OPTIMIZING THE CONSTRUCTION PLANNING
OF AIRPORT EXPANSION PROJECTS

BY

MAMDOUH YACOUB MAMDOUH AL-GHZAWI

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Civil Engineering
in the Graduate College of the
University of Illinois Urbana-Champaign, 2023

Urbana, Illinois

Doctoral Committee:

Professor Khaled El-Rayes, Chair and Director of Research
Professor Erol Tutumluer
Professor Mani Golparvar-Fard
Assistant Professor Ramez Hajj

Abstract

To address the steady increase in air travel in recent years, there is a pressing need to expand and modernize many of the existing airports in the US that serve more than three million daily passengers. Airport expansion projects often include construction of new terminals, expansion of existing terminals, and construction of new runways and taxiways. These projects often cause disruptions and delays in air traffic due to their impact on the number, length, and capacity of operational airport runways and/or taxiways. On the other hand, FAA regulations that require airport operations be minimally disrupted during expansion projects often lead to an overrun in construction cost. Accordingly, airport and construction planners need to carefully analyze and optimize the construction planning of airport expansion projects in order to minimize construction-related disruptions in airport operations while keeping total construction cost to a minimum.

The main goal of this research study is to develop novel models for optimizing the planning of airport expansion projects that provide the capability of quantifying and minimizing the disruptive impact of construction activities on air traffic and minimizing the total construction cost. To accomplish this goal, the research objectives of this study are to develop: (1) a novel optimization model for the planning of airport expansion projects that is capable of minimizing both airport operations disruptions cost and total construction cost; (2) an innovative machine learning methodology that can be used to create robust machine learning models for predicting the impact of alternative airport area closures on flights ground movement time without the need for repetitive and time-consuming simulation

computations; and (3) a novel methodology for optimizing the phasing plans of airport expansion project that identifies optimal daily and hourly work plans for all construction activities that strikes an optimal balance between construction-related airport disruptions and construction cost.

The performance of the developed models was analyzed using real-life case studies of airport expansion projects. The results of this analysis illustrated the original contributions of the developed models and their novel methodologies for (i) optimizing the planning of airport expansion projects and generating optimal tradeoffs between minimizing construction-related disruptions in airport operations and minimizing total construction costs; (ii) developing optimal schedules for all airport construction phases at different levels of details including daily and hourly work plans; (iii) accurately and efficiently predicting the impact of alternative phasing plans on flights ground movement time during airport construction activities and their associated construction-related disruption costs; and (iv) analyzing and minimizing the impact of air traffic on total construction cost of airport expansion projects. These original contributions and novel capabilities of the developed models are expected to improve the functional performance of operational airports during construction activities and enhance the cost-effectiveness of airport expansion projects.

To My Grandmothers Aamna & Sabha

"May their souls rest in peace"

To Mom & Dad

"The whole world considers me your son, I consider you the whole world"
You are the light of my life, to you I dedicate this work

Acknowledgments

First, I want to thank Allah the Almighty for blessing me with the strength, patience, and knowledge to finish this challenging step in my life. This dissertation would not be complete without giving credit to many people who have graciously guided and supported me during my PhD journey. I want to express my sincere appreciation and gratitude to my mentor and academic advisor, Professor Khaled El-Rayes. His advice, guidance, and relentless support during my doctoral program were invaluable to my successful completion. His leadership will forever be cherished and I look forward to his continuous support beyond my time at Illinois. I also want to extend my deepest appreciation to Professor Liang Liu, Professor Mani Golparvar-Fard, Professor Nora El-Gohary, Professor Ramez Hajj, and Professor Erol Tutumluer for their dedicated service on my thesis supervisory committee and all their guidance and constructive feedback.

Thanks should also go to Mr. Eric Boyajian the Director of Simmod Programs at ATAC Corporation for providing support and access to ”Simmod Pro!” to run the needed simulations. I am also thankful to Mr. Karim Jamous the Planning and Contracts Administration Manager at Airport International Group (AIG) for his help and support in providing me with airport planning data and summarising some current practices of airport expansion projects.

I would be remiss if I did not take the time to thank Ms. Joan Christian, Ms. Maxine Peyton, and the rest of the front line staff of the Department of Civil and Environmental Engineering. These individuals work tirelessly behind the scenes to help ensure the success of the department's graduate students and their dedication means the world to me. I am also thankful and honored to have received financial support through the Mavis future faculty fellowship from the College of Engineering.

I want to sincerely thank my colleagues in the research group Dr. Abbas Hassan, Dr. Abdallah AlOmani, Dr. Ahmad Adel, Dr. Amir Ibrahim, Dr. Ayman Halabya, Dr. Dario Acosta, Dr. Ernest-John Ignacio, Dr. Fouad Amer, Dr. Jacob Lin, Dr. Juan Diego Nunez, Dr. Mansour AlOtaibi, Dr. Mishal Alashari, Dr. Mohammad Almashaqbah, and Dr. Nidia Bucarelli for their support during my Ph.D. journey.

I would like to extend my sincere thanks to my dear friends who supported me during this journey, they comforted me during my hardships and celebrated each of my achievements. I also want to thank my ”Chambana” family, they all have made my PhD journey more gratifying and delightful.

I could not have undertaken this journey without the love, patience, and support of my siblings: Atheer, Waad, Ahmad, and Aseel; my siblings-in-law: Abdallah and Maram; and my niece and nephews: Essar, Saif, Youssef, and Sanad. I am also thankful to my uncles, aunts, and cousins. So much of my strength can be directly attributed to their love and support.

Finally, words cannot express my gratitude to my parents Nawal and Yacoub Al-Ghzawi. Mom and Dad, God has blessed me in so many ways, but the biggest of them all is both of you. Thank you for helping me to shape my life with great morals and values. Without you, I would have never been the person I am today. Thank you for everything! To both of you, I dedicate this dissertation as an appreciation for your countless support and endless love.

Table of contents

Chapter 1

Introduction

1.1 Overview and Problem Statement

There are more than 19,900 airports in the U.S. that provide service to 45,000 daily flights and 2.9 million daily passengers (Bureau of Transportation Statistics, 2021; FAA, 2021). Many of these airports are in urgent need for upgrades and expansion (ACI-NA, 2021; ASCE, 2021; FAA, 2020a; Hubbard et al., 2021). In its latest assessment of the conditions of infrastructure systems in the US, the ASCE provided an overall grade of "D+" for the aviation sector infrastructure systems (ASCE, 2021). To address these challenges, the Airports Council International in North America (ACI-NA) stated in its latest study in 2021 the need for five-year (2021-2025) investment of approximately $115 billion in U.S. airports to accommodate their increasing cargo activities, passenger growth, and renovation needs (ACI-NA, 2021; ASCE, 2021; FAA, 2020a).

Airport expansion and renovation projects often cause disruptions and delays in the daily operations of airports (FAA, 2017; Hubbard et al., 2021; Shami and Kanafani, 1997; Siewart and Le Bris, 2015; Stewart, 2001). For example, construction activities often require changes in the number and length of operational airport runways and/or taxiways, and accordingly they cause operation disruptions such as restricting aircrafts to specific runways and taxiways, suspension of operations, and/or decreased weights for aircrafts due to shortened runways (FAA, 2017). On the other hand, FAA regulations that require airport operations be minimally disrupted during expansion projects often lead to construction delays and cost overruns (Alnasseri et al., 2013; Shami and Kanafani, 1997; Stewart, 2001). For example, working during nighttime hours to mitigate disruptions in airport operations often lead to increases in construction cost and duration that are caused by lower construction productivity during nighttime shifts, double handling of materials due to the closure of quarries at night, and extra cost and time for setting up closure lights, barriers, and lighting towers for work areas (Stewart, 2001). Accordingly, project managers and planners of airport expansion projects are often confronted with a number of unique and critical challenges, including: (1) how to optimize the planning of airport expansion projects to mitigate the impact of construction activities on airport operations, (2) how to quantify the impact of airport construction activities and their phasing plans on flights ground movement time, and (3) how to group airport construction activities into phases and how to optimize the scheduling of these phases to minimize construction-related airport disruptions while minimizing total construction cost, as shown in Fig. 1.1. The following sections provide a concise discussion of these three challenges confronting airport and construction planners of airport expansion projects, as shown in Fig. 1.1.

1.1.1 Optimizing the Planning of Airport Expansion Projects

Optimizing the planning of airport expansion projects confronts airport planners and construction managers with a number of practical challenges including how to (1) identify optimal project start date and optimal activity start times for airport expansion projects; (2) determine optimal daily and weekly work plans for all airport expansion activities; (3) select optimal working hours for each construction day from a set of feasible alternatives; (4) quantify and minimize the impact of construction activities on airport operations during the optimal planning of airport expansion projects; (5) measure and minimize the impact of air traffic data and airport operations on total construction cost throughout the entire duration of airport expansion projects; and (6) generate a set of optimal construction plans

