This is contrary to the goal of making gate monitoring autonomous, but it might prove to be a valuable and necessary percept at times. This percept could take many forms, and therefore, will not be detailed in its designed goals.

To provide an example, malfunctions of equipment are an unfortunate but common occurrence in airport aprons, which demand circumstantial decision making and actions. In the event of a breakage or maintenance routine, a human could inform the centralized monitoring software that a non-standard procedure is occurring.

5.4.9 External Information Systems

Gate operations are interdependent with many other processes in the airport ecosystem, so it is fundamental that a centralized gate monitoring system can integrate data from other external, real-time information systems.

Apron managers and air traffic controllers are the decision-makers for when a gate operation begins and ends. Their decision making depends on air, runway, and taxiway traffic, which are outside the scope of a gate monitoring system. ATCs and apron managers need to consider the predefined schedule and the unfolding of a turnaround operation to make decisions on the spot, but in many cases, these decisions are independent of gate activities or the original schedule. There are sophisticated real-time information systems to aid them in the decision-making process and in communicating the information to all relevant parties, such as the ACDM framework. These existing systems would also provide the necessary percepts for improved gate monitoring and management. For example, if there is a large queue for the runways, an ATC might delay the pushback of an aircraft from a gate. That information can be used to instantaneously reschedule turnaround processes to avoid idle time and inefficient energy usage. In short, the pushback time and departure time slot are critical real-time percepts that need to be sourced from external information systems.

Passenger and luggage movements cannot be monitored directly at the gate apron, but they may influence a turnaround operation. Luggage and passenger handling could be the cause of delay. The passenger movements have direct dependencies on other critical turnaround processes such as catering, cleaning, and jet bridge operation. The moment passengers are on the aircraft, a pleasant temperature must be ensured, which has direct consequences on the use of energy for the operation. This critical information is very consequential for the gate turnaround and should be used as an external percept. There are already sophisticated luggage and passenger-tracking information systems that can be used to source the data in real time. The most relevant times that would need to be continuously reported would be:

- Predicted & Recorded Passenger Deboarding Start & Completion
- Predicted & Recorded Passenger Boarding Start & Completion
- Predicted & Recorded Cargo Offloading Start & Completion
- Predicted & Recorded Cargo Loading Start & Completion

5.5 Process Model

To draw valuable conclusions from the continuous data supply from percepts, a computerized system needs a model to represent how an operation unfolds. Ideally, an AI system would be able to learn the needed activities and their dependencies to construct a model. However, it is presumed that a modeler formulates a model design.

The process model is a module that establishes the activity sequences and rules that govern a process. In essence, it is code that describes the physics of the entire turnaround operation. It is primarily composed of a list of dependencies between activities and resources (i.e., GP can be provided only after GP connector has been plugged in).

The modeler is the person who decides the best model design to implement. Their goal is to make a model that is comprehensive enough to make precise, accurate, and actionable conclusions. However, it is unreasonable and incomputable to replicate all the complexities and physics of reality, making it important that a modeler identifies what to include and what to exclude. The modeler must build the model while carefully considering the available percepts and actuators that the system can leverage in its algorithm.

To understand how a model can be designed, the dependency mechanism between activities must be defined. Activities are delimited by two events: their start and their completion. The start time of an activity solely depends on the completion of all predecessor activities; it starts as soon as all its prerequisites are complete. The completion time of an event can be either simulated or observed in real time. If it is being simulated, the completion time can be determined by a constant, a random variable, or a function (Section 5.8). If the activity is observed, the completion will be signaled by a percept, and the duration can then be unequivocally deduced. The model's dual representation between observation and simulation is fundamental because in an adaptive scheduling framework, any past activity will have been observed, whereas future activities need to be simulated. As an operation unfolds over time, more of the model's durations for activities will be replaced by observed durations, and fewer future activities will need to be simulated. That is why the durations within the model are described through variables.

5.5.1 Simple Model Example

In this report we develop a simple model to explain how this architecture could work as an example upon which more comprehensive models can be built and demonstrated. It will look at an operation occurring at a single gate, where all workers and equipment are already present to service the aircraft (no procurement). Only a handful of gate-handling processes are assumed to prevent an aircraft from departing, and the scheduling interaction with ATC is ignored. It is assumed that the percepts available are:

- Image recognition cameras that can identify the completion of the following operational milestones:
    - Aircraft Parked
    - Jet Bridge Connected
    - GP Connected
    - GP Disconnected
    - Jet Bridge Disconnected
    - Aircraft Pushback
    - Refueling Initiated
    - Refueling Concluded
    - Luggage Unloading Initiated
    - Luggage Unloading Completed
    - Luggage Loading Initiated
    - Luggage Loading Completed
- The Airport Operations Database AODB will provide:
    - Predicted Pushback Time / Gate Hold
    - Airline
    - Aircraft Model
- External Data
    - Opportunity Cost of turnaround operation
    - Marginal Cost of GP Power based on use duration
    - Marginal Cost of APU Power based on use duration

Assume that the only actuators available are:
- An informational signal that tells the pilot to turn on the APU
- An estimated time for disconnecting the cable given to ground crews and pilots
- An estimated pushback time, dependent solely on gate processes

Knowing what percepts and actuators can be used, a model can be designed accordingly. In this case, only a limited number of processes are included. These are depicted in the flow chart in Figure 34. The percepts provide information only to infer the completion of large milestones from specific activity paths: the ground power usage, the luggage handling, and the refueling. An external actuator, Gate Hold, can be considered an additional activity path that can allow Air Traffic Control (ATC) to schedule the minimum duration of the whole operation.

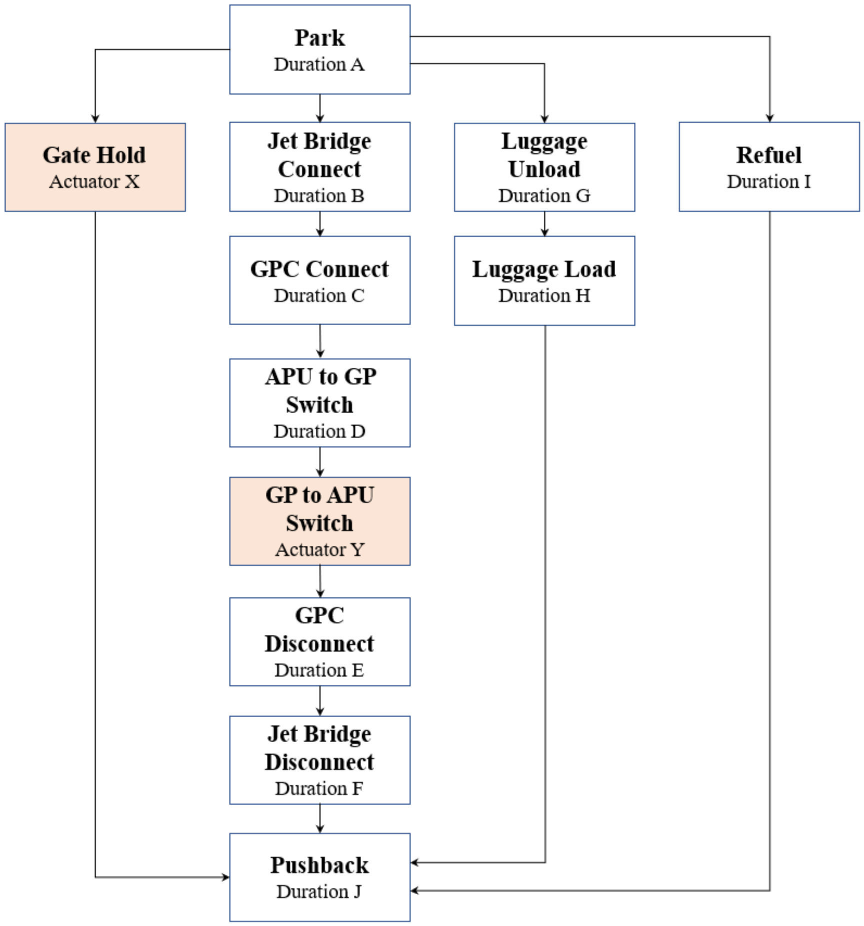


Figure 34: Dependencies of the simple model. Actuator activities that can be influenced are shaded orange, whereas normal activities that can only be observed are not shaded.

Table 21: Random variable distributions for the durations within the model

Activity	Normal Distribution Average (min)	Normal Distribution Standard Deviation (min)	Normal Distribution Minimum Cutoff (min)
Park	2	0.5	1
Jet Bridge Connect	2	0.5	1
GP Connect	2	0.5	1
APU to GP Switch	2	0.5	1
GP to APU Switch	**Actuator Y:** GP Hold Release (initially set to 0 min)		
GP Disconnect	2	0.5	1
Luggage Unload	12	2	1
Luggage Load	12	2	1
Refuel	20	5	1
Gate Hold	**External Actuator X:** Authorized Pushback (initially set to 0 min)		
Pushback	2	0.5	1

The simple model in Figure 34 captures the parallelized processes of ground power management, luggage handling, and refueling. Although not all processes are included, these activity paths mirror those described in the process description. Because the model physics indicates that activities start as soon as all their predecessors are completed, this model implies that luggage loading begins right after luggage unloading is completed, and refueling starts as soon as the aircraft parks. This is not necessarily correct; those activity paths have constraints that are not modeled but are omitted for the sake of simple explanation. A discussion in which further complexities can be introduced to the model to make it more realistic is presented in Sections 5.11 and 5.13.

Table 21 lists arbitrary distributions in activity durations associated with the model in Figure 34. These arbitrary values are in line with typical durations observed in the literature to showcase the stochastic nature of the model.

The activity "Gate Hold" is a non-tangible activity that describes the external decision making and scheduling that would lead the aircraft to stay at the gate; its completion would allow the aircraft to be pushed back if all other activity paths are completed. In reality, this is an actuator that airlines and ATC/ACDM can use for optimization and scheduling, but its specifics are outside the scope of this model. They can change the predicted and actual pushback time while the operation unfolds for reasons such as runway management, airline scheduling, and maintenance. This external decision has a defining impact on the scheduling of the ground handling and is a major contributor to variability. Initially, this model ignores this external agent by setting the hold duration to 0, but Section 5.11 discusses how it could be better integrated.

This simple model is designed around the percepts and actuators that were stated as available. Each activity can be monitored for completion from the percepts so that the computerized system can know its activity flow stage during an operation. The start of each activity is determined by the completion of its predecessors, as shown. Table 22 lists the dependencies and completion of the model.

Table 22: Conditions for activity start and completion

Activity	Predecessors	Completion Condition	Percept Source
Park	n/a	Chocks placed behind wheels	Video Recognition
Jet Bridge Connect	Park	Jet bridge stationary and attached to aircraft.	Video Recognition
GP Connect	Jet Bridge Connect	Cable connected in receptacle	Video Recognition
APU to GP Switch	GP Connect	Power being consumed through GP	GP Power Metering
GP to APU Use	GP Switch	Actuator Y: GP Hold Release	n/a
GP Disconnect	GP to APU Use	GP disconnected and stowed away	Video Recognition
Jet Bridge Disconnect	GP Disconnect	Jet bridge stationary and detached from aircraft.	Video Recognition
Luggage Unload	Park	Luggage stops coming out of cargo hold	Video Recognition
Luggage Load	Luggage Unload	Cargo Doors Closed	Video Recognition
Refuel	Park	Refueling line disconnected	Video Recognition
Gate Hold	Park	External Actuator X: Authorized Pushback (Initially set to 0)	AODB/ATC/ACDM
Pushback	Jet bridge Disconnect AND Luggage Load AND Refuel AND Gate Hold	Aircraft moves away from parking	Video Recognition

With the dependency mechanics and structure defined, the rest of the adaptive scheduling architecture can be built. The only remaining step is encoding the physics and dependencies in an event-based simulation engine such as MIT's SimPy (Scherfke & Lünsdorf, 2020).

5.6 Integrated Sensing

Percepts generate data that need to be merged and analyzed before they can provide useful information. The objective of the integrated sensing module is to clean data from the percepts and create a consistent database that indicates the state of the operation within the pre-defined process model.

Integrated sensing starts with systematically fusing acquired data. The percepts do not necessarily collect or transfer data with the same granularity; they are likely out of phase. For example, energy meters could transfer data every minute and image recognition every ten seconds. As a result, the following question arises: at what rate should the integrated sensing database be updated? If its refresh rate is slow, detail will be lost, and time will be wasted to make actionable conclusions. If its refresh rate is fast, inputs might not receive new data, or the full algorithm might not have the time to run before receiving a new input. Finding the optimal rate is crucial to the functioning of the overall algorithm and will be discussed in the Simulation Optimization module (Section 5.9).

At any iteration through operation, the integrated sensing database needs to describe exactly what is known about the state of the model and percept data available. Whenever a percept is updated, the unchanging part of the integrated sensing data should not simply be copied. That would introduce false certainty in a state that has not yet been fully perceived. Therefore, it is important that the data being copied carries the timestamp of when it was last updated. For example, consider activity B in Figure 35 is recorded in the integrated sensing database. Whereas the long-term memory updates every 10s, the completion percept for activity B only updates at 15 s and 35 s, while the actual activity ends at 27 s. If this precept is described as true or false at each integrated sensing update and is copied to fill in missing data, the copy would incorrectly infer that there was new information indicating whether, at a later step in time, the cable was connected or not. At 30s, although the percept did not observe it yet, activity B was completed; it would be wrong to say activity was not completed at 30s seconds because the last data input was at 15s. According to the integrated sensing, activity B may or may not have been completed in the time since the last percept update. To carry that ambiguity while also reporting a complete integrated sensing database update, the percept for event A must be described by two variables: both a binary true or false and a timestamp describing when the measurement was made (Table 23).

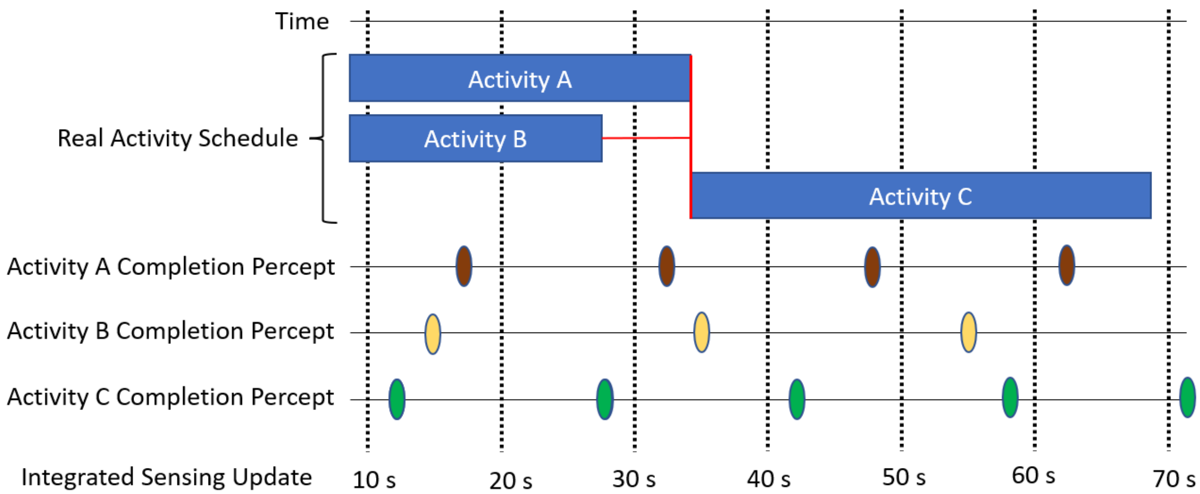


Figure 35: Example of integration of out-of-phase percepts

Table 23: Example of integration of out-of-phase percept with arbitrary values

Integrated Sensing Timestamp	Activity B Completed?	Percept Update Timestamp
10	False	n/a
20	False	15 s
30	False	15 s
40	True	35 s

The next step of integrated sensing is merging all the data. On a database indexed by timestamp, each row would contain all features describing what is known at that timestamp. The data for previous timestamps would not be modified according to new data acquisitions. As the operation proceeds in real time, more rows would be appended to the database.

Once the percept data is integrated at every timestamp, the dependencies and assumptions described in the process models can be used to further understand the state of the model. First, the completion conditions in Table 23 may be verified. When a completion condition is triggered, it is indicating that its corresponding activity has been completed at that time. Based on the dependencies also defined in Table 23, one can conclude that any activity with all of its predecessor activities completed, has been started. By applying this logic, all activities can be labeled as not started, in process, or completed. One ambiguity remains: it is not possible to conclude whether a "not started" activity has started or if a "in process" activity has been completed because the relevant percept data might not have been acquired yet. An activity recorded as not started could have already started, and an activity that is in process could have already finished.

To account for this time lag between capturing and recording data, the latest percept update time for each completion condition of each activity needs to be recorded. In such a way, any information that is carried in the integrated sensing database is accompanied by a timestamp that clarifies its currency.

To make sense of the timeline of the operation, each completed activity must be given a start time, a completion time, and an observed duration each time. The completion time will be directly sourced from the percepts that fulfill the completion conditions, and the start time can be sourced as the maximum completion on the predecessor activities. Similarly, each activity labeled “in process” can be given a definite start time.

This process is exemplified in Figure 35 and Table 24, with a focus on activity B. First, at each integrated sensing update, the state of predecessor activities A and B is assessed. At 32s and 35s, the completion percepts for activities A and B, respectively, are triggered. That data is recorded at the integrated sensing update at 40s, noting the time of data acquisition. Since the predecessor activities A and B are complete, the ISD at 40s knows activity C started at 35s. At 80s, the ISD also records that the completion percept for activity C was triggered at 72s. With this information, it is possible to infer the start, end, and duration of activity C as precisely as the percepts allow.

Table 24: Example of integrated sensing updates for activities A, B, and C in Figure 35

Integrated Sensing Update (seconds)	Predecessor Activity A		Predecessor Activity B		Activity C					
	State	Latest Percept Update	State	Latest Percept Update (seconds)	Predecessors Completed?	State	Latest Percept Update (seconds)	Start Time	End Time	Duration
0	In Progress	n/a	In Progress	n/a	False	Not Started	n/a	n/a	n/a	n/a
10	In Progress	n/a	In Progress	n/a	False	Not Started	12	n/a	n/a	n/a
20	In Progress	17	In Progress	15	False	Not Started	12	n/a	n/a	n/a
30	In Progress	17	In Progress	15	False	Not Started	28	n/a	n/a	n/a
40	Comple-ted	32	Comple-ted	35	True	In Progress	28	35	n/a	n/a
50	Comple-ted	48	Comple-ted	35	True	In Progress	42	35	n/a	n/a
60	Comple-ted	48	Comple-ted	55	True	In Progress	58	35	n/a	n/a
70	Comple-ted	62	Comple-ted	55	True	In Progress	58	35	n/a	n/a
80	Comple-ted	78	Comple-ted	75	True	Comple-ted	72	35	72	37

The greater the update rate of the integrated sensing database and data acquisitions, the smaller the discrepancy between the real-world behavior and the recorded observations. Nonetheless, it is important to recognize that the computerized system works with imperfect information. Even when the time lag between data capture and recording becomes too small for a human to notice, it is still relevant to a computerized system. Just as cleaning data is a critical part of a data analysis, carefully designing the mechanisms of the integrated sensing database is fundamental to the system described in this report.

In addition, the integrated database needs to append any concurrent metadata that could be used to assess an operation, not just its activity durations and timeline. Any relevant cost rate provided by the percepts will be essential in evaluating the cost-effectiveness of the operation. Any categorical information (i.e., aircraft type, airline, gate) is also relevant towards predicting future behavior.