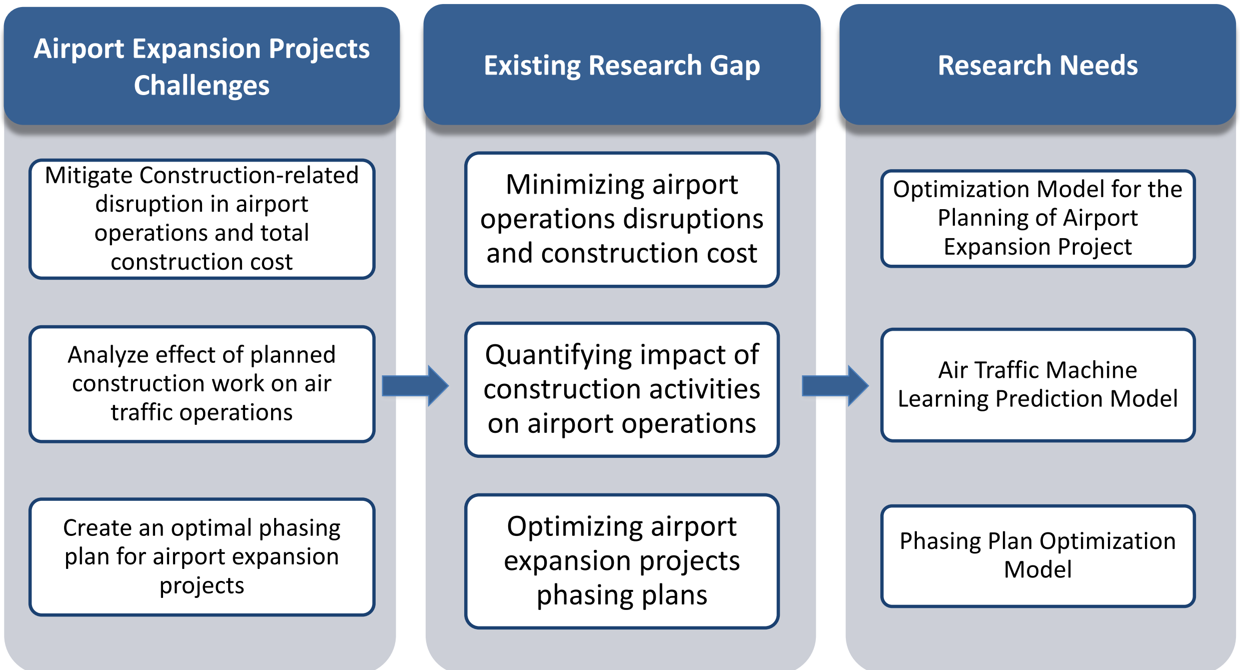

Fig. 1.1. Challenges and research needs in airport expansion projects.

that provide optimal trade-offs between minimizing the construction-related disruption in airport operations and minimizing the total construction cost.

Traditional scheduling methods do not consider the impact of construction work on airport operations, nor the impact of airport regulations on construction activities. For example, these methods often generate a plan that schedules airport expansion activities during weekly working days using regular daytime hours, as shown in plan A and alternative 1 in Fig. 1.2, respectively. This plan, however, causes higher airport operational disruptions because it schedules the construction activities during high daily and hourly air traffic volumes. To minimize this disruptive impact of construction activities on airport operations, planners can adjust plan A as follows: (1) change project start time (ST) and activity start dates (ST_i) to schedule construction activities during low air traffic days as shown in plan B in Fig. 1.2; (2) plan construction activities during weekly working days (ND) that have low air traffic such as weekends as shown in plan B in Fig. 1.2; and (3) perform daily construction activities during nighttime hours (NH) that have low air traffic, as shown in alternative 2 in Fig. 1.2.

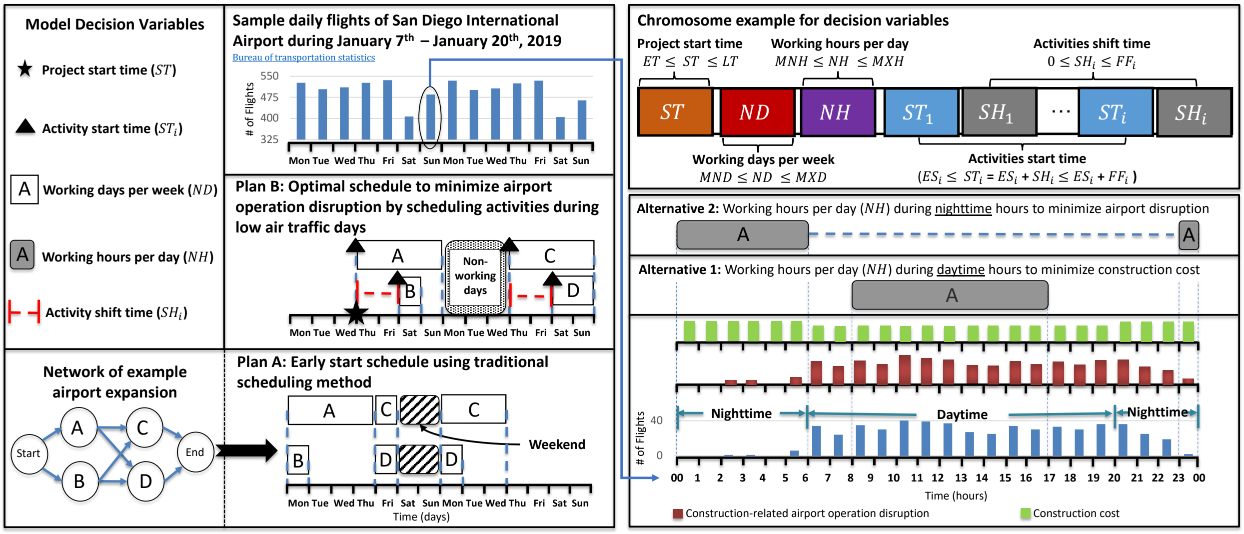

Fig. 1.2. Needed model for optimizing scheduling of airport construction projects.

These construction planning decisions also have a significant impact on construction cost. For example, the construction cost of the example in Fig. 1.2 can be minimized by: (1) adjusting project start time (ST) and activity start dates (ST_i) to schedule construction activities during regular construction working days as shown in plan A in Fig. 1.2; (2) planning construction activities during weekly regular working days (ND) to minimize the additional cost of labor overtime premiums, as shown in plan A in Fig. 1.2; and (3) performing construction work during regular daytime hours (NH) to minimize the additional cost of nighttime construction, as shown in alternative 1 in Fig. 1.2. This example clearly illustrates the significant impact of the aforementioned decision variables on both airport operation disruption and construction cost. Accordingly, the planning of airport expansion projects needs to be carefully analyzed and optimized to address the aforementioned challenges in order to minimize both the cost of construction-related disruption in airport operations and the total construction cost.

A number of related research studies were conducted that focused on: (1) planning of airport expansion and renovation projects (Shami and Kanafani, 1997; Stewart, 2001); (2) analyzing the mutual interaction and impact between airport operations and construction activities in airport expansion and renovation projects (Alnasseri et al., 2013; FAA, 2017, 2022; Hubbard et al., 2021; Khalafallah and El-Rayes, 2006a, 2008; Shami and Kanafani, 1997; Siow et al., 2002; Stewart, 2001); and (3) optimizing the scheduling and resource utilization of different types of construction projects (AlOtaibi et al., 2021; Altuwaim and El-Rayes, 2021; El-Rayes and Jun, 2009; Jun and El-Rayes, 2010; Said and El-Rayes, 2012).

The first group of related studies focused on developing procedures to consider the impact of construction activities on airport operations. For example, Shami and Kanfani (1997) developed a decision support system (DSS) to identify, analyze, and evaluate the interrelationships between airport operations and construction management systems using novel disturbance concept and total disturbance cost model (TDC). The DSS was developed to foster the TDC model by analyzing predefined construction/operation scenarios and selecting the best plans based on a minimum disturbance cost. Stewart (2001) presented practices used by Greater Toronto Airports Authority (GTAA) to strike a balance between maintaining full operational needs and realistic construction methods and production rates during airport expansion and renovation projects. These practices generated construction schedules that heavily relied on nighttime work and weekend shifts that were justified because their impact on increasing construction cost was considered reasonable compared to the benefits gained from mitigating disruption in airport operations.

The second group of available related studies focused on investigating and analyzing (a) the impact of airport expansion and renovation construction projects on airport operations; and (b) the impact of airport and FAA regulations, that require airport operations to be minimally disrupted during construction, on the construction cost and duration. For example, Siow et al. (2002) developed a methodology that identifies the critical phases of the airport expansion projects that need to be carefully planned and managed to minimize disruptions in airport operations. Khalafallah and El-Rayes (2006a, 2008) analyzed the proximity between construction activities and airport operations and developed two multi-objective optimization models for planning airport construction site layouts that focused on (a) minimizing construction-related hazards and site layout costs; and (b) minimizing construction-related security breaches while minimizing site layout costs. Alnasseri et al. (2013) presented a theoretical framework that integrates project and human resource strategies for airport operators to implement in order to enhance business operations when managing and controlling construction projects. Hubbard et al. (2021) conducted a literature review that focused on analyzing the impact of construction activities on airport operations and reported that the limited amount of relevant literature indicates that this area warrants further study. The same study highlighted the need for additional research to investigate the potential use of alternative construction scheduling strategies such as nighttime work to minimize construction-related disruptions in airport operations (Hubbard et al., 2021).

The third group of related studies focused on optimizing the planning of a wide range of construction projects to accomplish multiple project objectives. For example, a group of research studies developed models to optimize construction planning by identifying an optimal start time of construction activities in order to (a) maximize the efficiency of resource utilization in construction projects (El-Rayes and Jun, 2009); (b) minimize site logistics costs and project criticality of congested construction sites (Said and El-Rayes, 2012); and (c) generate optimal trade-offs among project duration, work interruptions, and overtime use of repetitive construction projects (Altuwaim and El-Rayes, 2021). Another related study developed a model for optimizing the planning of renovation work in leased residential buildings to minimize total renovation cost by identifying optimal project start date, crew formations, and unit renovation sequence (AlOtaibi et al., 2021).

Despite the significant contributions of the aforementioned research studies, they have limitations in optimizing the planning of airport expansion and renovation projects as they are incapable of (1) identifying optimal project start date and optimal activity start times for airport expansion projects; (2) determining optimal daily and weekly work plans for all airport expansion activities; (3) selecting optimal working hours for each construction day from a set of feasible alternatives; (4) quantifying and minimizing the impact of construction activities on airport operations during the optimal planning of airport expansion projects; (5) measuring and minimizing the impact of air traffic data and airport operations on total construction cost throughout the entire duration of airport expansion projects; and (6) generating a set of optimal construction plans that provide optimal trade-offs between minimizing the construction-related disruption in airport operations and minimizing the total construction cost. Accordingly, there is a need to develop a novel multi-objective optimization model for the planning of airport expansion projects that provides the capability of minimizing both airport operation disruptions and construction cost.