5.7 Long-Term Memory

Each time an operation is finished, the integrated sensing database created to describe it will be completed. The reported activity durations, rates, and metadata at the last observation for an operation can be stored in a long-term memory. This is essentially a database containing consistent and organized data describing how past operations unfolded. No computations need to be made in this module; it simply produces a database that can be leveraged for assessment and prediction purposes.

The acquisition of data for the long-term memory only needs to occur once at the conclusion of each operation. There is no need to collect incomplete information in the middle of the operation, as the data from the long-term memory will only be used for future operations.

Since gate operations have a lot of variety, only a large amount of previous data will be able to sufficiently represent the potential outcomes of operations. If the system is not provided with data, it will take time to collect enough observations to provide an accurate representation.

In the case of the explanatory model in Figure 34, a snippet of the long-term memory is shown in Table 25.

Table 25: Example for long-term memory in reference to model in Figure 34 with 10 operations

Op #	**Activity Duration (min)**										**Actuator (min)**		**Cost Rate ($/min)**		
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**X**	**Y**	**GP**	**APU**	**Opportunity**
1	1.3	1.7	1.2	0.8	3.2	5.3	15.4	21.2	25.3	1.2	0.0	20.5	0.04	1.5	60
2	2.4	1.9	1.7	1.2	2.0	2.0	17.3	19.4	23.9	1.1	0.0	26.3	0.04	1.5	60
3	2.1	1.9	1.3	0.9	2.3	2.9	21.1	19.8	22.2	2.2	0.0	29.4	0.04	1.5	60
4	1.6	2.8	1.9	0.8	4.2	2.3	13.9	20.9	24.6	1.9	0.0	21.8	0.04	1.5	60
5	1.7	1.7	1.8	1.0	1.9	3.4	16.9	18.9	19.0	1.5	0.0	24.7	0.04	1.5	60
6	1.7	2.2	1.1	0.9	3.9	2.0	16.2	24.7	22.0	1.5	0.0	27.9	0.04	1.5	60
7	2.0	2.4	2.0	1.3	3.4	4.9	20.3	21.8	22.7	2.8	0.0	27.6	0.04	1.5	60
8	1.4	1.9	1.3	1.1	2.7	3.5	17.2	16.3	25.2	1.3	0.0	20.8	0.04	1.5	60
9	1.9	2.5	1.4	0.9	3.0	4.1	14.0	23.6	21.1	1.2	0.0	22.8	0.04	1.5	60
10	2.3	2.1	1.8	1.0	4.2	3.8	18.7	20.7	24.2	1.5	0.0	24.8	0.04	1.5	60

5.8 Prediction Models

To make decisions that minimize expected costs, the computerized system needs to be able to predict the use and cost rates of resources during an operation. Only a limited number of parameters in the integrated sensing database and a set of historical data from the long-term memory are available to make the predictions. A modeler can formulate segmented models to predict any missing future values, using historical data to train their models and integrated sensing data to apply their models on the operation occurring. In this module, the prediction models are trained so that they can be applied in the simulation optimization module sections. The data and types of models can vary significantly, and it is the modeler's role to make the predictions as realistic and accurate as possible.

Predicting the duration of the activities in a turnaround operation is crucial for simulating how they will unfold. To predict the missing information from activities that are in process or have not started, we first assume that past results for similar operations will be good indicators for what will occur in the future. The simplest model to do this would take averages for the durations of each activity, but the stochasticity of the activity durations would be lost. This report uses a particle scattering method for making duration predictions, also called the Monte Carlo method. It is achieved by describing the durations of each activity as predictor functions that work by randomly sampling from the list of durations for each activity in the long-term memory. When running simulations with such predictor functions, only a specific duration would be returned for each function.

The representative list of activity durations drawn from the long-term memory would contain a set of all durations that respect the conditions of the present time. At any point during an operation, the computerized system can conclude one of three things about the duration of any activity:

- If the activity is labeled **completed**, its duration will be equal to what has been observed. No need to predict what has already occurred.
- If the activity is labeled **in process**, its duration will be greater than the interval of time between its start and its latest percept update; otherwise, it would be already completed.
- If the activity is labeled as **not started**, there is no bound on its duration.

As an activity is in process, the population of potential durations that would represent the duration for that activity would progressively decrease, as shown in Figure 36. It could occur that the activity's duration exceeds all previously observed values, in which case there would be no historical data to sample from. In this edge-case scenario, the system would default to using the minimum possible duration, equal to the present time minus the start time.

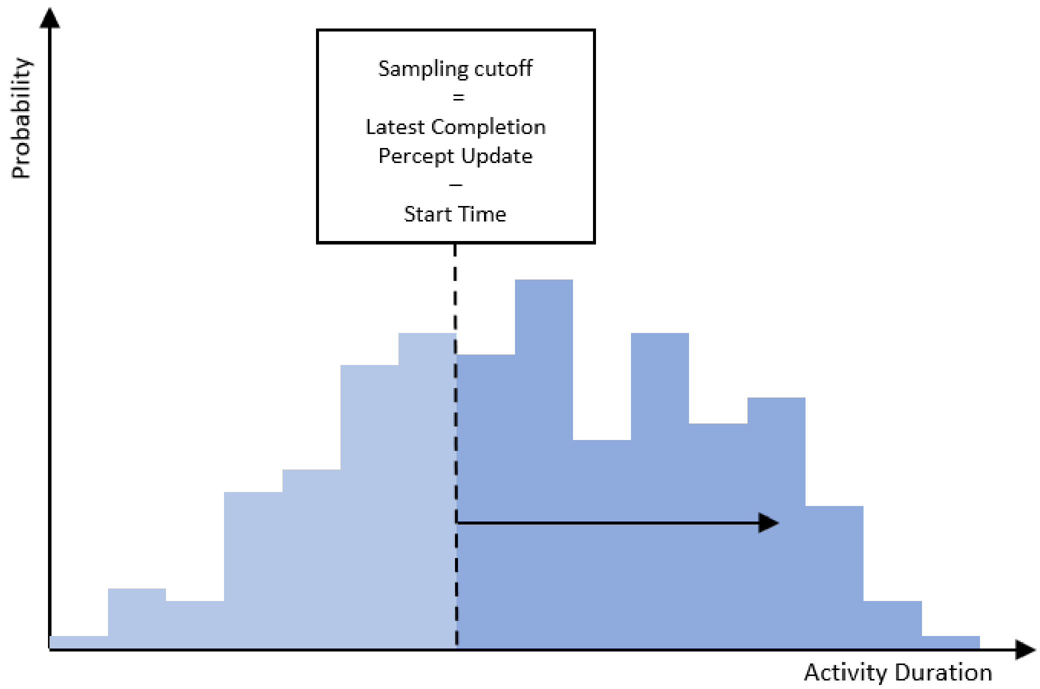


Figure 36: Decreasing sample of durations for an activity as the operation progresses

The other data that are provided within the long-term memory (e.g., cost rates, consumption rates) can also be valuable for creating informative predictions. This can be seen in Section 3, where a neural network is used to predict future power demand from aircraft. The type of prediction model can be chosen by the modeler, with the overarching trait of leveraging the long-term data as representative or training data. In the case of (Achatz Antonelli et al., 2020), several machine learning models (e.g., neural networks, linear regressions, random forests) were trained, tested, and compared to predict GP power demand based on aircraft model, airline, and gate.

For simplicity, this section will use the assumption that cost and consumption rates are constant. Based on the Phase 1 research, the cost rate used for APU use will be assumed to be $90/hr, which is representative of the typical monetary and environmental cost of running the APU at the gate for a narrow-body aircraft. Similarly, the cost rate for GP will be considered $2.4/hr. The opportunity cost will be considered $60/min. These are ball-point values that can be used to demonstrate the adaptive scheduling system without entertaining the variability of different aircraft, changing electricity costs, changing fuel costs, etc.

In an actual application, it is important to leverage all the long-term data available to make accurate predictions, customized for the circumstances of each operation. In the case of activity durations, the models can be improved by having them branch out depending on the data filters used from the long-term database. That will reduce the size of the training data that can be leveraged for each filter combination, but it will provide a more representative prediction. Some examples of these filters could be aircraft subtype and airline, as they have a substantial impact on resource consumption rates and activity durations.

It is also possible to use the durations of previous activities as features in the prediction models to represent how different activities might have dependent durations. For example, a modeler might want to model that the duration for “Jet Bridge Disconnect” is dependent on the duration for “Jet Bridge Connect” and use that as a feature in the model. For simplicity, in this report it is assumed that activity durations are independent.

In some cases, the prediction of a specific variable can be provided by an external information system. If those predictions are shared in real time, like a percept, they can be directly leveraged within the system described by this report. The expected duration of the “Gate Hold” activity is determined by external decisionmakers and could not be predicted solely by the data in the integrated sensing database. However, those external decision makers can provide real-time predictions of the duration of the activity. A scheduled pushback time on the continuously updated AODB is a prediction of the end of the “Gate Hold” process. This becomes an especially important concept when considering how the system discussed in this report works in conjunction with other real-time, decision-making systems already functioning in airports.

5.9 Simulation Optimization

The simulation optimization module integrates the process model, the prediction models, and the integrated sensing modules to determine whether any percept should be triggered. The simulation optimization module is run every time there is an update in the integrated sensing database. As the whole operation unfolds, any new information will generate a new optimal solution, and it will be replaced as more information comes in.

The purpose of using a simulation is to make realistic scenarios of what could occur in the future by leveraging available information from the past and present. The future scenarios generated are highly variable because the simulation is based on stochastic models. By themselves, those scenarios of the future would seem random, making it hard to determine what action is best for an uncertain future. However, a large population of probable future scenarios that show a trend can allow the system to decide on the best action.

In practice, the simulation optimization module runs many simulations each time it is activated to predict the best actuator. By running numerous simulations with constant initial parameters, it is possible to observe how those parameters perform on average. If the parameters are altered, the results from those simulations can be used to measure how those parameters compare to each other and which parameter works best. The parameters that are being tested should be those that can be practically influenced, namely the actuators. This approach is "scenario picking," a simple, depth-first search strategy that could then be improved by using more elaborate search methods and heuristics.

In the initial example used in this report (Figure 34), the only parameter that can be influenced by an actuator is the time at which the pilots and ground crews receive a signal to start up the ground power disconnection. This is the condition "GP Hold Release" that would be triggered as an actuator within the computerized system. So, the objective of the entire adaptive scheduling system is to identify when that trigger should go off. Each time the simulation optimization is completed, it should provide the timestamp at which the release would achieve the minimum expected cost. If this timestamp is greater than the present time, the release will not be triggered. If the timestamp is equal to or less than the current timestamp, it should be immediately triggered. However, there is no way to influence the past, so the only timestamps that need to be considered are those equal to or greater than the present time.

To find the best parameter values, the algorithm behind the simulation optimization module needs to be able to (i) generate a deterministic scenario and then (ii) evaluate it. In other words, before any cost analysis can be applied, every instance of the simulation needs to be complete with all relevant numerical data (activity duration, cost rates, parameter values) that describe it from start to finish. The instance of the simulation needs to be constructed from a combination of the results that have already been observed and the values that are yet to be decided or observed. First, an independent copy of the latest line in the integrated sensing database needs to be created. Then, the duration of the parameter being tested for must be set. Some of the activities will be completed and will have a defined start time, end time, and duration, so alterations will be limited. Some activities will be in-process and will have a defined start time, but their end time must wait to be determined. To find their duration, the prediction model for those specific activities may be leveraged to return a single numerical duration. Once that is done, those activities that were in progress can be marked as complete. That enables successor activities to start once all dependencies are fulfilled. Similarly, those newly-started activities will be associated with a specific duration and will be marked as complete. This algorithm proceeds iteratively until the end of the entire instance of the operation, where every activity can be marked as complete. Following the dependency structure from Table 22, a simple forward pass using the determinate durations of all activities will provide the exact schedule of that instance. This process is illustrated in the flow chart in Figure 37. By the end of the simulated instance, a single parameter value will be associated with a single schedule.

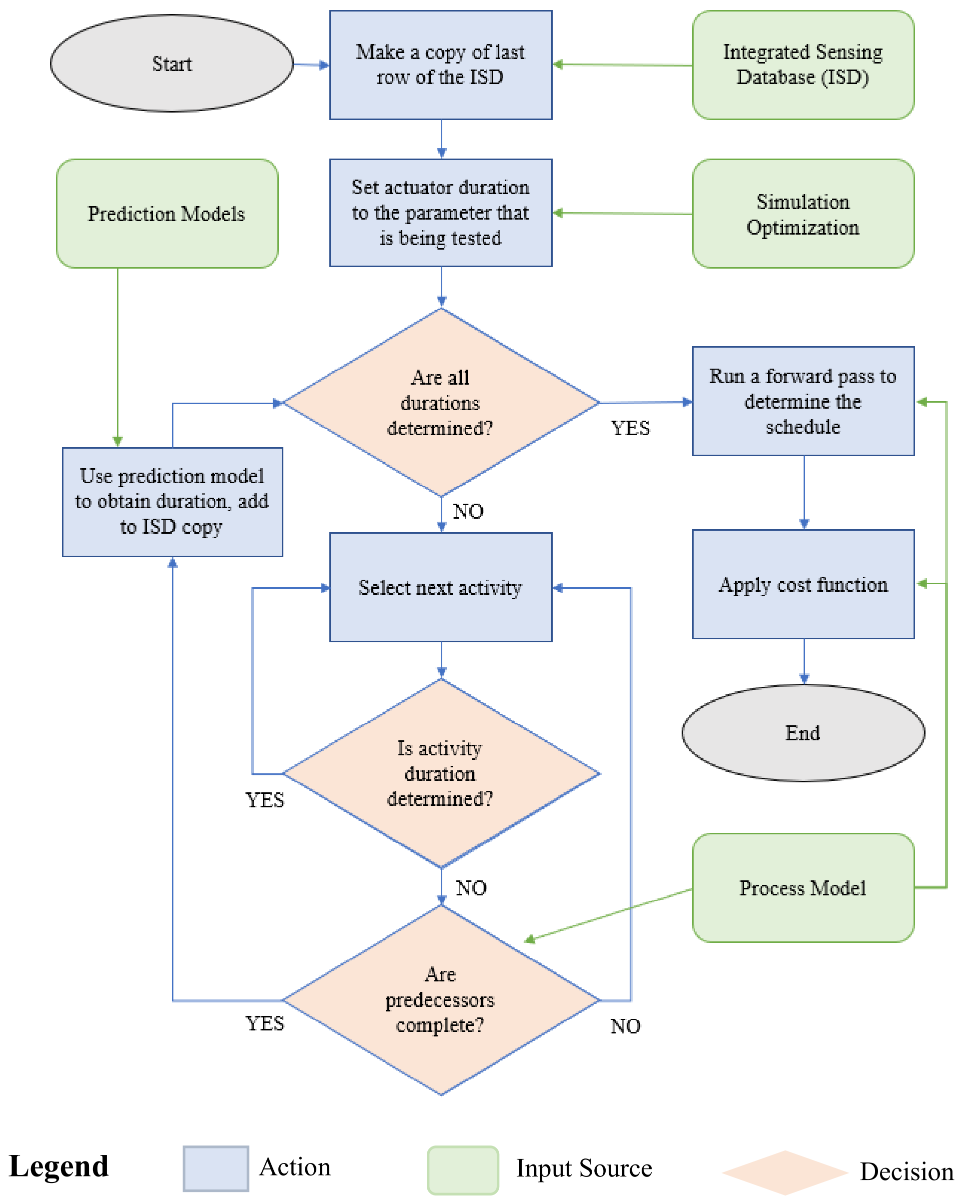


Figure 37: Decreasing sample of durations for an activity as the operation progresses

Along with the schedule, the other variables such as cost rates and consumption rates need to be determined for each simulated scenario. For past quantities, the values can simply be copied over. For unknown future quantities, their relative prediction model will need to once again be leveraged to provide an estimate.

Every defined schedule can be used to generate a cost estimate. Real-world costs can come in many forms, and it is the modeler's responsibility to best represent them in their estimation method. It is crucial that the scope and method for the cost estimate are:

- Comprehensive enough to represent the problem and its interdependencies
- Calculable from the data available in the integrated sensing database for each complete operation
- Objective enough to make quantitative comparisons between different metrics of costs

The cost function provides the foundation on which different parameters may be compared. With the cost function set, individual instances of the operations can be associated with a specific numerical cost, which is used as a metric for comparison. Comparing single instances would not be useful, as the variability caused by the stochasticity of the model would overshadow the influence of the parameter or actuator. To provide a good estimate for expected cost, many independent simulation instances need to be run for the same parameter and compared using the average cost. Additionally, the standard deviation in the total cost for each parameter can describe the variability in cost. Repeating the process for a range of different parameters will provide a curve showing the trend between the parameter and the expected cost, as shown in Figure 38.

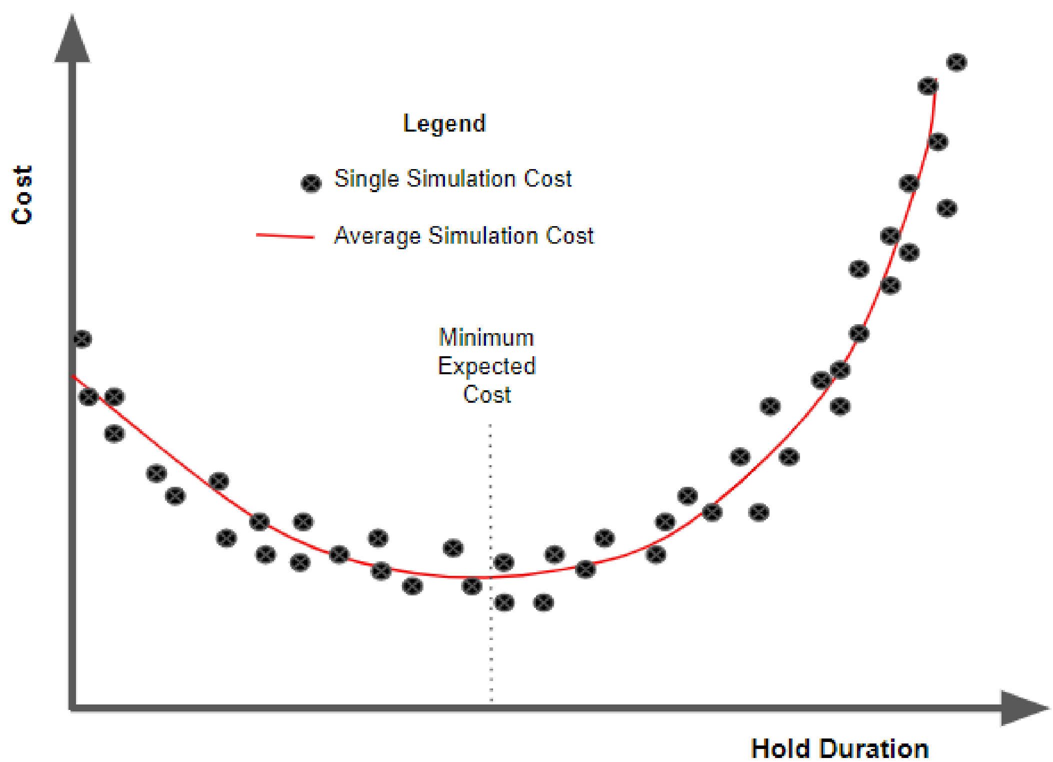


Figure 38: Conceptual diagram for identifying time with minimum expected cost

The range of parameters that are tested and compared needs to be considered. It is important that the range has a domain large enough to represent all possible values. There should also be many parameters spaced together as close as possible to provide a granular insight into the shape of the expected cost. The precision of the optimal parameter being tested can be defined as the step size of the parameter.

The simulation process is by far the most computationally expensive part of the adaptive scheduling algorithm. Every time the integrated sensing database is updated for the many possible parameters in continuous space, the simulation needs to be calculated multiple times. This is an infinitely large search space, and there is a limited amount of time for the computation to produce a result before a new integrated sensing update is delivered. Only a finite number of scenarios can be generated and compared, at the cost of losing precision. As a real-time machine, the overall software needs to equilibrate the precision of the result with its calculability. Its search function needs to strategically balance the search space and number of iterations. There are several ways to cut computing time to make the adaptive scheduler perform better:

- Parallelizing the calculations of the expected cost-independent simulation; running separate simulations on separate CPU cores or leveraging the power of cloud computing.
- Avoiding unnecessary precision in the calculation of a parameter until its value has a practical impact. For example, there is no need to know the optimal "GP to APU Switch" time with a certainty of 30 seconds if that action occurs in more than 30 minutes. Such precision is only necessary closer to the event time. A cutoff value for the precision in the duration of the parameter can be set by the following function:

  $$Precision\ Cutoff = \alpha * \left(t_{actuator\ start} + t_{actuator\ duration} - t_{present} + \beta\right) \quad \text{(Eq. 33)}$$

  Where α and β are constants.

- By using a slowly magnifying search space that follows the gradient of the cost curve, not all parameters are expanded with the same number of simulations. For example (Figure 39), the search function can run an imprecise estimate across a sample range parameter, identify the parameters that produce the lowest 30% of expected costs, and repeat the simulation within that smaller range of parameters with twice the number of simulations. Then, repeat the same process many times until the difference in the range of parameters becomes smaller than the precision cutoff, and return the average parameter.

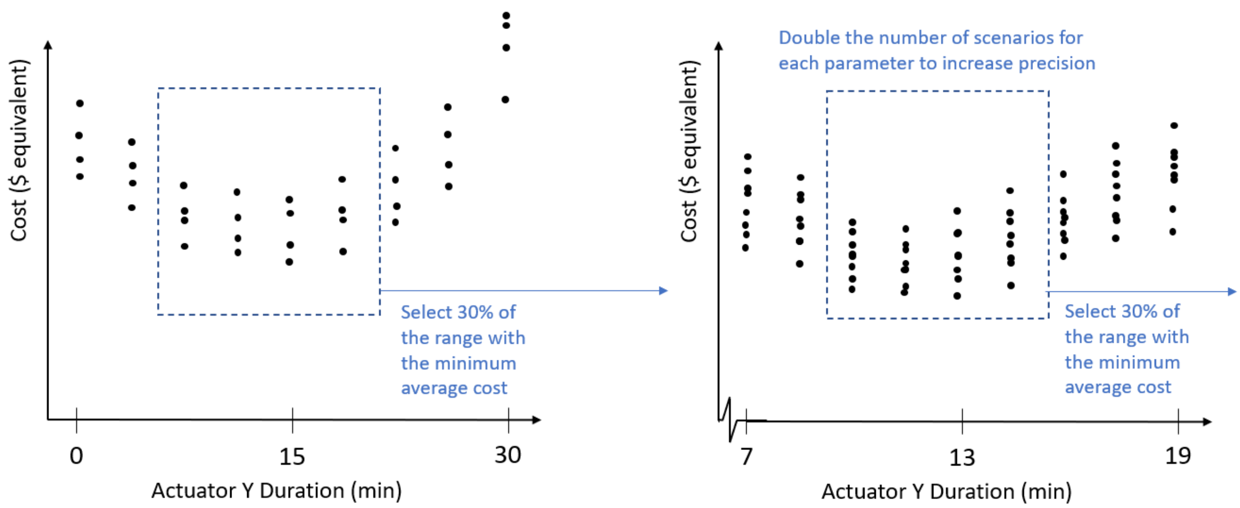


Figure 39: Progressively magnifying the search space while increasing precision

5.9.1 Simple Model Example

For the process model in Figure 34, the cost function considers only the costs that are most impactful to the GP use process and are within the scope of gate decision making. Operational costs for providing power are a major component. The opportunity cost will be constant through time, representing the value lost from keeping an aircraft at the gate. The cost of delay will be excluded. Labor costs are excluded since the team for each operation is assumed to always be present. Table 26 summarizes how to calculate the different components of cost. Table 27 provides an example for 10 simulation runs; thousands more would be necessary to identify the best actuator value.

Table 26: Simple cost estimate methodology for model in Figure 34

Cost	Description	Calculation Method
Operational Cost of GP	The monetary cost of GP used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{GP}} * Duration\ Y$ Where $CostRate_{GP} = \$2.4/hr$
Operational Cost of APU	The monetary cost of the APU used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{APU}} * (Total\ Duration - Duration\ Y)$ Where $CostRate_{APU} = \$90/hr$
Opportunity Cost of Turnaround Operation	The lost monetary gains by keeping aircraft at the gate.	$\text{Cost} = \text{CostRate}_{\text{Opportun.}} * Total\ Duration$ Where $CostRate_{Opprtun.} = \$3600/hr$

Table 27: Example for application of the cost function for model in Figure 34

Op #	Total Duration (min)	Actuator Y Duration (min)	Cost Rate ($/min)			Cost ($)			Total Cost ($)
			GP	APU	Opportunity	GP	APU	Opportunity	
1	39.1	20.5	0.04	1.5	60	0.82	28	2346	2375
2	40.2	26.3	0.04	1.5	60	1.05	21	2412	2434
3	45.2	29.4	0.04	1.5	60	1.18	24	2712	2737
4	38.3	21.8	0.04	1.5	60	0.87	25	2298	2324
5	39	24.7	0.04	1.5	60	0.99	21	2340	2362
6	44.1	27.9	0.04	1.5	60	1.12	24	2646	2671
7	46.9	27.6	0.04	1.5	60	1.10	29	2814	2844
8	36.2	20.8	0.04	1.5	60	0.83	23	2172	2196
9	40.7	22.8	0.04	1.5	60	0.91	27	2442	2470
10	43.2	24.8	0.04	1.5	60	0.99	28	2592	2621

5.10 Actuators

Actuators are the means by which the computerized system has an influence on the real world. Understanding which actuators may be leveraged is crucial for designing the real-time computerized system.

Actuators vary considerably in their form and effectiveness. Even if all other modules of the computerized system work perfectly, there is still no guarantee that the actuators will work reliably in the intended way. The functional and behavioral mechanisms behind any actuator, along with their shortcomings, need to be understood for the actuator to be better designed and interpreted.

In the case of this report, the actuators that have an impact on the real world are all triggers for satisfying a condition or initiating an activity.

5.10.1 Informational Signals for Humans

One of the simplest actuators is an instantaneous signal or communication that affects the human-centered management of an operation. A radio message sent to a pilot, a symbolic light signaling an action to the ground crews, or an informal knock on the aircraft hull are all examples of communications that affect the behavior of the agents in an operation and therefore its execution. If some of these communication strategies are implemented and standardized, they can serve as the actuators of the computerized system. The algorithm can take charge of when to send those signals, and they can have a direct impact on the schedule.

With these informational signals, there is no guarantee that action will take place as modeled. There are several factors that could get in the way of an idealistic cause-effect relationship between actuators and reality. For example, the signals could be unseen, unheard, or misunderstood. The appropriate actuator response could be delayed, or the people that interact with any signal could decide not to abide by it for external reasons (e.g., safety, maintenance). In the design of the actuating mechanism and the standardization of gate processes, these discrepancies may be mitigated, but not completely avoided. The signal should be provided in an immediate, noticeable, and unmistakable way. The actuator should ideally focus on the act of providing that signal and not the actions that follow, so that the signal can be instantaneous.

In the context of gate operations and the model in this report, the main actuator is a simple signal that tells the pilots to start spinning up the APU engine. This could be either a signal that indicates not to perform the action just yet or to perform it right away. The signal should be continuous, so it gets instant attention and does not get missed. Although further user research would be required, this report proposes that one of the following strategies could be used:

- A light within the cockpit, although that could be easily missed.
- A flashing light on the apron area, visible to the pilot from the cockpit.
- A beeping sound with incremental volume.
- A radio message to the cockpit.

In the model in Figure 34, the actuator GP to APU power is simple. It assumes that the moment the actuator is triggered, the APU immediately turns on, skipping several steps in between. In a realistic operation, when the actuator signal is initiated, the pilot needs to notice and decide to turn on the APU, and only after a few minutes will the APU have reached a spinning rate sufficient for providing power. If there were percepts available to determine the pilot's reaction time and the spinning time of the APU, the actuator signal could be separated from these additional activities in a more complex model. This report chooses to keep the model and actuator simple for the purpose of explanation.

5.10.2 Confidence Interval Countdown

An actuator does not need to be limited to a signal given at the optimal trigger time. Asking human agents to react immediately to a trigger that could go off at any moment would lead to stress and uncertainty, the opposite goal of what adaptive scheduling means to achieve. Providing the agents with an estimate of when their action is needed is crucial to allow them to prepare, enabling them to confidently take value from the signal.

A regularly updated countdown or time estimate for each relevant trigger would need to be communicated to the relevant agents. This could be provided through a display, such as that of a phone app or dashboard. As the schedule adapts, the time on the countdown would fluctuate and converge on its final value as the time is reached. Once the time is reached, the same mechanisms as described in 5.10.1.1 would occur.

To provide further insight into the changing schedule, the agents can also be provided with a confidence interval for the actuator time. As the operation progresses, the uncertainty decreases, and so does the confidence interval. This would enable the agents to know how much their schedule could deviate from their expectations, so they can plan accordingly and mitigate the risk of unexpected challenges.

5.10.3 Iteratively Updated Schedule

Since the computerized system already goes through the effort of simulating many scenarios and generating a cost-optimal schedule, it is valuable to show its results as intuitively and comprehensively as possible. Not every agent needs to know the actuators for every other agent of the operation; that could lead to unnecessary confusion. However, a visual representation of the probable schedule provides a holistic view of the operation that could provide value. A schedule would facilitate communication, an understanding of the interrelated activities and agents, and a more insightful understanding of how the adaptive computerized system is changing the operation.

The changing schedule would have to be shown digitally, such as through an app or a dashboard. A Gantt chart with the most probable scenario would be able to show the activity flows and times, although the cascading variability in the activity times would be more difficult to represent. An interactive activity flow chart could show those variabilities. It could illustrate these fluctuations, allowing individuals to be presented with the distributions in an activity's start and end times.

5.11 Multiagent Simulation

So far, the concept of an adaptive scheduling AI has only been applied to the simple decision of when to turn on the APU. Besides the bold assumptions that were made, the model in Figure 34 is not representative of the complex processes occurring at the gate. It ignores the influence of other concurrent decision-making mechanisms. The model simplifies the percepts and activities to the extent that there are few data points that can be used to adapt the schedule, limiting the cost savings. To apply adaptive scheduling effectively, the process model needs an upgrade that will dissect the operation further and that will consider the influence of other decisions.

This section proposes two improvements on the same system architecture described in Sections 5.5 through 5.10, but with a different model structure and complexity. This shows how the adaptive scheduling framework is modular in its components and customizable depending on the scope and focus of the problem.

5.11.1 Including Gate Hold

In real airport operations, there is a schedule that gate operations need to abide by so that the airport can maximize airside turnaround processes through gate assignment, taxiway movements, and runway usage. There is a dichotomy present; airports want to bolster their operation frequency as much as possible to increase airport capacity, but they do not want to schedule operations so tightly that they end up with chaotic delay and congestion. That real-time, deciding management role is fulfilled by airline, ATC, or ACDM systems at airports. Their decision to hold an aircraft at the gate is far more consequential in terms of total costs than the decision of when to initiate the APU. However, those decisions are intertwined. Holding an aircraft to the gate changes the optimal time at which to start the APU, and waiting to start the APU could affect the gate hold by causing a delay. While these decisions are being made by different parties, their impact is interdependent.

In the model in Figure 34, Actuator X, the “Gate Hold,” was originally set to 0 min. An aircraft would leave as soon as it was detached from the jet bridge, refueled, and had the luggage handled. In this section, “Gate Hold” is introduced as a second actuator that somewhat imitates the role of ATC. The goal of this actuator is to set an expected completion time for the operation and resist changes to the schedule unless they are necessary. Aside from this Actuator X, no new activities or percepts are introduced.

The cost function needs to change to be representative of the new model and behavior of ATC. Aside from the cost elements from the previous model, two new elements are introduced. The first is the monetary cost to reassign the gate hold time, which requires keeping a count of the reassignments in the ISD. The second is the additional monetary cost of missing the gate-hold time given by ATC, which causes further delay. Table 28 shows the calculation method for each cost element.

Table 28: Simple cost estimate methodology for model in Figure 34

Cost	Description	Calculation Method
Operational Cost of GP	The monetary cost of GP used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{GP}} * Duration\ Y$ Where $CostRate_{GP} = \$2.4/hr$
Operational Cost of APU	The monetary cost of the APU used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{APU}} * (Total\ Duration - Duration\ Y)$ Where $CostRate_{APU} = \$90/hr$
Opportunity Cost of Turnaround Operation	The lost monetary gains by keeping aircraft at the gate	$\text{Cost} = \text{CostRate}_{\text{Opportun.}} * Total\ Duration$ Where $CostRate_{Opprtun.} = \$250/hr$
Slot Time Reassignment Cost	The cost of changing the gate hold time once it was assigned	$\text{Cost} = \text{CostRate}_{\text{Slot}} * (\#\ of\ Reassignments - 1)$ Where $CostRate_{Slot} = \$1{,}000$
Original Cost of Delay	The cost of remaining at the gate past the gate hold time originally scheduled	$\text{Cost} = \text{CostRate}_{\text{OriginalDelay}} * Max(0, \text{OffBlockTime} - \text{OriginalGateHoldEnd})$ Where $CostRate_{OriginalDelay} = \$12{,}000/hr$
Marginal Cost of Delay	The cost of remaining at the gate past the latest gate hold time that was scheduled	$\text{Cost} = \text{CostRate}_{\text{MarginalDelay}} * Max(0, \text{OffBlockTime} - \text{FinalGateHoldEnd})$ Where $CostRate_{MarginalDelay} = \$6{,}000/hr$

In this upgraded model, two actuators must be determined to optimize the expected cost. Instead of solving a two-variable optimization problem to find an absolute minimum cost, this report suggests optimizing each variable independently and iteratively. The percepts, the process model, and the prediction models remain the same. In Section 5.9, Actuator X, the "Gate Hold," is optimized last since it has the greatest influence on the total cost. The simulation optimization runs through while keeping Actuator Y constant, initially setting it at 0. Once an optimal X is found, it is held constant, and the same process is repeated for Actuator Y. Once new information comes in, the process is repeated, and the combination of X and Y will slowly migrate towards scenarios with a lower expected cost.

Although the same model and information are used to optimize both actuators, this process can be seen as two independent agents. Each agent is performing a single-variable optimization based on the same data. The actuators of one agent are the percept of the other, and vice versa; they communicate their results.

5.11.2 Complex Multiagent Model

With a wider array of percepts to infer what is happening during the operation and actuators to influence it, complex models can be formulated. These models can start resembling the real world much more closely and in detail, while also considering the interdependencies of several decision-makers. Therefore, they are more effective at using the adaptive scheduling framework.

Figure 40 shows a complex model with 10 different actuators. This model expands the scope to include the approach to the gate and several new ground-handling processes: safety chock handling, PCA handling, passenger movements, catering, cleaning, and water servicing. It is assumed that passengers require working PCA when they are onboard.

The underlying assumption of the model is that there are effective percepts and actuators available to infer the state of each activity in the model. Similar to Table 22, each activity can be associated with a completion percept using one of the percepts in Section 5.4.

The cost function becomes more complex. In this model, different cost rates for different APU use rates were dissected: only bleed air, only electricity, both, and idle. Several cost factors were also added to the other ground handling activities, favoring activities that are completed at the latest responsible moment. The cost function is summarized in Table 29. The exact cost multipliers can be altered to represent the circumstances and priorities defined by specific airports and airlines.