1.1.2 Predicting the Construction-Related Disruptions in Airport Expansion Projects

Airport expansion projects often cause disruptions and delays in air traffic due to their impact on the number, length, and capacity of operational airport runways and/or taxiways (FAA, 2017). For example, airport traffic controllers need to adjust the flights ground movement routes due to the closure of the construction area to keep the airport operational. This often leads to longer taxi and/or wait times for the flights to move between assigned gates and runways during departure and arrival, as shown in cases A, B, and C in Fig. 1.3. These construction-related delays need to be carefully analyzed to minimize the disruptive impacts of construction activities on airport operations (Hubbard et al., 2021; Said and El-Rayes, 2010; Shami and Kanafani, 1997; Stewart, 2001).

Many airport expansion projects are often broken down into phases to minimize construction-related airport disruptions (FAA, 2017; Stewart, 2001), as shown in the simplified example in Fig. 1.3. In this example, the airport expansion project requires construction work in areas $C1$ and $C2$ to reconstruct these segments of the taxiway. Airport and construction planners need to carefully analyze the impact of possible combinations of airport area closures on flights ground movement time and on airport operations. For

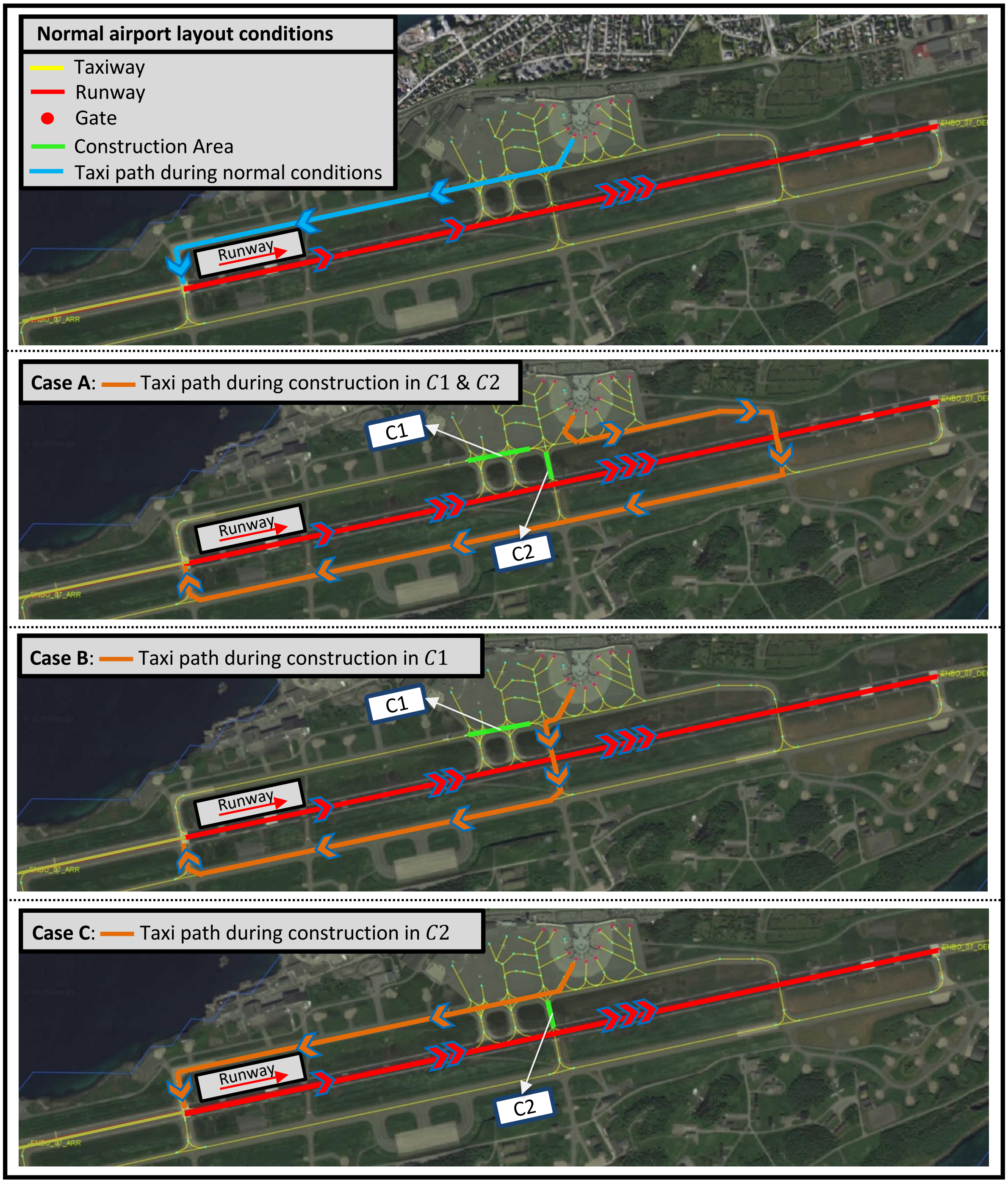

Fig. 1.3. Impact of scheduling airport area closures on flights ground movement time

example, airport and construction managers need to create a simulation for flights ground movement under the condition of closing (1) area $C1$ and $C2$ together, (2) area $C1$, and (3) area $C2$ to determine the best scheduling option and alternative, as shown respectively in Cases A, B, and C in Fig. 1.3.

The number of all possible combinations of airport area closures depends on the number of the area closures and equals to $2^n - 1$ where n represents the number of areas. For example, the number of all possible combinations of airport area closures for an airport expansion project that requires the reconstruction of 14 segments of Taxiway-B in San Diego International Airport (see Fig. 1.4) equals $2^{14} - 1 = 16,383$ combinations. The impact of each of these 16,383 possible combinations on airport operations needs to be carefully analyzed to select the best possible construction plan that minimizes total construction-related airport disruptions. This impact can be analyzed using air traffic simulation tools such as Simmod Pro (ATAC, 2021) to simulate and calculate flights ground movement time for each of these possible combinations of varying airport area closures. This requires time-consuming simulations and significant computational efforts which clearly illustrates the challenges confronting airport and construction planners during their scheduling of airport construction activities. To address these challenges, there is a pressing need for an accurate and reliable model for predicting the impact of alternative construction plans on flights ground movement time without the need for repetitive and time-consuming simulations.

A number of related studies were conducted that focused on: (1) identifying and analyzing the interaction between construction activities and air traffic operations during airport expansion and renovation projects (FAA, 2017, 2022; Hegazy and Kamarah, 2022; Hubbard et al., 2021; Khalafallah and El-Rayes, 2011; Shami and Kanafani, 1997; Siow et al., 2002; Stewart, 2001); (2) estimating and predicting flight taxi times using computational models (Balakrishna et al., 2008; Jordan et al., 2010; Lee et al., 2016; Lee et al., 2015; Legge and Levy, 2008; Lian et al., 2018; Ravizza et al., 2013; Srivastava, 2011; Yin et al.,

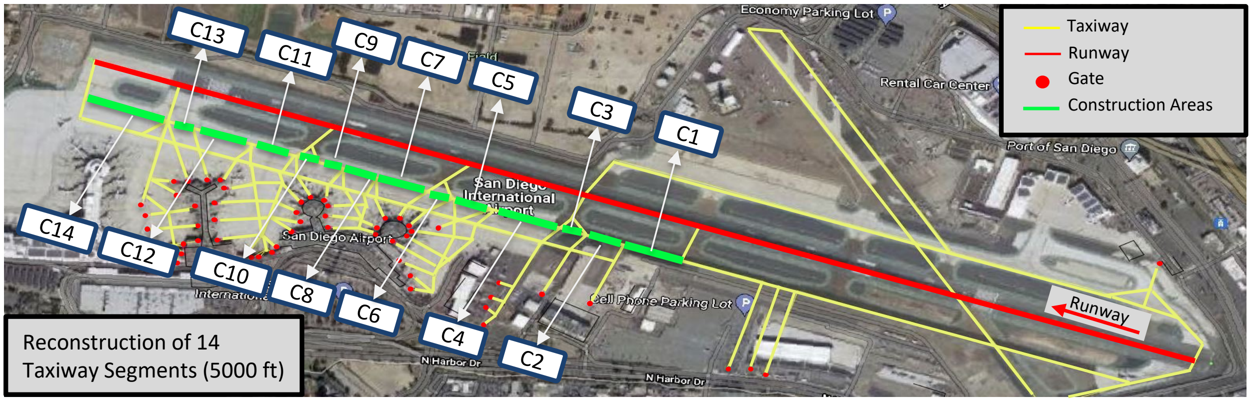

Fig. 1.4. Taxiway reconstruction areas at San Diego International Airport

2018; J. Zhang et al., 2022); and (3) predicting flight delays using machine learning models (Gui et al., 2019; Ye et al., 2020).

The first group of related studies focused on developing procedures to quantify the impact of construction activities on air traffic operations. For example, Shami and Kanfani (1997) developed a systematic framework to evaluate the disturbance interrelationship between construction activities and airport operations during airport expansion projects and linked these interrelationships in a disturbance matrix. Siow et al. (2002) developed a methodology to identify the critical phases of airport expansion projects in order to be analyzed carefully to assess and manage their impact on airport operations. Hubbard et al. (2021) presented a literature review about the construction impact on airport operations and highlighted the need to analyze relevant case studies to access relevant data due to lack of research and studies on this topic. FAA (2022) analyzes impacts that upcoming construction projects may have on airport and airspace capacity and issues airport construction impact reports quarterly. FAA also requires airport operators to identify airport areas affected by construction activities to help measure the impact of construction on airport operations (FAA, 2017).

The second group of available related studies focused on estimating and predicting flight taxi times. For example, Legge and Levy (2008) and Srivastava (2011) developed prediction models for departure taxi-out times by deriving linear equations from regression analysis using surveillance system data. Balakrishna et al. (2008) applied a reinforcement learning probabilistic framework algorithm to estimate and predict average taxi-out times at the airport at least 15 minutes before aircraft scheduled gate departure time. Jordan et al. (2010) utilized a statistical learning method to extract key variables and predict taxi time to support tower flight data managers. Another related study combined statistical approach and ground movement model to improve taxi-out times estimations at airports using multiple linear regression analysis (Ravizza et al., 2013). Lee et al. (2016, 2015) proposed two new methods to predict taxi-out times at Charlotte Douglas Airport. In the first study, a simulation tool was used to predict real-time taxi times and provide the estimates to the runway scheduler, and a data-driven machine learning method was used to assess the prediction accuracy (Lee et al., 2015). In the second study, surface surveillance data was first analyzed to select key factors affecting taxi-out times that were used in multiple machine learning methods to learn and predict taxi-out times (Lee et al., 2016).