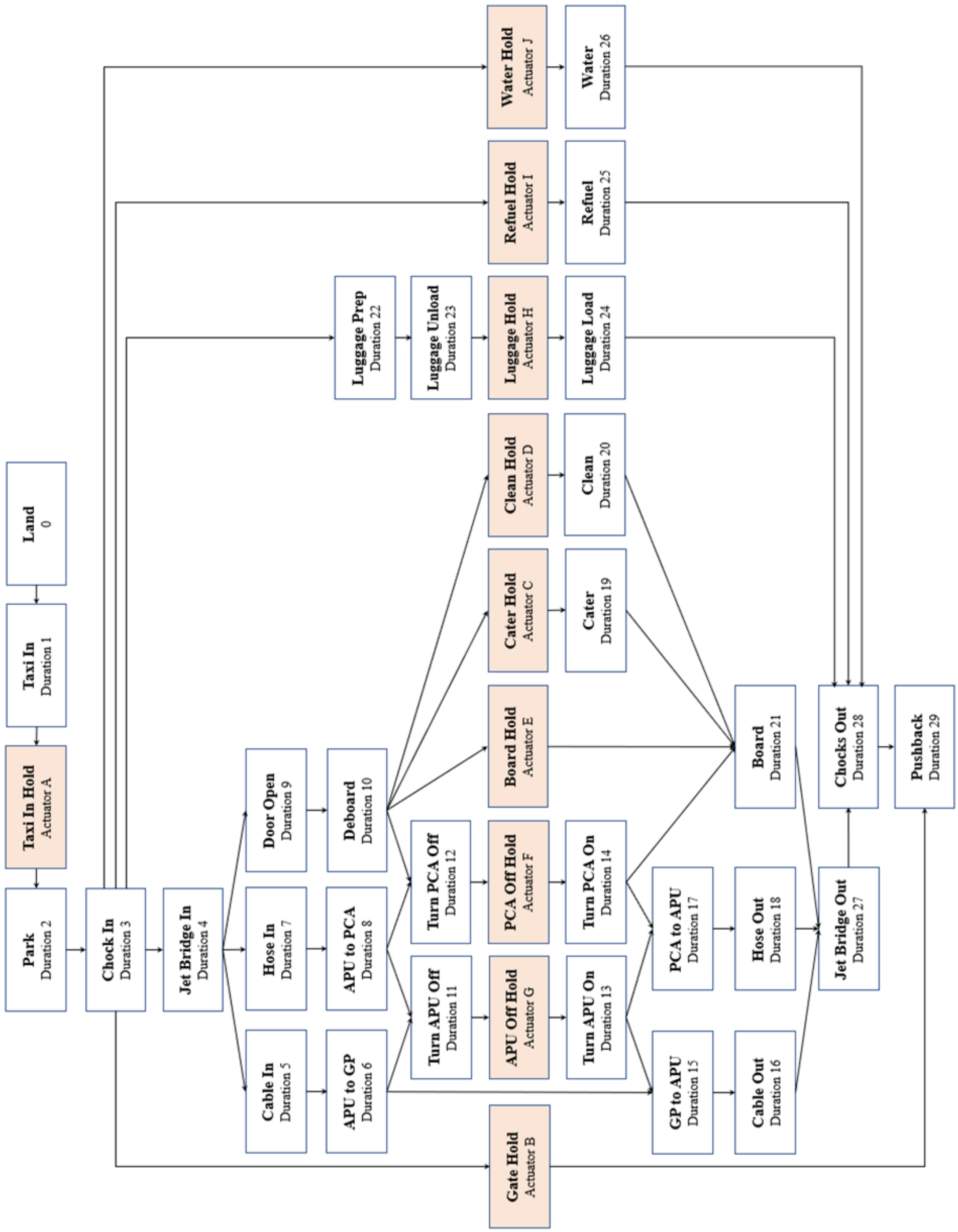


Figure 40: Complex process model with multiple actuators

Table 29: Cost function for complex model

Cost	Description	Calculation Method
GP	The monetary cost of GP used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{GP}} * (GPtoAPUend - APUtoGPend)$ Where $CostRate_{GP} = \$2/hr$
PCA	The monetary cost of the PCA used, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{GP}} * ((PCAtoAPUend - TurnPCAOnend) + (TurnPCAOff - APUtoPCAend))$ Where $CostRate_{GP} = \$10/hr$
APU No Load	The monetary cost of the APU used on the no-load setting, assuming the cost is based on duration of usage	$\text{Cost} = \text{CostRate}_{\text{APUNL}} * ((APUOffstart - \max(APUtoGPCend, APUtoPCAend)) + (\min(GPtoAPUend, PCAtoAPUend) - APUOnstart))$ Where $CostRate_{APUNL} = \$50/hr$
APU Air Only	The monetary cost of the APU used on the air only setting, assuming the cost is based on duration of usage	$Cost = CostRate_{APUAir} * (\max(0, APUtoPCAend - APUtoGPend) + \max(0, GPtoAPUstart - PCAtoAPUstart))$ Where $CostRate_{APUAir} = \$75/hr$
APU Power Only	The monetary cost of the APU used on the power only setting, assuming the cost is based on duration of usage	$Cost = CostRate_{APUPower} * (\max(0, APUtoGPend - APUtoPCAend) + \max(0, PCAtoAPUstart - GPtoAPUstart))$ Where $CostRate_{APUPower} = \$70/hr$
APU Air and Power Combined	The monetary cost of the APU used on the air and power combined setting, assuming the cost is based on duration of usage	$Cost = CostRate_{APUCombined} * (\min(APUtoGPend, APUtoPCAend) - ChockInend + ChockOutstart - \max(GPtoAPUend, PCAtoAPUend))$ Where $CostRate_{APUCombined} = \$100/hr$
Boarding Decay	The indirect cost associated with hosting passengers within the aircraft before departure	$\text{Cost} = \text{CostRate}_{\text{Board}} * (ChockOutstart - Boardstart)$ Where $CostRate_{\text{Board}} = \$30/hr$
Catering Decay	The indirect cost associated with holding catering resources prior to departure.	$\text{Cost} = \text{CostRate}_{\text{Cater}} * (ChockOutstart - Caterstart)$ Where $CostRate_{\text{Cater}} = \$20/hr$
Cleaning Decay	The indirect cost associated with keeping the aircraft clean before departure	$\text{Cost} = \text{CostRate}_{\text{Clean}} * (ChockOutstart - Cleanstart)$ Where $CostRate_{\text{Clean}} = \$1/hr$
Refuel Decay	The indirect cost associated with holding fuel in the aircraft before departure	$\text{Cost} = \text{CostRate}_{\text{Refuel}} * (ChockOutstart - Refuelstart)$ Where $CostRate_{\text{Refuel}} = \$1/hr$

Water Decay	The indirect cost associated with holding water in the aircraft before departure	$\text{Cost} = \text{CostRate}_{\text{Water}} * (ChockOutstart - Waterstart)$ Where $CostRate_{\text{Water}} = \$1/hr$
Luggage Decay	The indirect cost associated with holding the luggage in the aircraft before departure	$\text{Cost} = \text{CostRate}_{\text{Luggage}} * (ChockOutstart - LuggageLoadend)$ Where $CostRate_{Luggage} = \$40/hr$
Opportunity Cost of Turnaround Operation	The lost monetary gains by keeping aircraft at the gate.	$\text{Cost} = \text{CostRate}_{\text{Opportun.}} * Total\ Duration$ Where $CostRate_{Opprtun.} = \$250/hr$
Slot Time Reassignment Cost	The cost of changing the gate hold time once it was assigned	$\text{Cost} = \text{CostRate}_{\text{Slot}} * (\#\ of\ Reassignments - 1)$ Where $CostRate_{Slot} = \$1{,}000$
Original Cost of Delay	The cost of remaining at the gate past the gate hold time originally scheduled	$\text{Cost} = \text{CostRate}_{\text{OriginalDelay}} * Max(0, ChockOutstart - \text{OriginalGateHoldEnd})$ Where $CostRate_{OriginalDelay} = \$12{,}000/hr$
Marginal Cost of Delay	The cost of remaining at the gate past the latest gate hold time that was scheduled	$\text{Cost} = \text{CostRate}_{\text{MarginalDelay}} * Max(0, ChockOutstart - \text{FinalGateHoldEnd})$ Where $CostRate_{MarginalDelay} = \$6{,}000/hr$

5.11.3 Hierarchy of Actuator Parameters

The computability of the adaptive scheduling framework becomes more challenging as more actuators are introduced in the model. In theory, it becomes a multivariable optimization problem that can be approached in various ways.

One of the most computationally feasible ways to approach the problem is to iteratively optimize each parameter independently while keeping the others constant, just like in Section 5.11.1. The algorithm described would still be able to perform a gradient descent on the search space, but there would be no guarantee that the result would be an absolute minimum for expected cost rather than a local minimum.

It is important to define the hierarchy of the parameters that are being sequentially optimized. The parameters that are most consequential to the cost should be optimized last in each iteration to obtain the best cost savings with limited computation. For example, the “Gate Hold” has the most consequence and should be optimized last.

5.12 Numerical Demonstration

The system behind adaptive scheduling is explained in a modular and abstract way. To show it provides value, it needs to be tested numerically, and eventually it must be tested in relationship to real operations. In this section, we test a prototype for turnaround operation adaptive scheduling that uses the model in Figure 36.

5.12.1 Simulating Reality

Adaptive scheduling describes how a real-time computer can parse reality through percepts, update its model of that reality, and then control it. Before the system can be applied in the real world, it needs to be tested in a simulated environment. To simulate the real world, an independent model for gate turnaround operations must be used.

For simplicity, the model for the real world would be structured the same way as the model the computer uses to perceive that reality. One model represents what happens, and the other represents what the computer thinks is happening. The only way these two models communicate with each other is through the percepts that the computer uses to infer reality and by the actuators on the reality that the computer enacts at every timestep (Figure 41).

The simulated real-word model can sample activity duration directly from random-variable distributions, whereas the computer model can only collect lists of activity durations while never knowing what the original random variable is. Table 30 shows the random variable distributions used to simulate the real model, many of which were sourced from Asadi et al. (2020).

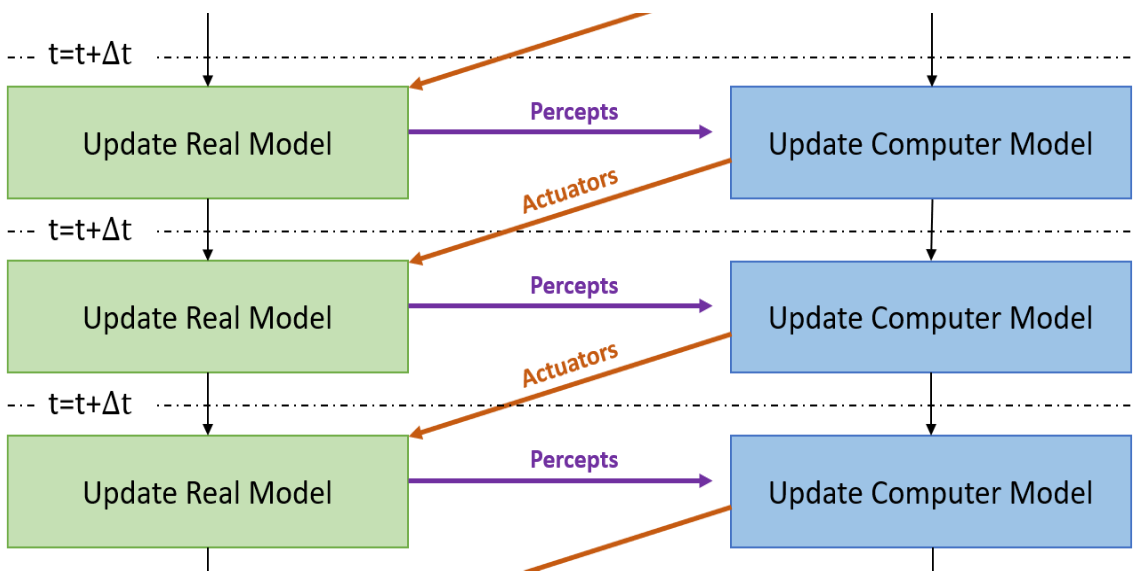


Figure 41: Relationship between real model and computer model

Table 30: Random variable distributions for the durations within the model

Activity Name	Description	Distribution of Duration for Real World Simulation (min)	Distribution Cutoff (min)
Land	Aircraft lands on runway	0	0
Taxi In	Aircraft moves from runway to apron	Normal (10, 2)	2
Park	Aircraft moves from apron to final position	Normal (2, 1)	1
Chock In	Safety chocks are placed behind the wheels	Normal (1, 0.5)	0.5
Jet Bridge In	Jet bridge is connected to the aircraft	Normal (2, 1)	1
Cable In	GP Cable is lowered and connected to the aircraft	Normal (2, 1)	1
APU to GP	Pilot switches power source to GP	Normal (1, 0.5)	0.5
Hose In	PCA Hose is lowered and connected to the aircraft	Normal (4, 2)	1
APU to PCA	Pilot switches to PCA conditioned air	Normal (1, 0.5)	0.5
Door Open	Passenger door is opened	Normal (1, 0.5)	0.5
Deboard	All passengers deboard	Gamma (6.81, 1.47)	2
Turn APU Off	The APU is shut down and comes to rest	Normal (1, 0.5)	0.5
Turn PCA Off	The PCA is turned off to save on air conditioning costs when not necessary	Normal (1, 0.5)	0.5
Turn APU On	The APU is started and progressively reaches its operational rpm	Normal (2, 1)	1
Turn PCA On	The PCA is turned back on for passenger boarding	Normal (1, 0.5)	0.5
GP to APU	The pilot transitions to APU power	Normal (1, 0.5)	0.5
Cable Out	Ground crews disconnect the cable and drag it to the jet bridge	Normal (3, 1)	0.5
PCA to APU	The pilot transitions to bleed air for air conditioning	Normal (1, 0.5)	0.5
Hose Out	PCA hose is disconnected and stowed	Normal (3, 1)	0.5
Clean	Aircraft interior is cleaned	Weibull (2.16, 1) * 11.29	6
Cater	Catering services switch out food carts	Weibull (2.18, 1) * 17.37	4
Board	Passengers board	Gamma (9.12, 1.64)	4
Jet Bridge Out	Jet bridge disconnects and moves away	Normal (2, 1)	1
Luggage Prep	Ground vehicles set up for luggage handling	Normal (2, 1)	1
Luggage Unload	Luggage is unloaded from aircraft	Gamma (11.29, 1.24)	6
Luggage Load	Luggage is loaded in the aircraft	Gamma (15.34, 1.24)	8
Refuel	Aircraft is refueled	Gamma (9.12, 1.64)	4
Water	Wastewater is cleared and new water is added	Normal (6, 2)	2
Chocks Out	Safety chocks are removed from behind the wheels	Normal (1, 0.5)	0.5
Pushback	Tow pushes the aircraft out of the gate	Normal (3, 1)	1

To illustrate that adaptive scheduling is lowering expected costs, it will be necessary to run the simulation model shown in Figure 40 above N times with a timestep of Δt. For each simulation, the expected cost from the computer model will be recorded at every time step. The cost at the conclusion of the operation will show the final cost affected by adaptive scheduling for each simulation. If the activity duration at the conclusion of the operation is combined with the actuator durations at t=0, the cost will be representative of a pre-planned operation with no adaptive rescheduling. If all the actuators are fixed at 0, the cost will be representative of a "push"-managed operation. These different outcomes can be compared to see the savings that adaptive scheduling can bring to each operation.

5.12.2 Testing with an Extensive Long-Term Memory

First, adaptive scheduling is tested with a computerized system with a long-term memory that is already rich with results, representing a late-stage function of the system. To create the long-term memory, it is sufficient to run the real-world simulations, the percept module, the process model module, the integrated sensing module, and the long-term memory module (Figure 42). This serves to quickly acquire data while skipping the computationally heavy simulation optimization module; it is the equivalent of a training and observation period.

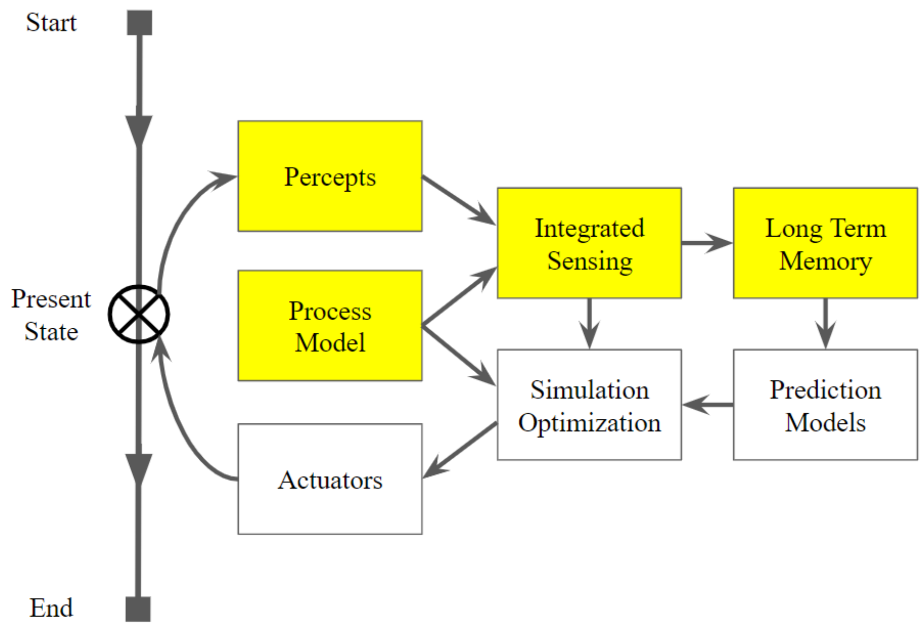


Figure 42: Training for long-term memory (only highlighted modules are necessary)

In this demonstration section, the training period involved 1,000 operations, meaning that each activity has a list of 1,000 durations to pick from. Since there are 30 non-actuator activities, there are $1{,}000^{30}$ combinations of activity durations that this long-term memory can simulate, more than the number of atoms in the universe. Each combination of actuator plus possible activity durations was simulated a minimum of 600 times and a maximum of 4,000 times, depending on the smart search algorithm described in Section 5.9. Although this number is incredibly small in comparison to the total possible schedules, it demonstrated a converging average expected cost.

Appendix Figure A1 and Table A16 illustrate the complete run of a single operation that lasts 72 minutes, estimating the expected cost as it optimizes each actuator every minute. By the end of the operation, all activity durations are known, regardless of the management method. However, the different management methods produce different holds and therefore different schedules, as summarized in Table 31, Figures 43, 44, and 45:

Table 31: Schedules for different management for a sample operation (all quantities in minutes)

Activity	Duration (min)	Adaptive Schedule (min)		Pre-planned Schedule (min)		Push Schedule (min)	
		Start	End	Start	End	Start	End
Land	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Taxi In	12.34	0.00	12.34	0.00	12.34	0.00	12.34
Park	1.07	12.34	13.41	12.34	13.41	12.34	13.41
Chock In	0.96	13.41	14.37	13.41	14.37	13.41	14.37
Jet Bridge In	1.23	14.37	15.60	14.37	15.60	14.37	15.60
Cable In	1.67	15.60	17.27	15.60	17.27	15.60	17.27
APU to GP	0.50	17.27	17.77	17.27	17.77	17.27	17.77
Hose In	3.32	15.60	18.91	15.60	18.91	15.60	18.91
APU to PCA	0.50	18.91	19.41	18.91	19.41	18.91	19.41
Door Open	0.67	15.60	16.26	15.60	16.26	15.60	16.26
Deboard	10.03	16.26	26.29	16.26	26.29	16.26	26.29
Turn APU Off	0.72	19.41	20.13	19.41	20.13	19.41	20.13
Turn PCA Off	0.81	26.29	27.10	26.29	27.10	26.29	27.10
Turn APU On	1.00	59.60	60.60	42.36	43.36	27.10	28.10
Turn PCA On	0.50	30.26	30.76	27.10	27.60	27.10	27.60
GP to APU	2.08	60.60	62.68	43.36	45.44	28.10	30.18
Cable Out	2.52	62.68	65.20	45.44	47.96	30.18	32.70
PCA to APU	1.24	60.60	61.84	43.36	44.60	28.10	29.34
Hose Out	1.91	61.84	63.75	44.60	46.51	29.34	31.24
Clean	9.63	26.29	35.92	26.29	35.92	26.29	35.92
Cater	14.02	26.29	40.31	26.29	40.31	26.29	40.31
Board	27.57	40.31	67.88	40.31	67.88	40.31	67.88
Jet Bridge Out	3.24	67.88	71.12	67.88	71.12	67.88	71.12
Luggage Prep	3.40	14.37	17.77	14.37	17.77	14.37	17.77
Luggage Unload	10.55	17.77	28.32	17.77	28.32	17.77	28.32
Luggage Load	20.13	30.26	50.39	28.32	48.44	28.32	48.44
Refuel	18.02	36.36	54.37	28.72	46.74	14.37	32.38
Water	6.29	56.16	62.45	14.37	20.66	14.37	20.66
Chocks Out	0.94	71.12	72.06	71.12	72.06	71.12	72.06
Pushback	2.03	72.06	74.09	72.06	74.09	72.06	74.09

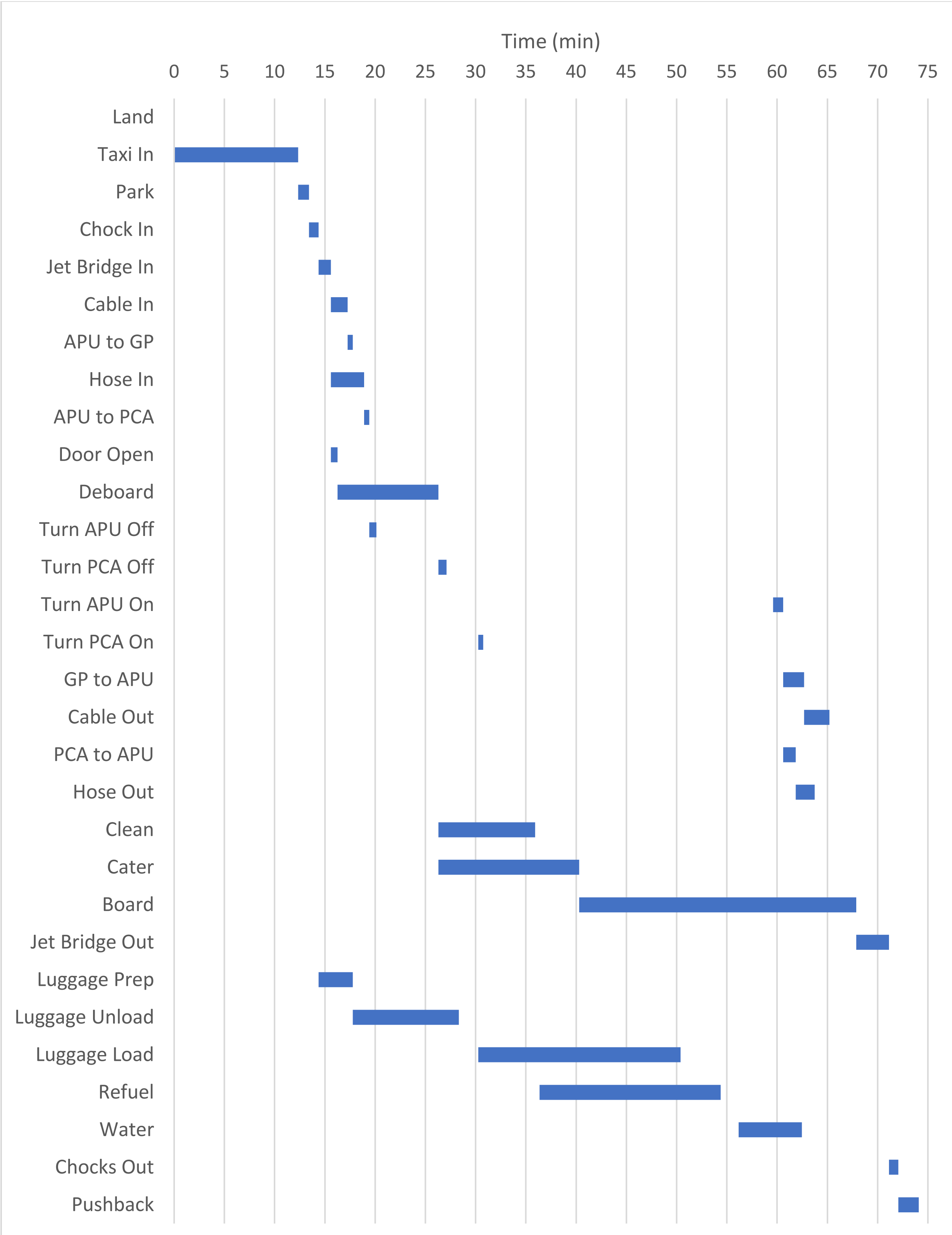


Figure 43: Gantt chart for sample operation when managed by the adaptive scheduler