The third group of related studies focused on predicting flight delays based on machine learning models to help air traffic controllers in improving airport efficiency. For example, Gui et al. (2019) developed two machine learning models which are random forest-based and long short-term memory-based architectures to predict individual flight delay, and they found that the random forest-based architecture presented better adaptation at a cost of the training accuracy when handling a limited data set. Ye et al. (2020) developed new models for predicting aggregate flight delays in airports by exploring four popular machine learning methods, and the best performing model provided high prediction accuracy and less error than previous studies.

Despite the significant contributions of the aforementioned research studies, they are all incapable of (1) quantifying the impact of airport area closures on air traffic during airport expansion projects; and (2) predicting the impact of alternative construction phasing plans on flights ground movement time during airport expansion projects without the need for repetitive and time-consuming simulation computations. Accordingly, there is a pressing need for the development of new models to address and overcome these limitations of existing studies.

1.1.3 Optimizing the Construction Phasing Plan of Airport Expansion Projects

Airport expansion projects often need to be planned and executed in phases to minimize disruptions in air traffic that needs to remain operational during construction (FAA, 2017; Shami and Kanafani, 1997; Stewart, 2001; Jaroch, 2020). These phases are typically planned and scheduled to minimize the impact of airport area closures due to construction on flights ground movement time and total construction cost (Hubbard et al., 2021; Philadelphia International Airport, 2019; Stewart, 2001; Jaroch, 2020). These airport construction phases can be scheduled to be executed concurrently, sequentially, or with a degree of overlapping among them, as shown in options I, II, or III in Fig. 1.5, respectively.

The concurrent scheduling of all construction phases to start at the same time always reduces the overall duration of construction activities and airport area closures, however, its impact on airport disruption cost varies significantly based on the airport layout and required area closures, as shown in Fig. 1.5. For example, the concurrent closure option of areas $C1$, $C2$, and $C3$ outperforms the sequential closure option in both the overall project duration and airport disruption cost, as shown in Example A in Fig. 1.5. The reason for the lower disruption cost of the concurrent closure is that the sequential closure of these three areas one after the other does not reduce air traffic disruption because closing area $C1$ requires all aircrafts to take a detour to cross the runway to reach the departure queue stage even if areas $C2$ and $C3$ are kept open for flights ground movement. Accordingly, the concurrent closure of these three areas leads to a shorter overall number of days for air traffic disruptions and lower airport operations disruption.

On the other hand, the concurrent closure option of areas $C4$, $C5$, and $C6$ results in a shorter overall project duration, however, it leads to a higher airport disruption cost than those of the sequential closure option, as shown in Example B in Fig. 1.5. The reason for the higher airport disruption cost of the concurrent closure is that it requires flights to take a longer taxi path around the three closed areas while the sequential closure requires flights to take a shorter taxi path around only one closed area at a time, as shown in Fig. 1.5. In addition to these concurrent and sequential phasing options, planners can develop and analyze the impact of intermediate alternatives that provide varying degrees of overlap among the construction phases, as shown in Option III in Fig. 1.5. This example clearly illustrates that the impact of phasing options on airport disruption cost is highly dependent on the layout of the airport and therefore needs to be carefully considered by airport and construction planners during the planning of airport expansion projects.

In addition to the construction phasing decisions, airport and construction planners need to consider and analyze the impact of other important planning decisions on airport disruption and construction costs including: (1) start date and time of construction phases (PS_p), (2) start time of construction activities ($AS_{p,i}$), (3) weekly working days (WD_p), (4) number of daily working shifts (WS_p), (5) working hours per shift ($WH_{p,ws}$), and (6) lag time between shifts ($lag_{p,ws}$), as shown in Fig. 1.6. For example, airport and construction planners can minimize the construction impact on airport disruption by scheduling the start time of construction phases and activities (PS_p, $AS_{p,i}$) during low air traffic periods. This can be achieved by planning the construction activities to be performed during low air traffic days and hours such as weekends and nighttime hours, as shown in Plan A in Fig. 1.6. Alternatively, planners can minimize the total construction cost by scheduling the start time of phases and activities (PS_p, $AS_{p,i}$) to perform construction work during weekdays and regular working hours to minimize overtime premiums, as shown in Plan B in Fig. 1.6. This example clearly illustrates the significant impact of the aforementioned airport construction planning decisions on both airport operations disruption cost and construction cost.

To minimize airport operations disruption cost and construction cost during airport expansion projects, planners are often confronted with a number of challenges that require

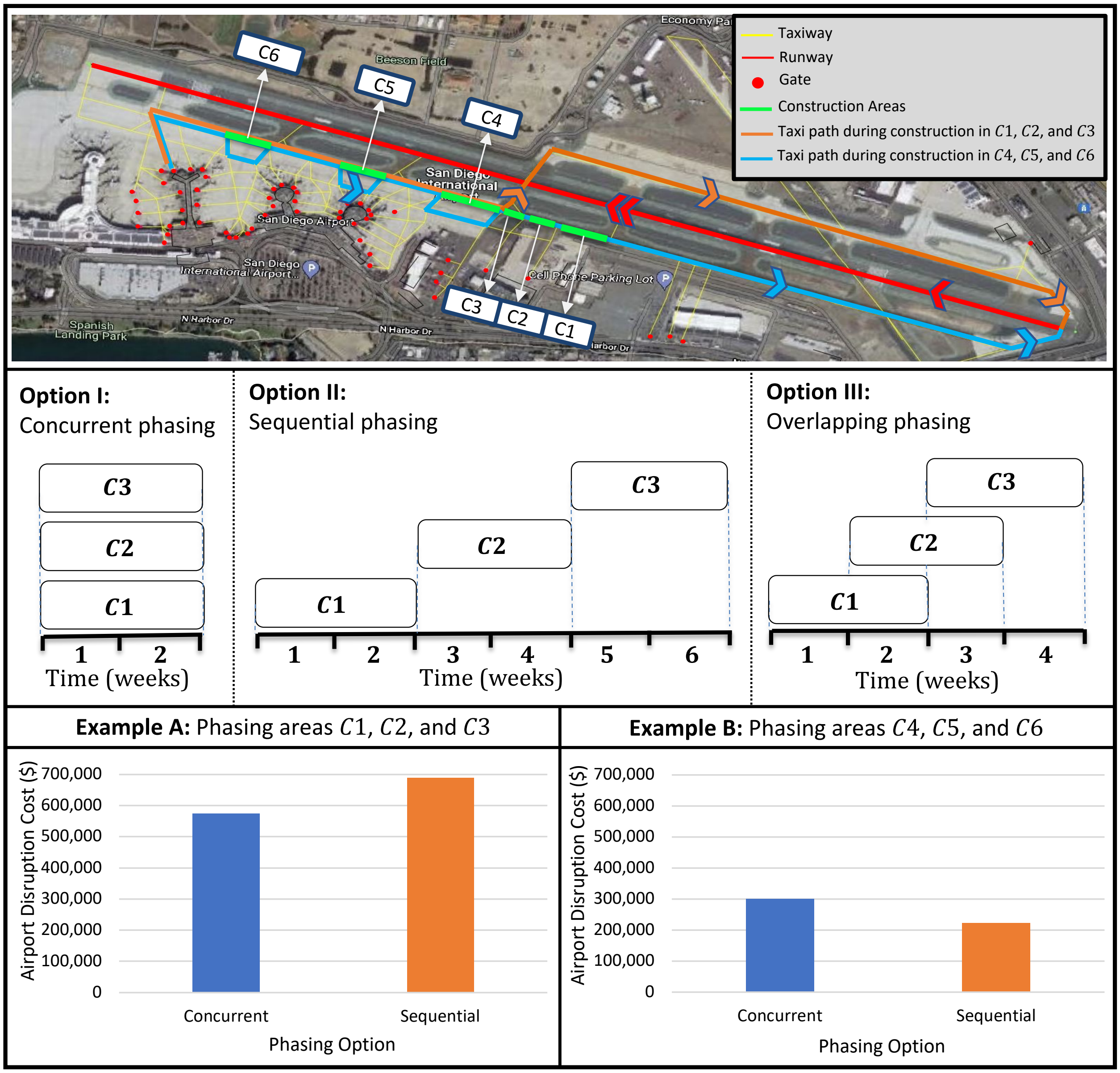

Fig. 1.5. Impact of concurrent and sequential phasing options on airport disruption cost

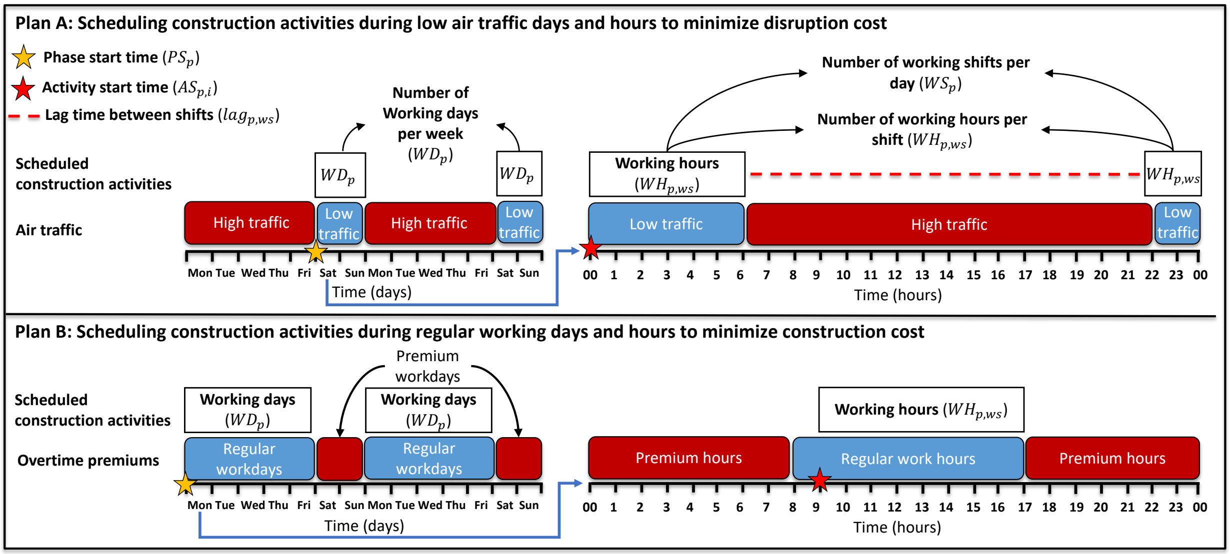

Fig. 1.6. Needed model for optimizing phasing plans of airport expansion projects

them to (1) identify optimal construction phasing plans including the start dates and times of each phase and activity; (2) determine optimal schedule of each construction phase at different levels of details including daily schedule and hourly work plans; (3) quantify and minimize the impact of construction phasing plans on flights ground movement time using machine learning; and (4) generate optimal phasing plans that provide optimal trade-offs between minimizing construction-related disruption in airport operations and minimizing total construction cost.

To support planners address the aforementioned challenges in the planning of airport expansion projects, a number of related studies were conducted that focused on: (1) analyzing the need for and impact of phasing plans during airport expansion projects (Ashford et al., 2011; Dubey, 2020; Horst and Murray, 2014; Hubbard et al., 2021; Khalafallah and El-Rayes, 2006a, 2008; Kwakkel et al., 2010; Lary and Rothnie, 1994; Stewart, 2001; Stockton, 2015; Jaroch, 2020); (2) assessing and improving air traffic and airport operations management (Castelli and Pellegrini, 2011; Herrero et al., 2005; Humbertson and Sinha, 2012); and (3) investigating the implementation of air traffic simulation tools and building information modeling environments in airport expansion projects (Biancardo et al., 2020; X. Li and Chen, 2018).

The first group of studies focused on analyzing the need for and impact of construction phasing plans during airport expansion projects. For example, Lary and Rothnie (1994) investigated two airport construction projects that involved runway, taxiway, and terminal apron pavement replacement and their complex construction phasing plans. These plans required a substantial portion of the construction work to take place in nighttime due to the high air traffic volume during regular daytime working hours. Stewart (2001) presented practices used by Greater Toronto Airports Authority (GTAA) to strike a balance between maintaining full operational needs and realistic construction methods and production rates. The same study highlighted that it was necessary to divide the project into various stages and sub-stages to maintain the required level of service. Jaroch (2020) investigated industry practices for developing phasing plans to reconstruct a taxiway in Van Nuys Airport by dividing the project into multiple phases to maintain access and mitigate operational impact during construction. Khalafallah and El-Rayes (2006a, 2008) developed two optimization models for planning airport construction site layouts that analyzed the proximity between airport operations and construction activities in order to minimize site layout costs, construction-related hazards, and construction-related security breaches.

The second group of available related studies focused on assessing and improving air traffic management to support airport operators in reducing delays in airport operations and flights. For example, Herrero et al. (2005) developed a decision support system to find the best routes and sequences for selected airport operations to minimize total airport ground delay. Castelli and Pellegrini (2011) evaluated the benefits and limitations of implementing collaborative decision making (CDM) process among airlines, airports, and air navigation service providers (ANSPs) in the planning and execution phases of a flight and reported that the implementation of the new proposed protocol appears to be beneficial for airlines and ANSPs but not for airports. Humbertson and Sinha (2012) investigated the use of available planning and recovery tools to improve air traffic management and to mitigate the impact of irregular airport operations caused by unforeseen events such as significant weather events.

The third group of related studies analyzed the performance of airport simulation tools and BIM models during the planning, design, construction and/or operating phases of airport expansion projects. For example, Li and Chen (2018) analyzed the application of different simulation tools such as Simmod Pro in airport planning and reported that the use of these tools has a great significance in optimizing airport construction plans and improving air traffic management. Biancardo et al. (2020) implemented Building Information Modeling (BIM) environment for an airport construction project of an elevated walkway connecting the gate with the runway and reported that the use of BIM environment resulted in reducing project cost and duration.

Despite the significant contributions of the aforementioned research studies, they have limitations in optimizing the phasing plans of airport expansion projects as they are incapable of: (1) identifying optimal construction phasing plans including the start dates and times of each phase and activity; (2) determining optimal schedule of each construction phase at different levels of details including daily schedule and hourly work plans; (3) quantifying and minimizing the impact of construction phasing plans on flights ground movement time using machine learning; and (4) generating a set of optimal phasing plans that provide optimal trade-offs between minimizing airport operations disruption cost and minimizing total construction cost. Accordingly, there is a pressing need to develop a novel methodology for optimizing the phasing plans of airport expansion projects that overcomes the aforementioned limitations of existing research studies and identifies optimal daily and hourly work plans for all construction activities in order to minimize both airport operation disruptions and total construction cost.

1.2 Research Objectives

The primary goal of this research study is to develop a novel methodology for optimizing the planning of airport expansion projects. To accomplish this goal, the objectives of this research study along with its research questions are summarized as follows:

Objective 1:

Conduct a comprehensive literature review on the latest research on (1) mutual disruption impact in airport expansion projects between airport operations and construction activities in airport expansion and renovation projects; (2) optimizing phasing plans of airport expansion projects; (3) available planning and scheduling optimization models of airport expansion and renovation projects; (4) flights taxi and travel times machine learning prediction models; (5) available site layout models for area-constrained construction site projects such as airport expansion projects; (6) new technologies such as autonomous vehicles and high-speed mass transit systems and their impact on the future use of airport facilities; and (7) decision-making and multi-objective optimization techniques that have the ability to address the challenges of airport expansion projects.

Research Questions:

(1) What are the mutual impacts between ongoing airport operations and construction activities? (2) What measures can be taken to mitigate the construction-related disruptions during airport expansion projects? (3) How can the phases of airport expansion projects optimally planned? (4) How can the planning of airport expansion projects mitigate airport operation disruptions and total construction cost? (5) What methods exist to optimize the planning and scheduling of an airport expansion project? and (6) What machine learning models can be used to predict the impact of construction phasing plans on flights ground movement time during airport expansion projects?

Objective 2:

Formulate a novel optimization model for the planning of airport expansion projects that provides the capability of minimizing both airport operation disruptions and total construction cost.

Research Questions:

(1) What metrics can be utilized to evaluate and analyze the impact of construction activities on airport operations? (2) How can these metrics be integrated to compute the total disruption cost and the overall construction cost for airport expansion projects? (3) How to optimize the planning of airport expansion projects to minimize both airport disruption cost and total construction cost? (4) What are the decision variables and constraints that need to be considered and optimized in this optimization problem? (5) How to formulate an optimization objective function that minimizes construction-related disruption in airport operations and total construction cost for airport expansion projects? and (6) How to evaluate the performance of the developed optimization model?

Objective 3:

Develop an innovative machine learning methodology that can be used to create robust machine learning models for predicting the impact of alternative airport area closures on flights ground movement time in any airport without the need for repetitive and time-consuming simulation computations.

Research Questions:

(1) How to quantify and predict the impact of construction airport area closures on flights ground movement time? (2) What are the predictor variables during airport expansion projects that have an impact on flights ground movement time? (3) How to create a representative dataset that can be used to train and test the performance of the developed machine learning models? (4) What data transformation techniques can be used to preprocess the data to improve the prediction accuracy of the developed model? and (5) Which machine learning methods can be utilized to develop models that are capable of accurately predicting the impact of airport area closures on flights ground movement time?

Objective 4:

Develop an original methodology for optimizing the phasing plans of airport expansion project that identifies optimal daily and hourly work plans for all construction activities in order to minimize both airport operation disruptions and total construction cost.

Research Questions:

(1) How to quantify the construction-relation disruption cost associated with airport area closures? (2) How to optimally break down airport expansion projects into multiple phases? How to select the optimal start time of each phase of the airport expansion project? (3) How to optimize the number of weekly working days, daily shifts, working hours per shift for each phase? (4) How to formulate an optimization objective function that minimizes construction-related disruption in airport operations and total construction cost for airport expansion projects? and (5) Which optimization techniques can be utilized to optimize phasing plans to minimize construction-related disruptions in airport operations? and (6) How to evaluate the performance of the developed optimization model?

1.3 Research Methodology

This section presents the proposed methodology for achieving the objectives of this research study. As shown in Fig. 1.7, the proposed methodology is composed of four major research tasks that are designed to: (1) conduct a comprehensive literature review, (2) formulate a novel optimization planning model for airport expansion projects, (3) develop an innovative machine learning methodology to create a prediction model for quantifying the impact of various construction phasing plans on flights ground movement time during airport expansion projects, and (4) develop an original multi-objective model for optimizing the phasing plans of airport and renovation expansion projects.