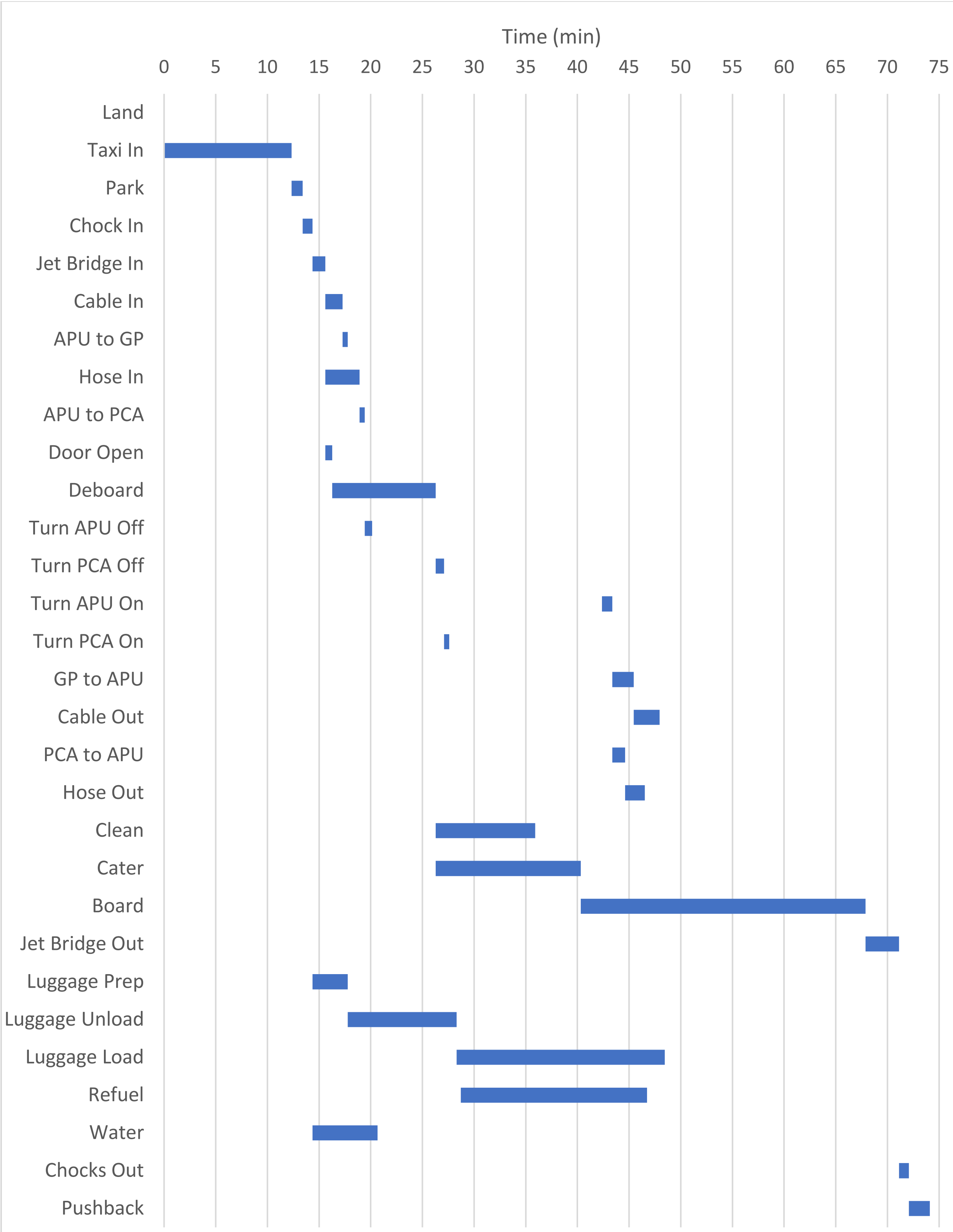


Figure 44: Gantt chart for sample operation when managed through data-driven pre-planning

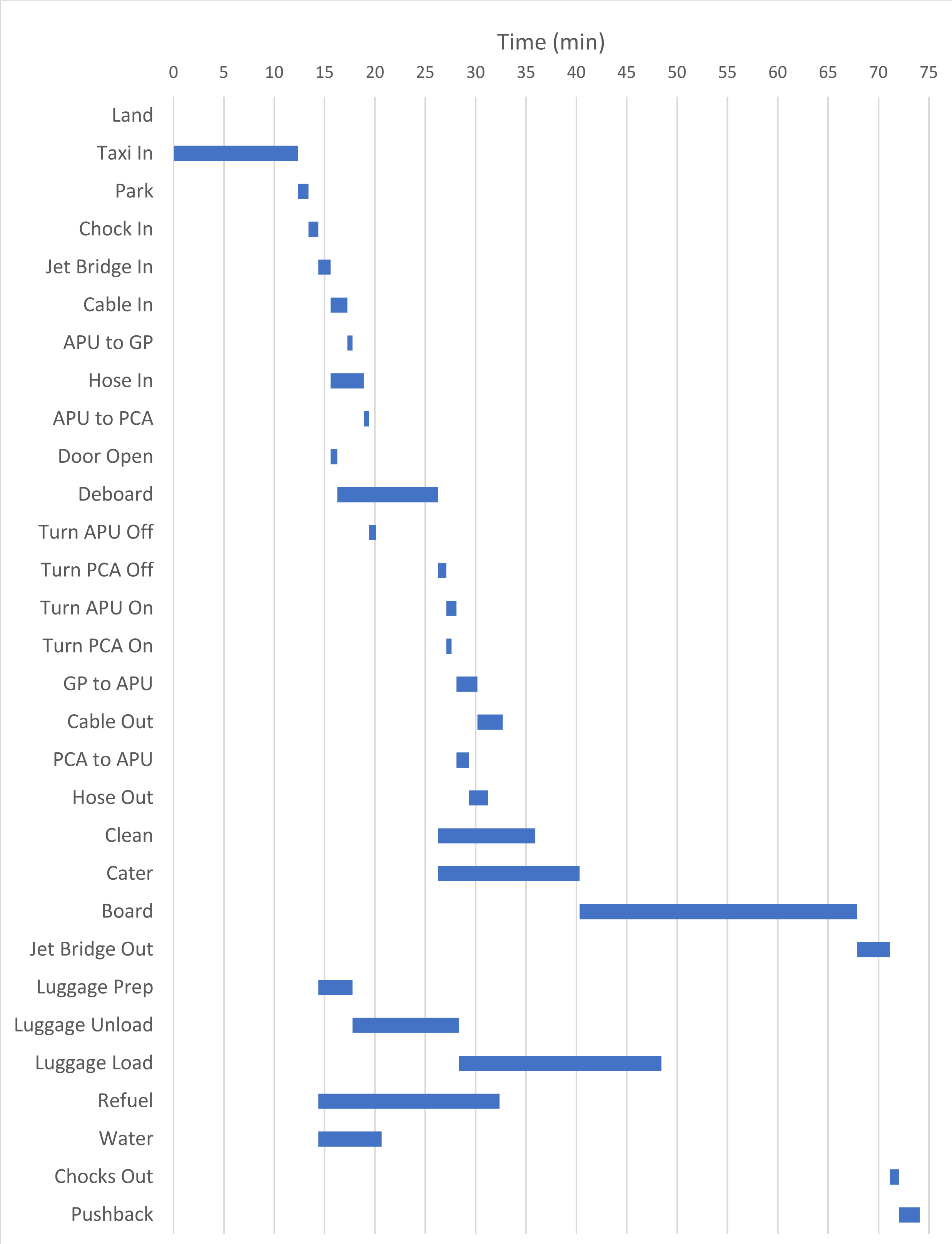


Figure 45: Gantt chart for sample operation when managed with a "push" mentality

It can be inferred that the adaptive scheduler was able to extend the duration of holds in comparison to a preplanned schedule. Increasing the hold durations in the preplanned schedule would be a mistake because there would be too much risk involved with delaying the turnaround operation. The adaptive scheduler is uniquely effective at seizing opportunities for savings as information is acquired. This does not guarantee that the adaptive schedule will always result in savings; exceptions can still happen, and the adaptive scheduler is not all-knowledgeable. However, it does iteratively follow savings wherever they appear, leading to overall savings. Table 32 shows the difference in cost when comparing the initial hold times of a pre-planned schedule with the holds obtained with an adaptive scheduler.

Table 32: Costs of sample operation with different management (in $ unless specified)

Cost Category ($)	Pre-planned Schedule	Adaptive Schedule	Savings	Savings (%)
Opportunity Cost of Turnaround Operation	214.97	214.97	0.00	0.00
APU No Load	2.09	2.09	0.00	0.00
APU Air Only	0.18	0.18	0.00	0.00
APU Power Only	0.00	0.00	0.00	n/a
APU Air and Power Combined	53.51	24.78	28.73	53.69
GP	0.65	1.22	-0.57	-88.46
PCA	3.05	5.39	-2.35	-77.02
Boarding Decay	32.50	32.50	0.00	0.00
Catering Decay	12.03	12.03	0.00	0.00
Cleaning Decay	0.60	0.60	0.00	0.00
Refuel Decay	0.86	0.86	0.00	0.00
Water Decay	0.86	0.86	0.00	0.00
Luggage Decay	2.25	0.95	1.29	57.60
Slot Time Reassignment	0.00	0.00	0.00	n/a
Original Cost of Delay	859.72	859.72	0.00	0.00
Marginal Cost of Delay	429.86	429.86	0.00	0.00
Total	1613.13	1586.02	27.10	1.68

For this specific operation, the adaptive scheduler was able to save $29 in APU costs while incurring an additional $3 in GP and PCA costs. The overall operation was not delayed, while GP and PCA use almost doubled. This is exactly the desired behavior from the adaptive scheduler. However, not all runs necessarily show this behavior. Only testing long-term trends can demonstrate the effectiveness of the adaptive scheduling method. Table 33 shows the long-term savings in each cost category across 20 operations. On average, the total GP, PCA, and APU costs can be reduced by $33 for each operation by using the adaptive scheduler with the given cost rates and activity duration distributions, without causing large losses due to increased delay or missed opportunity.

Table 33: Cost saving using adaptive scheduling instead of pre-planning for 20 operations

Cost Category	Mean ($)	Standard Deviation ($)
Opportunity Cost of Turnaround Operation	-0.02	0.07
APU No Load	0.12	0.24
APU Air Only	0.00	0.00
APU Power Only	2.76	3.59
APU Air and Power Combined	33.89	6.58
GP	-0.79	0.22
PCA	-2.61	0.73
Boarding Decay	-0.59	1.25
Catering Decay	-0.40	0.83
Cleaning Decay	-0.02	0.04
Refuel Decay	-0.02	0.04
Water Decay	-0.02	0.04
Luggage Decay	1.70	2.69
Slot Time Reassignment	0.00	0.00
Original Cost of Delay	-1.06	3.17
Marginal Cost of Delay	-0.53	1.58
Total	32.41	9.57

5.12.3 Testing Without Initial Long-Term Memory

How much long-term data is sufficient to reliably provide savings? The adaptive scheduler learns to predict better with every operation it observes, but in the initial phases of its training, it leverages relatively few data points to represent a highly stochastic environment. If the model is not able to make holistic predictions, the chances of making risky or wrong decisions are higher. Section 5.12.2 showed that after 1,000 runs, the adaptive scheduler can find cost savings without making a mistake that causes huge losses.

In this section we show how an adaptive scheduler is a learning system that makes mistakes with a decreasing recurrence as it runs. Figures 46 and 47 show the evolution of cost savings achieved by using an adaptive schedule instead of a pre-planned schedule. The simulations start with no initial memory for 200 operations. Figure 47 shows that APU cost savings can be achieved very quickly; although each operation's savings have a lot of noise, average savings above $25 per operation appear almost immediately after the first 10 operations. This is understood, since the effectiveness of pull-management of the APU, GP, and PCA only needs a rough schedule to understand how long the APU can stay off. In contrast, the evolution in total savings in Figure 46 shows a very problematic initial learning phase. The first few runs show very large losses associated with operation delay caused by the adaptive schedule. This is because although it is easier to take a riskier decision to increase GP and PCA use, there is not enough data to quantify the vast losses that they could cause in edge-case scenarios. Even if the adaptive scheduler may usually save $20-40, even a single exceptional $2,000 loss due to excess delay may annul those savings. Fortunately, as those edge cases appear, the system starts using those data points in the simulations and starts being risk-averse to those high-loss scenarios. By 200 runs, the long-term total expected savings become positive, and as observed in Section 5.12.2, by 1,000 runs, the adaptive scheduler can run to produce reliable net savings.

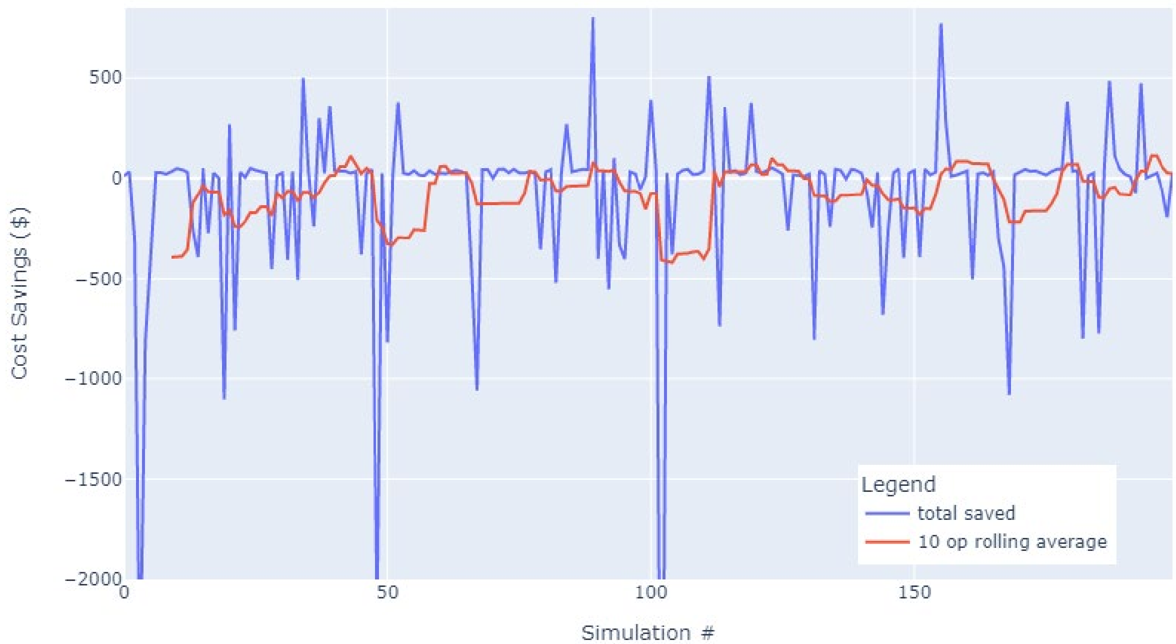


Figure 46: Total cost savings from using adaptive scheduling instead of preplanning for 200 operations with no initial long-term memory.

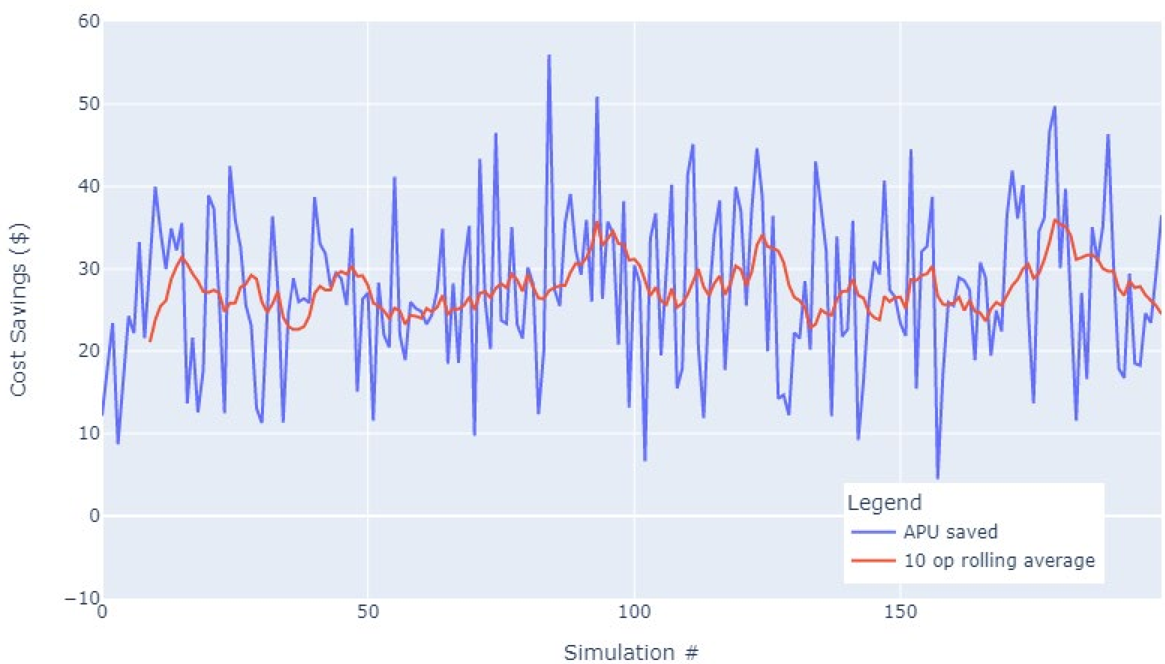


Figure 47: APU cost savings from using adaptive scheduling instead of preplanning for 200 operations with no initial long-term memory.

5.13 Discussion

The main conclusion that this section of the report drives is the concept of how adaptive scheduling works. The technology used to implement the required percepts and actuators exists, the architecture is defined, and the simulated demonstration of the system shows that net savings can be achieved. With a clear value proposition, the system has a foundation on which it can be improved, detailed, and used in the industry.

The algorithms and hardware used in this report were the minimum viable solution to demonstrate adaptive scheduling in relationship to GP, PCA, and APU management. The single-variable gradient descent used in the demonstration is slow and can easily get stuck at a sub-optimal local minimum. Academic literature already proposes much more powerful search optimization algorithms (e.g., genetic algorithms) that may improve the speed and precision of the overall system. Cloud computing and parallelization offer even greater opportunities to increase speed and precision. In turn, improved computability opens opportunities to increase the complexity of the optimization problem.

The complex process model and its relative cost function barely represent the complexity of turnaround operations. The greater the detail and the flow of information, the more the adaptive scheduling system gains the ability to infer circumstances and seize opportunities for savings. In the complex model, entire processes are represented by single activities, which could be split up into smaller modules. A more complex process model not only enables more information flow but also allows predictions for single activities to be more precise. If the relative percepts exist, activities like passenger boarding, luggage loading, and catering can provide information about their progress through several milestones, rather than solely providing information on their completion. The representation of ATC and ACDM decision making through the "Gate Hold" actuator is simplistic and could be broken down further or connected to real-time systems. More actuators can be included to represent other critical decision-making processes.

The greatest advantage of adaptive scheduling is that it is highly customizable, modular, and flexible. In this report, a specific process model, specific random variable distributions for activity durations, and specific cost rates were chosen to perform the demonstration. In practice, all of these components can be altered, and the system will still work. A process model can be redesigned depending on exact airport equipment configurations. Activity durations do not need to be specified or associated with a specific random variable distribution; they simply need to be observed by the percepts and recorded in the long-term memory. Cost rates can be customized depending on airport and airline priorities, or they can be connected to their own percept inputs. Additionally, the adaptive scheduler can be applied to a mixed fleet of aircraft and equipment if the data entries in the long-term memory are labeled and filtered with the identifying data. Generally, adaptive scheduling is a structure for data-driven decision support that is not restricted to any data set or problem.

Despite being a powerful decision-support tool, adaptive scheduling is not perfect and can still make mistakes. It is important to recognize both the fact that it initially requires a learning period and that even a well-trained system is not going to produce savings for all operations. The mitigation of unexpected variability goes hand in hand with accepting the lack of full control.

5.14 Conclusion

An adaptive scheduling system can blend contingency planning, active management, and cost estimation into one system. By collapsing probable turnaround operations schedules into their relative costs, the system can balance the probability and cost associated with each decision it makes. As the system gains more circumstantial information, what could have been a very risky cost-saving decision could become a very reasonable one. By making the best decision according to the data available in real time, an adaptive scheduler provides net benefits in the long-term across many operations.

Evaluating the performance of operations with hindsight ignores the fact that operation stakeholders make their decisions in real time and with limited information. For example, if an airport sets a stringent policy of turning on an APU 10 minutes prior to off-block time, it might be easy for them to use their monitoring system to retrospectively see if that policy was respected or not. However, such a policy does not capture the risky decision making that pilots and ground crews are faced with. Perhaps using an APU for 25 minutes prior to departure might be justified if there is high uncertainty in the off-block time, whereas using an APU 10 minutes prior to departure time might be unjustified if all other processes are complete and the off-block time is certain. An arbitrary APU use time policy is a worthwhile airport strategy that may help stakeholders strive for improved performance, but it is somewhat detached from the complexity of reality. If an airport implemented an adaptive scheduling system, they would not only be able to provide net savings to airlines, but they would also have the insight to build more circumstantial and responsive policies and incentive mechanisms.

Adaptive scheduling is not a new concept in the airport management world. Many interconnected systems are already using it to support a transportation network that needs to be both robust and flexible. This report makes a unique contribution by including GP, PCA, and APU management into the larger framework of adaptive scheduling. It demonstrates that energy savings and sustainability can be advanced in a small-scope project without jeopardizing the function of the larger system and instead contributing to it.

6. Discussion

Hypothetically, even if perfect monitoring, assessments, and adaptive scheduling systems were used at every airport, APU overuse would still be a problem. This report outlines some of the strategies that can help stakeholders strive for seamless turnaround operations, while acknowledging that they are only a component of the solution. Making turnaround operations even slightly better, rather than seamless, may be the most feasible way to provide immediate value. Overall turnaround operations performance falls on a heterogenous spectrum, independent of which metric is used to define it. Shifting that spectrum by identifying and decreasing the likelihood of poor performance while supporting and increasing the likelihood of good performance will inevitably improve the average performance of these operations.

Although each section of the report is presented independently, they have many synergies. The GP use section provides necessary input data for the operation assessment and is a critical percept for the adaptive scheduling section. The assessment section contextualizes the results of GP use while providing a detailed methodology to make cost estimates that can be leveraged in the adaptive scheduling section. The adaptive scheduling section provides a schedule and operational data that can be essential for predicting power demand in the GP use section and provides a basis to evaluate GP use without the benefit of hindsight. Since these systems depend on the same percepts and the availability of a real-time computer system, it makes sense to implement them jointly to maximize the value of an investment in such a system.

Developing and adopting technology in large and highly-established industries is an exceedingly difficult goal. Aviation's top priorities are security and safety, which can pose large obstacles and liabilities to a system that proposes real-time data sharing and AI-assisted management as a foundation. Aviation stakeholders are highly fragmented and have different priorities, making it challenging to suggest a centralized solution. Aviation is an inherently international business, making it difficult to approach legally and organizationally. But perhaps the greatest barrier to adoption is changing the way people have worked for decades; individual airlines and ground crew workers will resist change because learning to use and trusting a new tool takes education, time, and effort. However, with a clear value proposition and by striving to make people's lives easier, it is possible for improved monitoring, refined assessment, and adaptive scheduling to gain traction.

Each turnaround stakeholder can be a catalyst towards adoption. Governments and worker's unions can push for a regulatory approach that would require airports and airlines to improve and monitor their performance, forcing them to implement effective solutions. Airports can develop a centralized system to overhaul their gate management, attract airlines, and further their sustainability agenda. Airlines can develop the systems to improve their cost savings and overall operational efficiency. Ground handling equipment manufacturers may develop the systems through software augmentation that makes their products more competitive. Independent ground-handing organizations might want to use the systems for improved resource and schedule management. Additionally, any of these stakeholders might have a marketing incentive to develop green technology since sustainability is a sensitive topic, especially for flying customers.

7. Conclusion

Increasing the use of existing gate electrification infrastructure is a desirable outcome for all stakeholders. Financial success and sustainability often find themselves at odds in many industrial problems, but when considering GP, PCA, and APU use, those goals are closely related. Increasing energy efficiency for turnaround operations increases airline profits, reduces global emissions, improves airport air quality, and safeguards the health of apron workers.

Although it is theoretically desirable for all stakeholders, maximizing the use of GP and PCA is challenging and often not a priority. This report reveals a discrepancy between the use of gate electrification infrastructure assumed by airports (and their funding organizations such as VALE) and the use that truly occurs. In an unsupervised environment, some airlines use gate electrification infrastructure far more than others. Some airlines seem to almost neglect the resource completely. As disheartening as this might be, it also suggests that improvement is possible. If every turnaround operation respected a stringent but realistic APU use time of 15 minutes, an average of $50 in jet fuel and 180 kg of CO_2 could be saved in comparison to current utilization rates. With approximately 200,000 flights at SFO per year (Greer et al., 2021), the total for the airport would amount to $10M in fuel and 36,000 $mTCO_2$.

This report creates a framework for monitoring, assessment, and adaptive scheduling and provides strategies to achieve improved energy efficiency. Establishing a system to closely monitor GP, PCA, and APU use is the foundation for any form of accountability, policy enforcement, data-driven decision making, and predictive management. An airport-centric monitoring system can be implemented with existing databases for GP systems to predict power demand and identify performance patterns. Assessment impact methods reveal the costs associated with GP, PCA, and APU management. A computerized adaptive scheduling system can actively support pilots and ground crews in managing risk and seizing opportunities for savings without compromising the overall progress of the turnaround operation. Together, these strategies may synergize to mitigate the problem of APU overuse while also bringing value to the overall turnaround operations procedure and airport management (Figures 48 and 49).

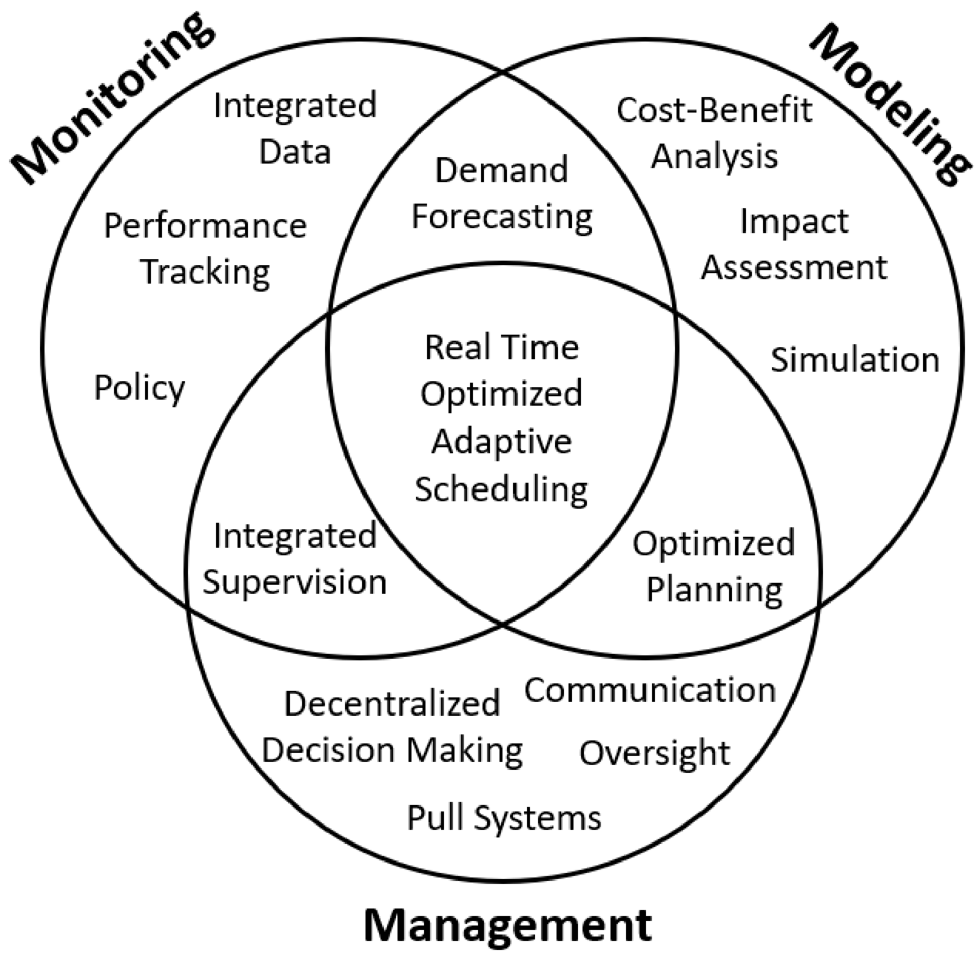


Figure 48: Generalized monitoring, modeling, and management framework

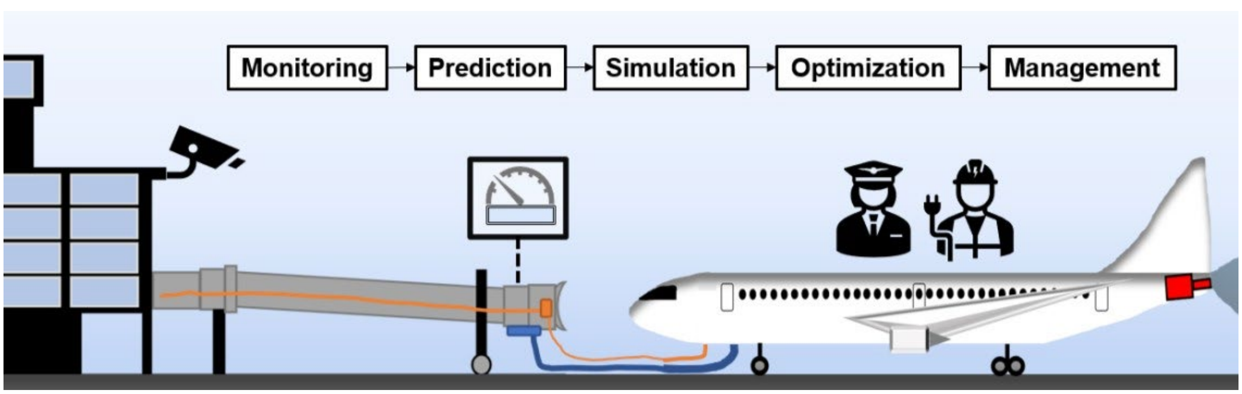


Figure 49: Schematic summary of the framework to improve GP use and reduce APU use

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Appendix

Table A1: Subtype code, APU group, AAC, ADG, model, pax, category (Part 1 of 2)

Aircraft Subtype Code	APU Emissions Group	Aircraft Approach Category (AAC)	Airplane Design Group (ADG)	Model Name	Passenger Capacity (approx.)	Category
319	100-200 new	C	III	Airbus A319	126	Narrow Body
320	100-200 new	C	III	Airbus A320	160	Narrow Body
321	100-200 new	C	III	Airbus A321	195	Narrow Body
328	100-200 new	C	III	Airbus A320	160	Narrow Body
739	100-200 new	D	III	Boeing 737-900	178	Narrow Body
19C	100-200 new	C	III	Airbus A319	126	Narrow Body
19F	100-200 new	C	III	Airbus A319	126	Narrow Body
19G	100-200 new	C	III	Airbus A319	126	Narrow Body
19S	100-200 new	C	III	Airbus A319	129	Narrow Body
20C	100-200 new	C	III	Airbus A320	160	Narrow Body
20S	100-200 new	C	III	Airbus A320	160	Narrow Body
37K	100-200 new	D	III	Boeing 737-900	178	Narrow Body
3SE	100-200 new	C	III	Airbus A320	160	Narrow Body
73C	100-200 new	D	III	Boeing 737-900	178	Narrow Body
73H	100-200 new	D	III	Boeing 737-800	170	Narrow Body
73J	100-200 new	D	III	Boeing 737-900	178	Narrow Body
73Q	100-200 new	D	III	Boeing 737-800	170	Narrow Body
73R	100-200 new	D	III	Boeing 737-900	178	Narrow Body
73Y	100-200 new	D	III	Boeing 737-800	170	Narrow Body
75B	100-200 old	C	IV	Boeing 757-200	200	Narrow Body
75E	100-200 old	C	IV	Boeing 757-300	243	Narrow Body
75K	100-200 old	C	IV	Boeing 757-200	200	Narrow Body
75S	100-200 old	C	IV	Boeing 757-200	200	Narrow Body
76A	200-300	D	IV	Boeing 767-300	260	Wide Body
76C	200-300	D	IV	Boeing 767-300	260	Wide Body
77E	200-300	C	V	Boeing 777-200	340	Wide Body
77G	200-300	C	V	Boeing 777-200	340	Wide Body
77J	200-300	C	V	Boeing 777-200	340	Wide Body
77M	200-300	C	V	Boeing 777-200	340	Wide Body
77N	200-300	C	V	Boeing 777-200	340	Wide Body
77Q	200-300	C	V	Boeing 777-200	340	Wide Body
77U	200-300	C	V	Boeing 777-200	340	Wide Body

Table A2: Subtype code, APU group, AAC, ADG, model, pax, category (Part 2 of 2)

Aircraft Subtype Code	APU Emissions Group	Aircraft Approach Category (AAC)	Airplane Design Group (ADG)	Model Name	Passenger Capacity (approx.)	Category
77W	200-300	C	V	Boeing 777-300ER	340	Wide Body
77X	200-300	C	V	Boeing 777-300ER	340	Wide Body
77Y	200-300	C	V	Boeing 777-200	340	Wide Body
78H	200-300	C	V	Boeing 787-8	230	Wide Body
78J	200-300	C	V	Boeing 787-10	330	Wide Body
78V	200-300	C	V	Boeing 787-9	290	Wide Body
78Z	200-300	C	V	Boeing 787-9	290	Wide Body
A20N	100-200 new	C	III	Airbus A320Neo	160	Narrow Body
A21N	100-200 new	C	III	Airbus A321Neo	215	Narrow Body
A319	100-200 new	C	IV	Airbus A319	126	Narrow Body
A320	100-200 new	C	III	Airbus A320	160	Narrow Body
A321	100-200 new	C	III	Airbus A321	195	Narrow Body
A332	200-300	C	V	Airbus A330-200	230	Wide Body
A333	200-300	C	V	Airbus A330-300	380	Wide Body
A343	>300 new	C	V	Airbus A340-300	359	Wide Body
A359	>300 new	C	V	Airbus A350-900	330	Wide Body
A388	>300 new	D	VI	Airbus A380-800	700	Jumbo-Wide Body
B736	100-200 new	C	III	Boeing 737-600	113	Narrow Body
B737	100-200 new	C	III	Boeing 737-700	145	Narrow Body
B738	100-200 new	D	III	Boeing 737-800	170	Narrow Body
B739	100-200 new	D	III	Boeing 737-900	178	Narrow Body
B744	>300 new	D	V	Boeing 747-400	550	Wide Body
B752	100-200 old	C	IV	Boeing 757-200	200	Narrow Body
B763	200-300	D	IV	Boeing 767-300	243	Wide Body
B772	200-300	C	V	Boeing 777-200	340	Wide Body
B77L	200-300	C	V	Boeing 777-200LR	340	Wide Body
B77W	200-300	D	V	Boeing 777-200ER	340	Wide Body
B788	200-300	C	V	Boeing 787-8	230	Wide Body
B789	200-300	C	V	Boeing 787-9	290	Wide Body
CR7	BJ/RJ	C	II	CRJ-700	70	Regional Jets
CRJ	BJ/RJ	C	II	CRJ-200	50	Regional Jets
CRJ9	BJ/RJ	C	III	CRJ-900	76	Regional Jets
E75	BJ/RJ	C	III	Embraer 175	76	Regional Jets
E75L	BJ/RJ	C	III	Embraer 175	76	Regional Jets
MD83	100-200 old	D	III	MD-83	160	Narrow Body

Table A3: APU fuel and emissions indices for the no-load condition (ACRP, 2012)

Category	Fuel Flow (kg/s)	$EICO_2$ (g/kgfuel)	EICO (g/kgfuel)	EIHC (g/kgfuel)	$EINO_x$ (g/kgfuel)
Narrow Body	0.021	3,155	31.75	6.53	5.45
Wide Body	0.035	3,155	10.26	0.87	7.55
Jumbo Wide	0.033	3,155	9.38	0.88	7.41
Regional Jet	0.012	3,155	6.26	1.69	6.14
Turbo Prop	0.012	3,155	6.26	1.69	6.14

Table A4: APU fuel and emissions indices for the ECS condition (ACRP, 2012)

Category	Fuel Flow (kg/s)	$EICO_2$ (g/kgfuel)	EICO (g/kgfuel)	EIHC (g/kgfuel)	$EINO_x$ (g/kgfuel)
Narrow Body	0.033	3,155	5.72	0.43	6.85
Wide Body	0.052	3,155	1.14	0.19	10.99
Jumbo Wide	0.061	3,155	0.53	0.12	10.3
Regional Jet	0.019	3,155	6.47	0.49	4.93
Turbo Prop	0.019	3,155	6.47	0.49	4.93

Table A5: APU fuel and emissions rates (Winther, 2015; ICAO, 2011)