1.3.1 Task 1: Conduct a Comprehensive Literature Review

This task focuses on conducting a comprehensive literature review to identify and investigate the latest research focusing on the airport expansion projects challenges. The work in this research task can be subdivided into the following subtasks:

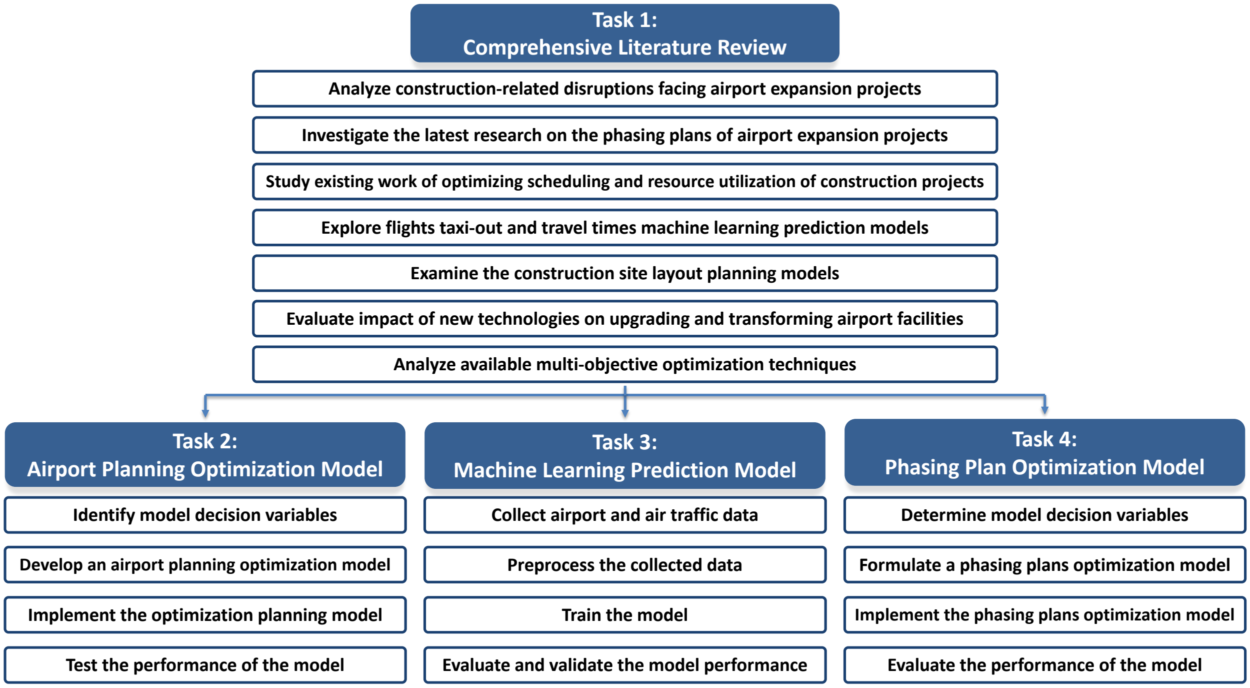

Fig. 1.7. Research methodology.

Analyze construction-related disruptions facing airport expansion projects

The purpose of this task is to analyze the construction-related disruption facing airport expansion projects and identify measures that can be taken to mitigate the disruption and its consequences. The disruption to be investigated include the impact that construction activities and airport operations cause to each other. The consequences of these disruptions are delay in construction activities, delay in airport operations, and delay in delivering projects in the form of extra construction and operation costs.

Investigate the latest research on the phasing plans of airport expansion projects

This task investigates the available research and studies of optimizing the phasing plans of airport expansion projects using different optimization techniques to achieve different objectives. This task also evaluates the formulation of these models, their performances, and abilities to handle the different type of decision variables and objective functions of this type of projects.

Study existing work of optimizing scheduling and resource utilization of construction projects

This task studies the existing studies and work of optimizing the scheduling and resource utilization of construction projects in general and airport expansion projects in particular. These models are also investigated in this task to assess their ability in handling the formulation of optimization problems of this type of projects.

Explore flights taxi and travel times machine learning prediction models

This task explores the existing statistical and machine learning models that is capable of estimating and predicting the flights taxi and travel times. Moreover, this task will evaluate the accuracy of these models and their capability of accurately predicting flights delays especially during airport expansion projects.

Examine the construction site layout planning models

This task examines the available methodologies and models of optimizing construction site layout planning including heuristics and genetic algorithms. Moreover, this task will evaluate the performance of these techniques in handling the decision variables and the required constrained of construction site layouts including boundaries and zone conditions.

Evaluate impact of new technologies on upgrading and transforming airport facilities

This task evaluates the latest research on the upgrading and transformation plans of airport existing facilities. Applicable areas of research include the related new technologies and their impacts on the future need of the existing airport facilities to maximize the use of the ongoing facilities over the time.

Analyze available multi-objective optimization techniques

This task focuses on analyzing the latest decision making and optimization techniques, which will be utilized to address the unique challenges of airport expansion projects. This task considers heuristics algorithms, genetic algorithms, and weighted linear programming optimization techniques.

1.3.2 Task 2: Formulate Optimization Planning Model

This objective of this task is to formulate a multi-objective optimization planning model of airport expansion projects that is capable of minimizing construction-related disruptions in airport operations and minimizing total construction cost. This model intends to support airport planners, stakeholders, and construction planners in their efforts to upgrade the aviation infrastructure with minimal impact on ongoing airport operations while minimizing total construction cost. The work in this research task can be subdivided into the following subtasks:

Identify model decision variables

The purpose of this task is to identify new decision to formulate the optimization problem. These decision variables, include project start date, construction activities start times, number of weekly working days, and number working hours per shift.

Develop an optimization planning model

This task develops a multi-objective optimization planning model that is capable of generating optimal tradeoffs between minimizing the construction-related disruptions in airport operations and minimizing the total construction costs.

Implement the optimization planning model

The objective of this task focuses on implementing the developed optimization planning model using the NSGA-II genetic algorithm (Deb et al., 2002).

Test the performance of the model

This task tests and refines the performance of the developed optimization planning model using a case study of San Diego International airport expansion project.

1.3.3 Task 3: Develop Machine Learning Prediction Model

This objective of this task is to develop a machine learning model of airport expansion projects that is capable of quantifying and predicting the construction-related disruptions in airport operations. This model is expected to support airport planners and construction managers in their efforts to minimize the construction-related disruptions in airport operations during construction for airport expansion projects. The work in this research task can be subdivided into the following subtasks:

Collect Data

The purpose of this task is to focus on analyzing the airport data to determine the factors that has a significant impact on the mobility of the aircrafts during its ground movement, such as, airport layout, flights schedule, departure and arrival gates, taxi paths, and allocated runways. This task also collects this data using an advanced air traffic simulation tool (Simmod PRO!).

Preprocess the Data

This task preprocesses the collected data to normalize and standardize it to prepare it for the training model. Different normalization and standardization techniques are used based on the type of data to get the best results, such as, min-max scalar for continuous type of data, and one hot encoding for categorical type of data. Dijkstra's algorithm is also used in this task to find the shortest taxi path for each flight to normalize the airport layout.

Train the model

In this task, the model focuses on training the normalized and standardized data by splitting it in time series. Different machine learning models are used in this task for training the model and compare the results to determine the best machine learning model that gives the highest accuracy. The model tests its accuracy by comparing the predicted results for the test data that was split before with its actual results.

Evaluate and Validate the model

This task focuses on evaluating the performance of the developed model using the training dataset and validating its results by comparing the predicted values to the true values in the testing dataset that was never seen before by the model. The prediction accuracy of the model is measured in different metric such as the mean absolute percentage error, mean square error, mean absolute error, and others.

1.3.4 Task 4: Develop Optimization Phasing Plans Model

This objective of this task is to develop a multi-objective optimization phasing plans model of airport expansion projects that is capable of minimizing construction-related disruptions in airport operations and minimizing total construction cost. This model intends to optimize the phasing plans of airport expansion projects to support airport planners, stakeholders, and construction managers and planners in their efforts to upgrade the airports with minimal impact on ongoing airport operations while minimizing total construction cost. The work in this research task can be subdivided into the following subtasks:

Determine model decision variables

In this task, new decision variables will be determined to formulate the optimization problem. These decision variables, include phases start date, construction activities start times, number of weekly working days, number of daily shifts and working hours per shift.

Formulate an optimization phasing plans model

The objective of this task is to formulate a multi-objective phasing plans optimization model that is capable of generating optimal tradeoffs between minimizing the construction-related disruptions in airport operations and minimizing the total construction costs.

Implement the optimization phasing plans model

This task implements the developed phasing plans optimization model using the NSGA-II genetic algorithm (Deb et al., 2002).

Evaluate the performance of the model

This task focuses on evaluating and refining the performance of the developed phasing plans optimization model using a case study of an airport expansion project.

1.4 Research Significance

The developments of this research study are expected to have significant and broad impacts on: (1) quantifying and minimizing the construction-related disruptions and total construction cost of airport expansion projects; (2) accurately and efficiently predicting the impact of airport area closures during airport expansion projects on flights ground movement time; and (3) supporting airport and construction planners in identifying optimal daily and hourly work plans for all airport construction activities to minimize construction-related disruptions and total construction cost.

1. Minimizing the construction-related disruptions and the total construction cost

The present study is expected to support airport planners and construction managers in minimizing construction-related disruptions and total construction cost. The proposed multi-objective optimization model is designed to generate a wide spectrum of Pareto optimal solutions that represent unique and optimal tradeoffs between the two optimization objectives functions of minimizing construction-related disruptions in airport operations and total construction cost. Accordingly, project planners can select schedule plans from the spectrum of Pareto-optimal solutions that best fit the maximum acceptable level of disruptions in air traffic or complies with the maximum available budget. This capability will result in the construction of cost-effective and high-performance sites that will lower the disruptions in airport operations during construction.

2. Quantifying and predicting the impact of construction activities.

This research study holds a strong potential to quantify and accurately predict the construction-related disruptions in airport operations by conducting a simulation of the air traffic and operations of the airports in normal conditions and during construction using an advance air traffic simulation tool (Simmod PRO!). The model then learns and predicts the impact of the construction activities on air traffic to enable planners to accurately analyze their plans for airport expansion projects and determine any needed changes to maintain the minimal level of disruptions in air traffic during construction.

3. Optimizing the phasing plans and construction schedules of airport expansion projects

The developed phasing and planning optimization model provides planners of airport expansion projects planners with the capability of minimizing construction-related disruptions and total construction cost. The model provides much-needed support for airport planners and construction managers and enables them to identify an optimal and cost-effective phasing plans and construction schedules that minimizes construction-related disruptions in air traffic and total construction cost. This can lead to numerous and significant improvements in the performance of constructing this type of projects.

1.5 Report Organization

The organization of this report along with its relation to main research objectives, is discussed as follow:

Chapter 2 details a comprehensive literature review that establishes baseline knowledge of the latest research conducted on (1) analyzing the mutual interaction and impact between airport operations and construction activities in airport expansion and renovation projects, (2) planning of airport expansion and renovation projects, (3) optimizing the scheduling and resource utilization of different types of construction projects, (4) taxi and flight times and delays machine learning prediction models, (5) construction site layout planning models, (6) the transformation models for airport facilities that are expected to be under-utilized in the future, and (7) available decision-making and optimization techniques.