Metrics		APU Group	BJ/RJ	200-300	100-200 old	100-200 new	>300 old	>300 new
	Start	NOx (kg/hr)	0.274	0.798	0.565	0.364	1.137	1.21
		NO2 (kg/hr)	0.094	0.273	0.193	0.124	0.389	0.414
		CO (kg/hr)	1.019	0.982	1.289	3.734	5.4	1.486
		HC (kg/hr)	0.107	0.243	0.105	2.662	0.302	0.18
		PM (kg/hr)	0.016	0.033	0.034	0.031	0.04	0.031
		Fuel (kg/hr)	50	105	110	100	300	235
	Normal	NOx (kg/hr)	0.452	1.756	1.064	0.805	2.071	2.892
		NO2 (kg/hr)	0.155	0.601	0.364	0.275	0.708	0.989
		CO (kg/hr)	0.799	0.248	0.336	0.419	3.695	0.149
		HC (kg/hr)	0.044	0.07	0.036	0.094	0.153	0.078
		PM (kg/hr)	0.028	0.058	0.034	0.031	0.037	0.032
		Fuel (kg/hr)	90	187	110	100	283	240

Table A6: GP consumption (kW) over 7 kW grouped by aircraft model

Model	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
Airbus A319	7.1	13.4	21.5	23.2	25.2	33.6	61.4	23.7	5.5
Airbus A320	7.1	13.8	22.1	24.5	26.6	35.0	90.8	24.7	6.0
Airbus A320Neo	16.9	17.0	17.7	38.3	38.8	39.8	40.0	32.4	10.1
Airbus A321	7.1	13.7	23.6	25.4	27.5	30.8	87.4	24.8	4.9
Airbus A321Neo	7.1	12.7	19.6	21.1	23.4	30.0	35.9	21.6	4.6
Airbus A330-200	8.8	11.5	22.7	24.6	25.2	25.6	25.7	21.4	7.1
Airbus A330-300	11.0	27.2	41.9	48.2	58.5	59.4	64.3	47.1	12.0
Airbus A350-900	7.3	16.1	32.6	42.8	53.1	64.9	92.4	42.6	14.4
Airbus A380-800	17.8	21.8	35.2	61.0	68.7	76.9	80.3	55.1	19.3
Boeing 737-600	16.0	17.1	19.2	20.5	23.2	24.4	24.7	20.8	2.6
Boeing 737-700	7.3	10.9	18.6	22.0	23.8	27.7	32.0	20.9	4.9
Boeing 737-800	7.1	11.9	17.0	19.4	23.6	29.0	38.5	20.2	5.0
Boeing 737-900	7.1	11.4	16.2	19.6	23.3	28.7	74.4	19.9	5.1
Boeing 747-400	7.7	29.6	42.9	52.8	72.9	75.2	80.8	54.2	17.4
Boeing 757-200	7.4	16.2	21.6	23.6	26.6	30.0	39.5	23.7	4.5
Boeing 757-300	7.2	17.4	20.4	22.2	25.2	30.0	31.7	22.6	3.9
Boeing 767-300	7.6	22.0	31.9	37.1	41.2	48.8	54.7	36.2	8.2
Boeing 777-200	7.1	26.7	42.9	48.2	56.6	74.7	86.5	49.5	13.6
Boeing 777-200ER	7.2	20.2	47.6	60.5	69.1	75.8	105.4	56.6	16.3
Boeing 777-200LR	19.7	21.7	29.6	39.6	40.8	41.8	42.0	33.8	12.3
Boeing 777-300ER	7.3	26.2	45.4	54.8	64.7	81.6	99.6	54.9	15.9
Boeing 787-8	7.1	18.1	27.6	71.6	76.9	92.5	99.8	59.7	25.2
Boeing 787-9	7.1	20.9	62.5	70.9	76.2	88.1	138.5	64.3	20.8
CRJ-200	7.1	7.1	7.2	7.6	8.0	11.5	12.2	8.1	1.4
CRJ-700	7.2	7.9	9.2	9.6	10.4	11.0	11.5	9.7	1.0
CRJ-900	7.2	7.9	11.2	12.5	13.1	14.2	15.1	11.9	1.8
Embraer 175	7.1	7.9	10.3	10.8	11.2	12.5	79.9	10.7	2.3
MD-83	9.5	11.9	25.6	26.0	26.6	28.0	28.3	23.5	6.5

Table A7: Power consumption (kW) over 7 kW grouped by gate

Gate	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
A11A	8.2	12.5	15.9	16.7	17.2	18.9	19.1	16.2	2.1
A1B	10.0	12.2	13.4	15.8	18.5	20.9	21.0	15.9	3.2
A2	7.2	12.7	19.6	23.4	25.9	32.5	42.4	22.8	5.5
A3	7.3	8.9	13.7	18.2	25.1	29.2	32.0	18.9	7.0
A4	7.1	12.3	17.2	22.7	26.2	39.2	90.8	23.3	9.9
A5	9.2	29.0	50.9	61.0	68.9	80.2	90.6	58.5	14.8
A6	7.1	15.5	23.3	27.0	47.4	74.6	89.6	34.6	18.9
A7	7.3	21.7	40.8	62.0	70.0	75.7	87.8	54.5	19.3
A8	7.2	12.3	18.8	25.3	29.7	52.5	105.4	27.6	13.7
A9	14.2	32.7	50.7	58.3	69.2	76.5	79.0	57.7	14.0
D50A	7.1	8.8	10.8	14.4	24.1	32.2	43.0	17.6	7.8
D50B	7.1	8.4	10.7	14.1	23.8	31.6	42.5	17.2	7.8
D51A	7.1	10.0	12.8	22.4	25.7	33.4	41.6	21.0	7.5
D51B	7.1	9.6	12.4	21.4	25.1	33.4	40.7	20.3	7.4
D52	7.1	10.2	13.7	22.7	25.9	33.5	40.6	21.0	7.3
D53	7.1	9.0	11.0	19.6	24.1	32.1	58.8	18.7	7.5
D54A	7.1	11.6	19.2	23.3	25.9	33.6	62.5	22.6	6.5
D54B	7.1	9.4	13.6	21.6	25.2	33.6	74.4	20.6	7.5
D55	7.1	9.5	13.2	22.1	25.4	33.3	41.6	20.8	7.4
D56A	7.1	12.0	20.6	24.7	26.8	29.9	44.2	23.3	5.4
D56B	7.2	10.7	19.8	24.4	26.2	29.4	87.4	22.8	5.7
D57	7.1	13.3	22.4	25.6	27.7	30.5	53.3	24.5	5.5
D58A	7.1	13.2	22.2	24.6	27.0	29.4	38.2	23.7	4.8
D58B	7.1	11.4	22.9	26.5	28.3	34.0	42.8	25.1	6.0
D59	7.1	10.0	22.8	24.5	26.3	35.6	41.9	24.3	6.9
E60	7.1	13.2	16.6	19.7	23.5	29.6	39.8	20.2	5.0
E61	7.1	13.0	17.4	20.9	23.6	30.4	40.3	20.8	5.0
E62	7.1	12.4	17.0	20.9	23.5	29.8	70.7	20.5	5.1
E63	7.1	12.0	16.9	20.5	23.5	30.2	44.9	20.5	5.1
E64	7.1	12.3	17.0	20.5	23.9	32.0	74.0	21.0	6.3
E66	7.1	13.0	18.1	22.1	25.1	32.2	97.3	22.0	6.2
E67	7.1	12.7	18.7	22.8	25.8	32.0	56.2	22.5	5.6
E68	7.1	12.5	18.6	22.2	25.1	31.0	61.4	22.0	5.3
E69	7.1	12.8	17.9	21.7	24.6	31.1	40.3	21.5	5.4
F70	7.1	9.1	12.8	19.6	23.8	30.6	39.8	19.1	6.7
F71A	7.1	8.5	10.7	11.8	20.9	26.5	41.0	15.5	6.4
F71B	7.1	7.7	9.8	10.8	11.0	12.4	28.3	10.5	1.4
F77B	9.0	9.1	9.5	10.0	10.2	10.4	10.4	9.8	0.7
F79	8.3	17.3	30.9	33.2	46.4	47.1	79.9	37.0	11.2
G100	7.3	18.0	27.4	54.4	70.7	83.6	101.2	51.3	22.4
G91	7.1	11.9	21.5	24.8	29.6	72.9	118.1	28.8	16.4
G92	7.1	12.7	22.1	25.9	54.7	78.2	97.4	36.9	22.3
G93	7.1	15.7	23.9	33.1	68.6	82.1	138.5	43.4	24.1
G94	7.1	15.3	23.8	37.6	62.5	78.5	99.8	42.6	22.3
G95	7.2	15.9	24.0	35.9	62.1	78.6	101.5	42.1	22.1
G96	7.1	15.1	23.9	46.3	67.4	81.9	109.9	46.1	23.1
G97	7.1	14.6	23.9	41.5	73.1	84.0	110.9	47.3	25.9
G98	7.2	14.9	24.7	43.2	71.0	81.7	99.6	47.2	24.1

Table A8: Power consumption (kW) over 7 kW grouped by aircraft design group (ADG)

ADG	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
II	7.1	7.2	7.7	9.2	10.3	11.2	12.2	9.1	1.4
III	7.1	10.1	16.0	21.2	24.7	31.6	90.8	20.6	6.6
IV	7.1	13.7	22.2	23.9	26.5	35.0	59.4	24.6	6.1
V	7.1	20.6	45.1	63.8	73.2	84.4	138.5	58.3	20.1
VI	17.8	21.8	35.2	61.0	68.7	76.9	80.3	55.1	19.3

Table A9: Power consumption (kW) over 7 kW grouped by airline

Airline	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
A	7.1	12.6	23.5	25.8	35.7	75.6	99.8	32.4	18.1
B	7.1	9.4	12.0	21.4	25.2	33.1	74.4	20.1	7.6
C	7.1	11.9	21.2	25.0	27.2	30.1	87.4	23.8	5.5
D	7.1	7.9	12.0	15.7	25.1	25.4	25.6	17.7	7.5
E	7.3	11.4	16.9	18.7	25.6	62.3	90.8	25.3	15.9
F	7.1	17.2	24.1	25.8	27.7	34.6	42.4	25.9	4.8
G	7.2	11.6	19.9	23.5	28.7	72.9	89.6	30.0	18.1
H	7.4	22.1	53.5	65.5	70.8	76.6	105.4	60.1	15.7
I	7.3	13.4	25.2	39.8	53.2	68.5	92.4	39.8	18.0
J	7.1	10.4	16.6	21.2	24.6	42.7	138.5	22.8	12.3

Table A10: GP utilization rate (%) grouped by aircraft model

Model	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
Airbus A319	0.0	0.0	50.0	68.8	80.0	92.4	100.0	59.4	29.1
Airbus A320	0.0	0.0	43.8	68.8	81.3	93.3	100.0	58.1	30.8
Airbus A320Neo	0.0	0.0	0.0	0.0	10.0	61.3	100.0	11.6	24.2
Airbus A321	0.0	0.0	3.4	10.0	65.0	90.0	100.0	31.4	33.6
Airbus A321Neo	0.0	0.0	0.9	58.1	76.5	90.3	100.0	46.6	34.5
Airbus A330-200	0.0	0.0	0.0	0.0	0.0	10.0	31.6	2.3	7.9
Airbus A330-300	0.0	1.3	5.9	9.1	38.4	70.3	77.8	24.8	31.1
Airbus A350-900	0.0	0.2	37.7	55.2	71.0	83.3	100.0	50.1	27.2
Airbus A380-800	0.0	1.1	5.6	21.9	44.1	56.3	59.4	26.2	25.3
Boeing 737-600	0.0	0.0	0.0	7.1	8.3	58.5	60.0	12.2	20.2
Boeing 737-700	0.0	0.0	0.0	10.0	60.0	78.1	100.0	29.4	31.1
Boeing 737-800	0.0	0.0	7.7	65.0	81.8	92.9	100.0	51.3	35.5
Boeing 737-900	0.0	0.0	50.0	72.7	84.6	93.8	100.0	61.4	30.7
Boeing 747-400	0.0	0.8	33.1	66.7	72.9	77.8	78.6	51.0	34.3
Boeing 757-200	0.0	0.0	7.7	66.7	82.1	89.5	95.7	51.7	34.4
Boeing 757-300	0.0	3.9	72.0	78.6	84.0	93.5	94.1	68.2	30.4
Boeing 767-300	0.0	0.0	33.6	63.8	79.8	91.3	100.0	56.3	32.0
Boeing 777-200	0.0	0.0	8.9	50.0	77.8	90.5	94.4	47.1	32.9
Boeing 777-200ER	0.0	0.0	16.0	60.6	71.4	80.2	100.0	49.0	29.5
Boeing 777-200LR	58.8	58.8	58.8	58.8	58.8	58.8	58.8	58.8	
Boeing 777-300ER	0.0	20.2	58.5	72.5	83.2	89.2	96.9	67.1	21.8
Boeing 787-8	0.0	0.0	5.1	27.3	52.5	74.3	81.8	30.1	27.0
Boeing 787-9	0.0	0.0	3.8	28.6	57.8	78.6	100.0	32.0	28.6
CRJ-200	0.0	0.0	0.0	0.0	11.1	58.3	95.0	9.8	18.5
CRJ-700	0.0	0.0	0.0	4.6	22.2	75.7	85.7	15.9	24.3
CRJ-900	0.0	0.0	9.1	14.3	22.2	50.0	100.0	17.6	16.4
Embraer 175	0.0	0.0	0.0	12.5	61.1	83.3	100.0	29.4	31.7
MD-83	0.0	0.9	4.5	9.1	50.0	82.7	90.9	33.3	50.1

Table A11: GP utilization rate (%) grouped by gate

Gate	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
A11A	0.0	0.0	0.0	0.0	9.4	68.7	79.6	15.2	28.5
A1B	76.4	76.7	77.6	78.8	79.9	80.8	81.1	78.8	3.3
A2	0.0	0.0	0.0	47.7	64.2	87.8	99.8	39.9	32.1
A3	0.0	0.0	0.0	0.0	13.0	99.1	100.0	15.6	32.3
A4	0.0	0.0	0.0	29.8	62.1	95.9	100.0	33.8	33.7
A5	0.0	0.0	0.0	0.0	49.7	71.2	79.7	19.0	28.5
A6	0.0	0.0	19.8	47.5	65.7	95.0	99.2	45.6	31.5
A7	0.0	0.0	0.0	55.2	68.7	84.9	95.3	43.9	31.1
A8	0.0	0.0	9.4	58.3	75.6	98.0	100.0	50.5	36.2
A9	0.0	0.0	0.0	0.0	0.0	48.6	70.9	4.9	15.5
D50A	0.0	0.0	13.9	55.2	71.3	85.9	99.1	46.7	30.8
D50B	0.0	0.0	25.1	55.9	73.9	87.3	98.7	48.3	30.4
D51A	0.0	0.0	31.6	59.5	72.3	87.7	100.0	50.7	29.2
D51B	0.0	0.0	33.3	59.0	75.7	87.1	98.1	51.6	28.9
D52	0.0	0.0	33.1	55.5	70.4	87.3	98.2	49.5	27.4
D53	0.0	0.0	25.9	56.7	72.8	86.1	96.7	48.4	30.0
D54A	0.0	0.0	48.9	66.4	80.2	91.5	97.5	60.6	26.0
D54B	0.0	0.0	0.0	54.6	72.4	88.7	98.7	46.0	32.1
D55	0.0	0.0	39.1	60.7	73.6	87.8	96.9	53.3	27.5
D56A	0.0	0.0	0.0	0.0	60.3	86.5	99.8	28.7	33.7
D56B	0.0	0.0	0.0	0.0	60.3	86.4	96.8	27.4	34.0
D57	0.0	0.0	0.0	0.0	46.2	82.9	97.6	20.8	31.1
D58A	0.0	0.0	0.0	0.0	61.6	86.0	97.0	29.6	33.6
D58B	0.0	0.0	0.0	50.9	69.8	87.9	98.9	41.3	33.5
D59	0.0	0.0	42.1	57.9	76.8	87.2	95.4	55.2	26.3
E60	0.0	0.0	55.4	71.8	83.6	93.0	100.0	65.4	25.4
E61	0.0	0.0	60.5	76.5	86.5	94.6	100.0	69.4	23.9
E62	0.0	0.0	56.0	71.1	81.6	91.6	98.2	64.8	24.6
E63	0.0	0.0	36.9	65.3	79.6	88.8	97.7	55.3	30.7
E64	0.0	0.0	35.4	60.8	75.5	88.8	96.9	52.6	29.6
E65	0.0	0.0	0.0	0.0	0.0	0.0	2.2	0.0	0.1
E66	0.0	0.0	51.0	67.9	80.1	90.3	97.6	60.5	27.0
E67	0.0	0.0	50.8	68.5	81.4	90.6	100.0	61.8	25.6
E68	0.0	0.0	53.3	71.0	82.4	92.7	99.5	64.0	25.8
E69	0.0	0.0	56.9	73.2	83.1	92.7	99.3	66.7	23.4
F70	0.0	0.0	37.2	62.3	79.4	90.6	99.9	55.0	29.5
F71A	0.0	0.0	7.0	42.7	67.8	87.1	98.1	40.2	30.7
F71B	0.0	0.0	4.7	32.4	60.5	79.6	95.5	34.8	28.4
F77B	0.0	0.0	0.0	0.0	0.0	0.0	8.8	0.0	0.3
F79	0.0	0.0	0.0	0.0	0.0	0.0	77.7	0.3	4.1
G100	0.0	0.0	35.3	56.0	71.9	89.9	96.3	51.0	28.6
G91	0.0	0.0	0.0	0.0	63.5	85.0	99.4	30.2	33.3
G92	0.0	0.0	0.0	36.1	67.3	86.2	96.7	35.0	33.4
G93	0.0	0.0	20.5	55.2	71.6	87.4	99.1	47.2	30.1
G94	0.0	0.0	34.1	55.6	73.0	86.2	94.7	50.7	27.5
G95	0.0	0.0	19.6	56.0	74.6	87.1	100.0	48.7	30.4
G96	0.0	0.0	38.4	57.0	76.4	87.2	94.7	53.0	28.0
G97	0.0	0.0	7.2	51.2	71.1	83.9	96.0	43.7	31.7
G98	0.0	0.0	26.3	51.2	67.6	87.7	98.9	46.6	28.1