Chapter 3 describes the development of a novel multi-objective optimization model for the planning of airport expansion projects that provides the capability of minimizing both airport operation disruptions and construction cost. This chapter presents the model in four main modules (1) simulation module that calculates and quantifies the impact of airport construction activities on air traffic and airport operations; (2) optimization module that searches for and identifies an optimal construction schedule that generates optimal trade-offs between the two important objectives of minimizing construction-related disruptions in airport operations and minimizing construction cost; (3) scheduling module that calculates the start and finish times of each activity in airport expansion projects; and (4) cost module that computes the total cost of construction-related disruptions in airport operations, and the total construction cost for each generated solution in the optimization module. A real-life case study of planning an airport expansion project is analyzed to demonstrate the use of the model and display its unique capabilities.

Chapter 4 presents the development of an innovative machine learning methodology to develop a prediction model for quantifying the impact of various phasing plans on flights ground movement time during construction of airport expansion project. The methodology implementation is organized in four stages: (1) data collection stage to gather all required airport data for training and testing the prediction model; (2) data preprocessing stage to identify, classify, transform, and split all predicted and predictor variables data into training and testing datasets; (3) model training stage to select the machine learning methods and fit each of them to the training dataset by adjusting its parameters to minimize the error; and (4) evaluation and validation stage to evaluate the performance of each selected method on the training dataset and validate its results by applying it on unseen testing dataset to verify its generalizability to make predictions on new unseen data. The performance of the developed machine learning models was evaluated by analyzing a real-life case study.

Chapter 5 discusses the development of a novel methodology for optimizing the phasing plans of airport expansion projects that provides the capability of minimizing both the cost of construction-related disruptions in airport operations and the total construction cost. This chapter presents the integration of a machine learning model to predict the impact of generated phasing plans on flights ground movement time during construction, and a multi-objective genetic algorithms optimization model to identify optimal construction phasing plans for airport expansion projects. A real-life case study of phasing the construction plan of an airport expansion plan is analyzed to illustrate the use of the developed models and demonstrate their capabilities.

Chapter 6 presents the conclusions, research main contributions, and recommended future research of the present study.

Chapter 2

Literature Review

2.1 Introduction

A comprehensive literature review has been conducted to investigate existing research on the topics most relevant to airport expansion projects in order to establish a solid starting point to pursue this research study. This chapter summarizes and organizes the reviewed literature in eight main sections: (1) the mutual disruption impact in airport expansion projects between airport operations and construction activities; (2) phasing optimization models; (3) planning and scheduling optimization models; (4) flights taxi and travel times machine learning prediction models; (5) site layout planning models; (6) the future impact of new innovative technologies on the existing facilities; (7) decision-making and optimization techniques; and (8) limitations of existing models and research needs.

2.2 Disruption in Airport Expansion Projects

The causes of delayed flights are categorized into five different categories: (1) Air Carrier, (2) Aircraft Arriving Late, (3) Security Delay, (4) National Aviation System Delay, and (5) Extreme Weather (Bureau of Transportation Statistics, 2022a). National Aviation System Delay examines and includes the delay data because of closure runways. For example, In April 2017, 78.15% of the flights were recorded on time while 7.55% of the flights were recorded delayed due to National Aviation System (NAS), as shown in Fig. 2.1. Moreover, 21.82% of the delayed flights caused by the NAS were because of runway closure (Bureau of Transportation Statistics, 2022b).

The Impact of runway closure was significantly more in some airports that has construction or development projects underway during that specific period of time. For instance, San Francisco International Airport had many construction projects going on, as the rehabilitation program of a major runway construction project (Runway 28L) that had to be upgraded through April – June 2017 was going underway, reducing the capacity of the runway by 50% causing more than a thousand delayed or cancelled flights over a weekend (Brinkley, 2017; Sciacca, 2017). Bureau of Transportation Statistics (2022b) showed that only 57.5% of the flights were recorded on time in San Francisco International Airport in April 2017. On the other hand, 25.83% of the flights were delayed because of NAS reasons. However, 54.67% of these delayed flights was because of the closed runway recording 150% more delay because of runway closure than the average in all major airports, as shown in Figs. 2.2 and 2.3 (Bureau of Transportation Statistics, 2022b).

Nevertheless, in the same airport for the period of (May 2015 – May 2016) when there were no major construction projects are going on, 75.41% of the flights were on time where 10.4% of the flights were delayed due to NAS and only 1.75% of these flights were delayed because of closed runway. This shows that airport expansion and development projects have a direct impact on airport operations, as it causes delays for flights due to runway closure and many other reasons (Bureau of Transportation Statistics, 2022b).

Airports are divided into landside and airside with the need for infrastructure for a ground access. According to Shami and Kanfani (1997) the impact is mutual between the airport system and the construction system, as any disturbance that could happen to any component of the airport divisions would necessarily lead to a disruption in the airport operations or the construction activities. Disruption of airport operations means delay that

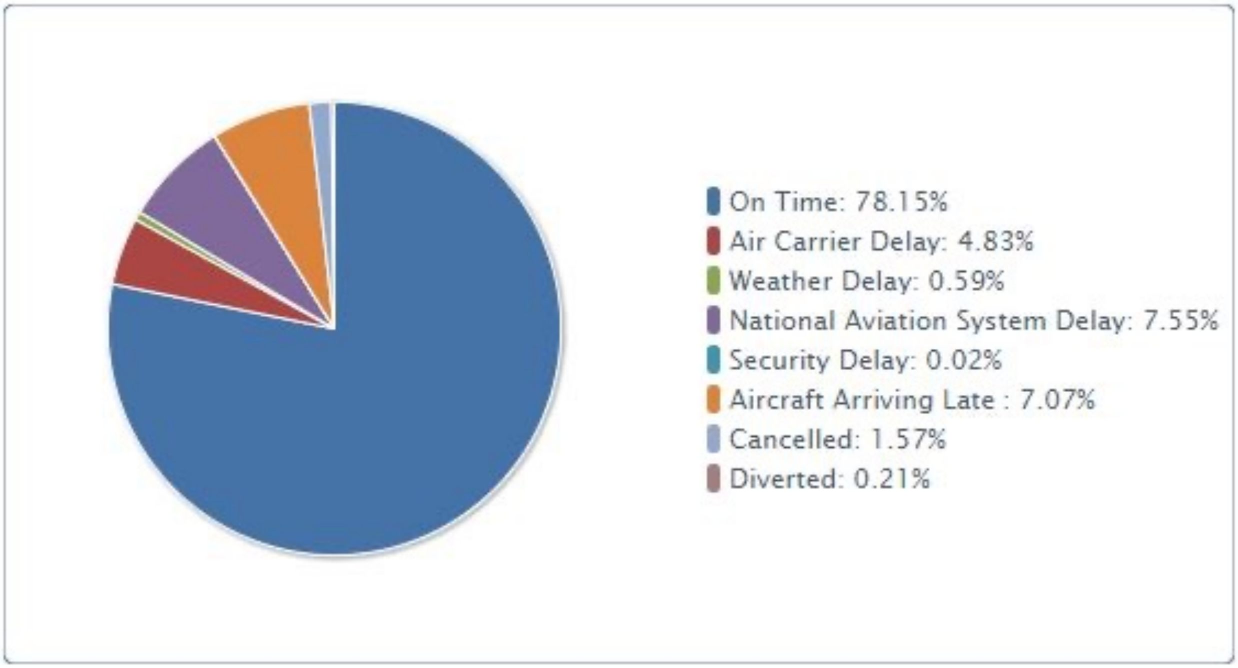

Fig. 2.1. All US airports on time arrival performance in April 2017 (Bureau of Transportation Statistics, 2022b)

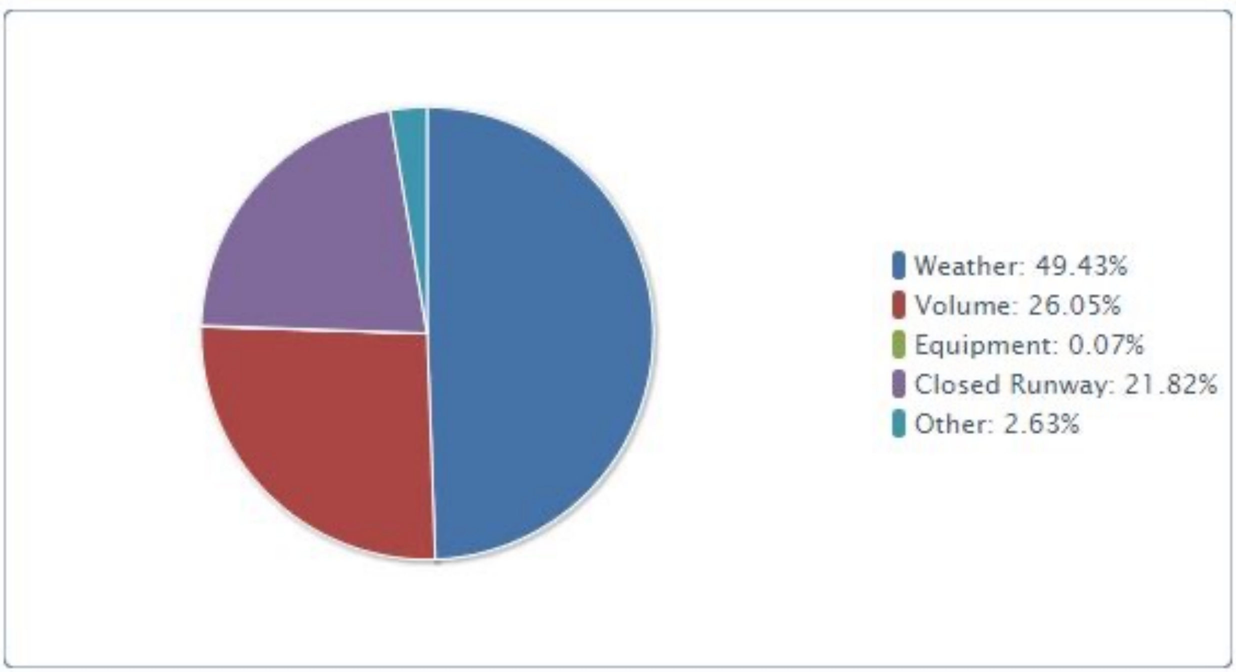

Fig. 2.2. Causes of NAS delays in all US airport in April 2017 (Bureau of Transportation Statistics, 2022b)