Table A12: Total APU time (min) grouped by aircraft model

Model	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
Airbus A319	1.1	7.7	16.3	24.3	38.3	73.0	174.0	30.7	22.5
Airbus A320	0.0	7.5	16.4	25.4	41.3	76.0	178.0	31.7	22.4
Airbus A320Neo	0.0	32.1	58.1	71.5	83.3	92.9	133.0	69.0	25.6
Airbus A321	0.1	11.4	30.4	54.1	71.0	111.0	174.0	54.9	30.5
Airbus A321Neo	1.5	10.7	22.4	36.7	98.0	127.2	142.0	54.6	40.5
Airbus A330-200	72.0	81.7	121.5	129.0	144.3	177.3	178.0	131.9	30.0
Airbus A330-300	22.6	35.5	79.6	97.0	105.5	116.3	119.0	86.3	34.6
Airbus A350-900	4.8	27.2	48.3	70.7	102.9	153.7	171.0	77.2	39.2
Airbus A380-800	68.5	71.8	85.0	102.3	127.9	163.2	172.0	111.1	40.5
Boeing 737-600	23.0	25.0	52.0	60.0	68.5	85.3	88.0	58.9	18.0
Boeing 737-700	0.0	16.5	30.1	49.0	60.0	75.0	121.0	46.5	20.3
Boeing 737-800	0.0	8.5	16.4	29.2	56.0	111.0	178.0	41.3	33.0
Boeing 737-900	0.0	8.1	15.4	25.2	44.0	92.0	178.0	34.2	27.5
Boeing 747-400	34.0	37.2	47.0	53.6	93.9	161.3	176.0	77.9	52.9
Boeing 757-200	10.0	13.8	21.9	35.1	69.0	93.6	125.0	44.5	28.4
Boeing 757-300	4.2	7.7	15.7	21.1	34.3	80.8	130.0	33.5	31.0
Boeing 767-300	6.9	10.2	19.0	34.0	53.4	83.0	102.0	39.6	24.8
Boeing 777-200	11.4	23.2	34.8	64.6	101.4	132.0	146.0	69.9	37.9
Boeing 777-200ER	1.3	30.9	45.1	61.6	98.0	145.0	165.0	73.8	38.3
Boeing 777-200LR	41.7	41.7	41.7	41.7	41.7	41.7	41.7	41.7	
Boeing 777-300ER	12.3	20.8	32.5	43.2	61.1	108.1	165.4	52.2	31.4
Boeing 787-10	87.0	87.0	87.0	87.0	87.0	87.0	87.0	87.0	
Boeing 787-8	8.0	23.9	45.3	66.0	81.0	104.4	144.0	64.6	26.5
Boeing 787-9	2.0	29.3	54.4	87.4	123.2	155.3	179.0	89.6	41.4
CRJ-200	11.5	23.0	32.2	47.0	64.0	101.0	174.0	51.6	25.4
CRJ-700	20.5	23.0	40.6	67.0	87.0	125.0	160.0	67.6	32.5
CRJ-900	0.9	22.0	29.0	35.0	41.3	56.0	109.0	36.2	11.3
Embraer 175	2.5	16.3	27.1	39.0	58.0	101.0	179.0	46.4	27.4
MD-83	13.1	16.7	31.0	49.0	61.5	71.5	74.0	45.4	30.6

Table A13: Total APU time (min) grouped by gate

Gate	0% (Min)	5% (Perc.)	25% (Perc.)	50% (Median)	75% (Perc.)	95% (Perc.)	100% (Max)	Mean	STD
A11A	8.3	24.4	56.8	68.0	78.8	117.6	137.4	67.8	31.1
A1B	14.0	14.2	14.9	15.7	16.6	17.3	17.4	15.7	2.4
A2	0.2	8.0	20.7	34.3	52.3	76.6	109.0	38.6	22.6
A3	0.0	0.2	46.0	61.0	89.0	143.0	164.0	67.0	41.7
A4	0.0	6.2	23.9	45.0	60.6	89.5	112.0	45.2	25.3
A5	14.4	39.4	56.0	70.6	98.0	143.2	172.0	78.8	34.0
A6	1.0	8.7	25.5	42.5	54.1	123.3	152.0	49.8	35.1
A7	4.5	17.0	45.1	54.8	85.1	141.1	176.0	66.3	37.6
A8	0.0	6.0	23.1	32.8	52.3	82.8	106.9	38.8	24.4
A9	33.9	41.0	60.6	88.0	111.5	143.1	151.0	87.8	32.0
D50A	0.8	9.3	19.6	29.4	41.2	66.1	151.0	32.6	18.0
D50B	0.7	9.8	18.8	29.0	40.6	70.5	120.0	32.5	19.3
D51A	0.0	9.1	19.1	27.0	40.0	72.5	140.0	32.3	20.6
D51B	0.3	10.5	19.1	28.0	40.2	70.7	176.5	32.6	20.8
D52	1.0	10.5	21.9	31.3	43.1	75.8	163.0	35.2	21.7
D53	2.0	12.6	21.1	30.3	43.0	67.0	161.0	34.3	19.4
D54A	0.6	8.7	18.7	26.5	40.4	74.1	111.0	32.1	20.0
D54B	3.0	10.5	20.7	32.3	50.0	90.8	171.0	38.8	25.9
D55	2.0	10.1	19.5	27.7	39.6	68.0	160.0	32.1	19.1
D56A	0.1	12.5	29.8	49.0	61.6	92.4	154.0	48.7	24.8
D56B	2.2	10.8	28.3	52.5	66.0	94.2	172.5	50.8	27.0
D57	1.0	13.7	41.3	55.0	68.0	101.8	152.0	54.9	25.5
D58A	2.9	12.8	30.2	51.0	64.0	98.5	178.0	51.2	27.3
D58B	0.6	9.1	20.6	37.2	64.0	95.0	173.0	43.8	29.7
D59	3.3	12.9	25.0	30.0	41.3	60.9	70.0	33.2	14.6
E60	0.0	6.6	14.0	22.0	35.3	65.6	160.0	26.9	19.4
E61	0.0	5.6	11.4	17.6	26.7	52.7	161.0	21.9	16.6
E62	2.6	8.5	14.8	20.4	30.3	65.0	174.0	25.9	19.5
E63	1.7	10.6	16.1	24.9	42.0	87.8	171.0	33.4	25.3
E64	3.5	10.7	19.9	30.1	45.0	86.0	174.0	36.2	24.5
E65	29.0	42.0	56.0	75.0	97.5	137.9	178.0	79.9	30.4
E66	3.1	8.7	16.0	23.4	36.0	75.0	166.9	29.7	21.9
E67	0.0	7.6	14.6	22.0	34.5	58.8	129.0	26.9	17.6
E68	0.5	6.2	13.2	20.7	33.3	57.5	178.0	25.8	19.7
E69	1.0	7.1	12.9	19.6	28.0	49.8	172.0	23.2	16.5
F70	0.0	8.0	14.5	23.9	36.8	72.2	139.3	29.6	21.7
F71A	1.5	10.8	21.4	30.9	48.4	95.9	174.9	38.9	26.7
F71B	2.5	13.5	24.1	35.0	55.8	104.9	172.0	44.3	29.0
F77B	17.0	24.0	36.0	53.0	73.0	112.0	177.0	58.0	27.9
F79	14.0	26.0	37.0	53.0	72.0	121.1	179.0	59.0	29.5
G100	4.8	14.2	32.4	52.3	76.9	128.4	162.0	57.2	33.9
G91	0.4	9.3	21.4	30.8	39.0	63.0	154.0	32.8	20.4
G92	3.1	13.3	27.0	36.9	54.9	117.6	175.0	46.6	31.5
G93	0.8	7.9	20.2	39.4	70.0	123.2	177.0	48.9	37.2
G94	7.0	12.9	27.0	39.3	76.2	131.3	171.0	54.7	37.5
G95	0.1	11.1	25.4	40.1	67.8	122.4	169.7	51.3	36.1
G96	5.3	10.8	26.8	41.4	75.0	130.5	174.0	54.8	38.4
G97	1.1	7.6	26.6	46.8	96.8	154.9	179.0	61.4	45.4
G98	2.0	17.0	31.5	55.0	78.0	109.4	141.0	57.3	31.0

Table A14: Phantom power loads for SFO gates

Gate	Phantom Power Consumption (kW)
A11A	0.84
A1B	0.84
A2	0.48
A3	0.12
A4	0.84
A5	0.84
A6	0.84
A8	0.84
A9	0.84
D50A	0.48
D50B	0.48
D51A	0.48
D51B	0.48
D52	0.84
D53	0.48
D54A	0.48
D54B	0.48
D55	0.84
D56A	0.84
D56B	0.6
D57	0.84
D58A	0.48
D58B	0.84
E60	0.6
E61	0.6
E62	0.48
E63	0.48
E64	0.84
E65	0.24
E66	0.84
E67	0.96
E68	0.72
E69	0.48
F70	0.36
F71A	0.48
F71B	0.48
G100	0.84
G91	0.84
G92	0.96
G93	0.84
G94	0.36
G95	0.84
G96	0.84
G97	0.84
G98	0.84
Other (Assumed)	0.84

Table A15: Largest aircraft category that each gate accommodated

Gate	Category
A1	Wide Body
A10	Wide Body
A11A	Narrow Body
A12	Wide Body
A1B	Narrow Body
A2	Wide Body
A3	Wide Body
A4	Narrow Body
A5	Jumbo-Wide Body
A6	Jumbo-Wide Body
A7	Wide Body
A8	Wide Body
A9	Jumbo-Wide Body
D50A	Narrow Body
D50B	Narrow Body
D51A	Narrow Body
D51B	Narrow Body
D52	Narrow Body
D53	Narrow Body
D54A	Narrow Body
D54B	Narrow Body
D55	Narrow Body
D56A	Wide Body
D56B	Narrow Body
D57	Wide Body
D58A	Narrow Body
D58B	Narrow Body
D59	Narrow Body
E60	Narrow Body
E61	Narrow Body
E62	Narrow Body
E63	Narrow Body
E64	Wide Body
E65	Narrow Body
E66	Wide Body
E67	Narrow Body
E68	Narrow Body
E69	Narrow Body
F70	Narrow Body
F71A	Narrow Body
F71B	Regional Jets
F77B	Regional Jets
F79	Regional Jets
G100	Wide Body
G91	Wide Body
G92	Wide Body
G93	Wide Body
G94	Wide Body
G95	Wide Body
G96	Wide Body
G97	Wide Body
G98	Wide Body

Table A16: Evolution of hold durations and expected cost for a simulated sample operation that uses adaptive scheduling (Part 1 of 2)

Time (minutes)	Taxi In Hold	APU Off Hold	PCA Off Hold	Board Hold	Cater Hold	Clean Hold	Luggage Hold	Refuel Hold	Water Hold	Gate Hold	Total Cost
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.2	50.6	12238
1.0	0.0	0.0	2.6	7.6	0.0	0.0	4.7	0.0	8.2	50.6	2125.6
2.0	0.0	24.3	5.8	4.3	0.0	0.0	4.7	15.5	8.2	50.6	2148.7
3.0	0.0	18.3	7.0	4.3	0.0	0.0	1.9	15.5	8.2	50.6	2119.0
4.0	0.0	19.3	4.7	4.3	0.0	0.0	2.8	11.3	8.2	50.6	2070.4
5.0	0.0	19.3	7.6	8.9	0.0	0.0	2.8	11.3	24.5	50.6	2092.8
6.0	0.0	19.3	4.6	8.9	0.0	0.0	4.9	14.5	24.5	50.6	2130.5
7.0	0.0	19.3	4.6	8.9	0.0	0.0	4.9	14.5	29.6	50.6	2127.0
8.0	0.0	11.8	4.9	5.9	0.0	0.0	2.1	22.2	24.6	50.6	2098.5
9.0	0.0	11.8	4.9	3.7	0.0	0.0	2.1	22.2	24.6	50.6	2153.6
10.0	0.0	18.3	3.6	3.7	0.0	0.0	2.1	12.8	15.5	50.6	2103.2
11.0	0.0	19.6	3.6	2.0	0.0	0.0	2.1	12.8	15.5	50.6	2076.8
12.0	0.0	19.6	3.7	2.0	0.0	0.0	5.1	18.6	19.8	50.6	2116.2
13.0	0.0	17.5	3.7	2.0	0.0	0.0	5.1	18.6	28.0	50.6	2131.4
14.0	0.0	17.5	5.2	5.8	0.0	0.0	3.5	17.1	15.6	50.6	2129.7
15.0	0.0	17.5	5.2	5.8	0.0	0.0	4.3	17.1	15.6	50.6	2175.7
16.0	0.0	17.5	5.2	4.9	0.0	0.0	4.3	17.1	18.4	50.6	1933.8
17.0	0.0	21.4	5.1	4.9	0.0	0.0	4.3	13.0	15.7	50.6	1878.9
18.0	0.0	24.8	5.1	4.9	0.0	0.0	4.3	13.0	15.7	50.6	1862.8
19.0	0.0	23.9	5.1	4.9	0.0	0.0	4.3	13.2	15.7	50.6	1949.5
20.0	0.0	18.5	5.8	4.4	0.0	0.0	4.3	20.6	15.7	50.6	1887.2
21.0	0.0	18.5	2.5	3.0	0.0	0.0	2.4	20.6	18.7	50.6	1901.5
22.0	0.0	22.7	2.5	3.0	0.0	0.0	2.3	22.2	18.7	50.6	1918.6
23.0	0.0	20.7	2.5	3.0	0.0	0.0	2.3	22.2	18.7	50.6	1940.2
24.0	0.0	26.5	4.4	3.0	0.0	0.0	2.3	23.5	24.0	50.6	1958.8
25.0	0.0	23.0	5.9	3.0	0.0	0.0	2.3	23.5	19.5	50.6	2028.4
26.0	0.0	23.0	5.9	8.0	0.0	0.0	4.8	20.5	19.5	50.6	2116.2
27.0	0.0	21.2	5.9	8.0	0.0	0.0	4.8	19.0	19.5	50.6	1857.2
28.0	0.0	26.3	5.9	8.0	0.0	0.0	3.0	19.0	27.1	50.6	1888.2
29.0	0.0	26.3	7.7	6.3	0.0	0.0	3.0	21.3	28.3	50.6	1739.9
30.0	0.0	26.3	7.2	9.0	0.0	0.0	3.0	21.3	24.9	50.6	1807.4
31.0	0.0	26.3	5.8	7.5	0.0	0.0	6.1	21.3	27.5	50.6	1796.6

Table A17: Evolution of hold durations and expected cost for a simulated sample operation that uses adaptive scheduling (Part 2 of 2)

Time (minutes)	Taxi In Hold	APU Off Hold	PCA Off Hold	Board Hold	Cater Hold	Clean Hold	Luggage Hold	Refuel Hold	Water Hold	Gate Hold	Total Cost
33.0	0.0	26.4	5.8	9.3	0.0	0.0	6.8	20.4	27.5	50.6	1808.4
34.0	0.0	24.2	5.8	9.3	0.0	0.0	6.8	20.4	27.5	50.6	1814.7
35.0	0.0	24.2	5.8	9.3	0.0	0.0	8.6	20.4	27.5	50.6	1873.9
36.0	0.0	26.2	5.8	9.3	0.0	0.0	10.8	20.4	27.5	50.6	1739.1
37.0	0.0	26.2	5.8	9.3	0.0	0.0	10.2	20.4	35.4	50.6	1759.1
38.0	0.0	26.2	5.8	9.3	0.0	0.0	10.2	20.4	35.4	50.6	1806.4
39.0	0.0	26.2	5.8	9.3	0.0	0.0	10.2	20.4	34.1	50.6	1816.5
40.0	0.0	24.9	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1891.7
41.0	0.0	24.9	5.8	9.3	0.0	0.0	10.2	20.4	34.0	50.6	1011.4
42.0	0.0	24.9	5.8	9.3	0.0	0.0	10.2	20.4	34.5	50.6	1010.9
43.0	0.0	24.9	5.8	9.3	0.0	0.0	10.2	20.4	34.1	50.6	1009.8
44.0	0.0	29.6	5.8	9.3	0.0	0.0	10.2	20.4	34.1	50.6	1036.4
45.0	0.0	31.5	5.8	9.3	0.0	0.0	10.2	20.4	34.1	50.6	1009.1
46.0	0.0	31.5	5.8	9.3	0.0	0.0	10.2	20.4	35.7	50.6	1023.1
47.0	0.0	31.5	5.8	9.3	0.0	0.0	10.2	20.4	35.6	50.6	972.3
48.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	37.1	50.6	1029.5
49.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1021.6
50.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1024.9
51.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1026.1
52.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1034.9
53.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1001.7
54.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	974.9
55.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1021.2
56.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1014.7
57.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1009.9
58.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	997.0
59.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	942.3
60.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	957.7
61.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	949.5
62.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	998.9
63.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1162.7
64.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1320.2
65.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1555.5
66.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	1790.7
67.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2053.6
68.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2123.7
69.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2150.3
70.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2261.2
71.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2484.4
72.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2530.6
73.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2469.8
74.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2469.8
75.0	0.0	30.6	5.8	9.3	0.0	0.0	10.2	20.4	36.5	50.6	2469.8

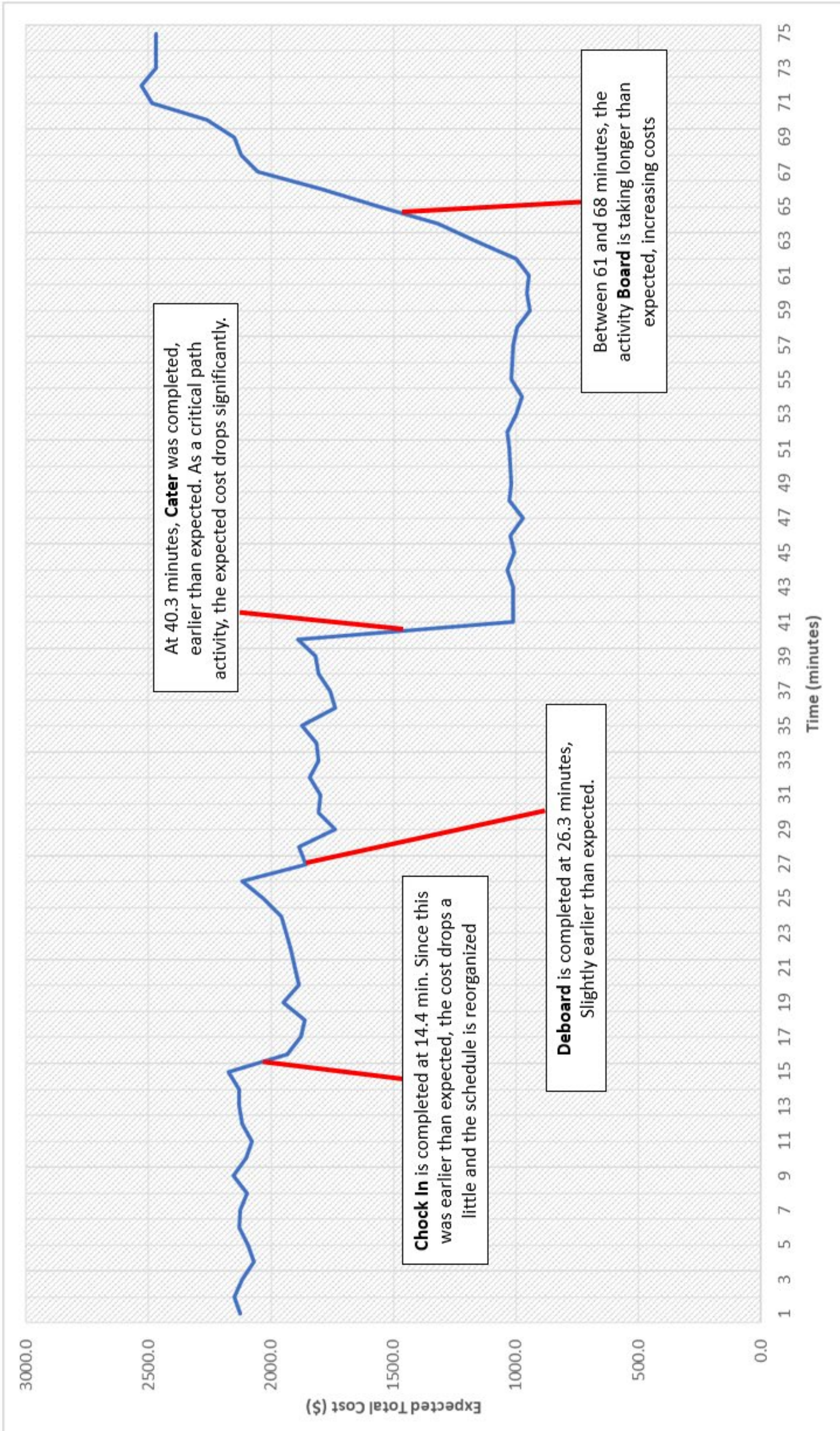

Figure A1: Evolution of expected cost in a sample operation