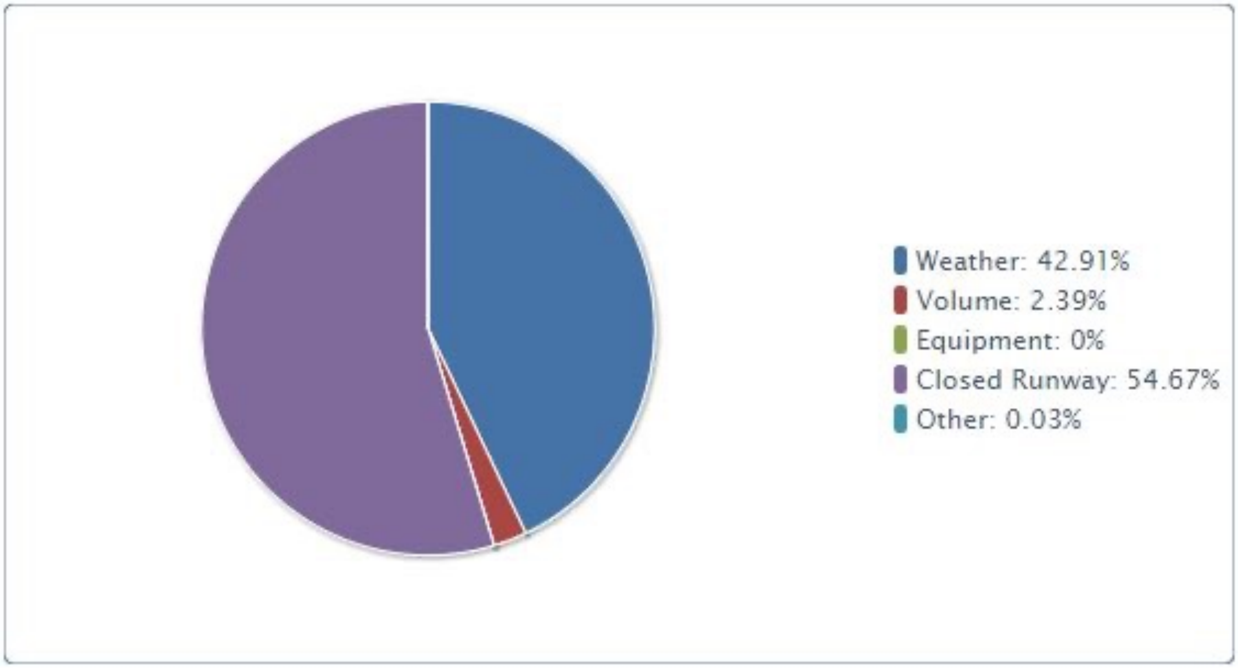

Fig. 2.3. Causes of NAS delays at SFO in April 2017 (Bureau of Transportation Statistics, 2022b)

can be represented by time or cost and could happen in many shapes and not limited to; (1) more time needed to serve the planes, (2) more time the plane needs to spend on its way from the gate to the runway and vice versa, (3) more time added to the scheduled flight at the time of construction compared to its normal duration, (4) The additional time that the passengers are asked to take it into consideration in order to arrive earlier to the airport because of construction, (5) Detour to arrive to the terminal that would increase the time of the trip to the terminal, and (6) the decrement of airport's capacity, in addition to other ways of possible delays. On the other hand, the airport system constrains the construction activities in many ways, since the airport usually require staying fully functional or to face the minimum disruption during the construction phase (Shami and Kanafani, 1997).

The statistics show that the National Aviation System sector (NAS) is responsible for a significant amount of delayed flights. The NAS sector consists of; (1) Weather, (2) Volume, (3) Equipment, (4) Closed Runway, and (5) Others (Bureau of Transportation Statistics, 2022a). However, the weather is the dominant reason among other NAS component that causes delay. Nonetheless, it is worth it to mention that logically weather is hard to be predicted in manner to take the change in the flights schedule into consideration. On the other hand, construction is a long process that requires a set of plans and detailed schedules that help the airlines to take actions and consider the construction into their flights schedule.

Allison Hope (2017) mentioned that airlines consider many variables to determine the time of each flight they are responsible on, that makes it a very complicated process to formulate the schedule. The airport infrastructure is a main variable that plays a big role in that, including the number of gates is available and the status of the runways in addition to the construction projects. This would help the airline to extend the time block of certain flights to avoid the delayed status on their trips which affects the accuracy of the impact of the construction on the flights time. Although the airlines denied the claim, the industry insiders name this process “schedule padding” which is used to enhance the punctuality. For example, despite new technology and developed airplanes that we travel on nowadays, OAG schedules Analyzer shows that the scheduled time of flights have increased significantly over the past years. For example, the average flight times from New York La Guardia Airport to Chicago O’hare Airport have increased by 20 minutes, from around 2 hours and 30 minutes to 2 hours and 50 minutes (Morries and Smith, 2018), as shown in Fig. 2.4

2.3 Phasing Models of Airport Expansion Projects

This section discusses a number of related studies were conducted that focused on: (1) developing operational procedures and phasing plans for airport expansion projects; (2) planning and improving air traffic and airport operations management; and (3) investigating and analyzing the implementation of information and communication technologies and simulation tools in airport expansion projects.

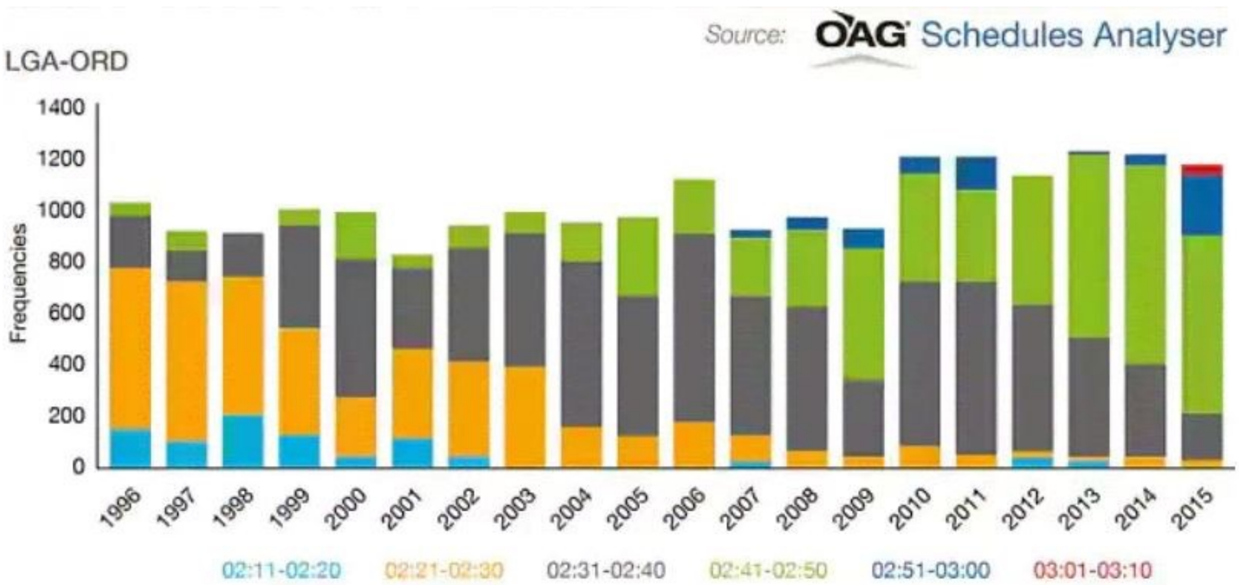

Fig. 2.4. New York La Guardia to Chicago Evolution of Block Hours (Morries and Smith, 2018)

2.3.1 Operational procedures and phasing plans

Lary and Rothnie (1994) studied two airport construction projects that involved replacement of runway, taxiway, and apron pavement with cement concrete pavement. Some of the new replaced cement concrete pavement must return in service within hours after replacement due to the high traffic volume at the airports where these projects take place. Therefore, these projects were formulated, designed, and executed under nighttime conditions to mitigate any disruptions in airport operations.

Stewart (2001) presented industry practices used by the Greater Toronto Airport Authority (GTAA) to insure effective communication between all concerned parties especially to find a rapid resolution for any change in response to unforeseen conditions. These procedures require developing operational plans to focus on airside work challenges, such as night work, short closures, and segmenting of work. These plans aims to maintain the required level of service during airport expansion and renovation projects by dividing the project into segments. Furthermore, airport and construction managers plans the precise number, size, and timing of each segment to strike a balance between maintaining full airport operational needs and realistic construction methods and production rates. The result for the studied project was a construction schedule that is divided into many segments assigned for short shifted night work and weekend working hours. The study highlighted that the additional costs which were associated with segmenting the project and working during premium time nights and weekend hours is considered a small price for maintaining the same level of operational service and safety.

Kwakkel et al. (2010) explored three adaptive alternatives to Airport Master Planning (AMP) which is the dominant approach for Airport Strategic Planning (ASP) that focuses on the development of plans for the long-term development of an airport. AMP aims to provided a detailed view for how the airport would look like in the future. The study highlighted this method performs poorly when the real future turns out to be different from the assumed view since the master plan is static. This study concluded that the three new approaches are complementary and worth be combined into a new adaptive approach to ASP. These three approaches, Dynamic Strategic Planning (DSP), Adaptive Policy Making (APM), and Flexible Strategic Planning (FSP), have different emphasizes, as DSP focuses on real options, APM provides a detailed framework for the development of adaptive plans, and FSP covers a broad spectrum of planning concepts that together result in a thorough treatment of many and diverse airports face uncertainties.

Horst and Murray (2014) identified some key differences in the requirements and practical developments of Construction Safety and Phasing Plans (CSPPs) throughout many International Civil Aviation Organization (ICAO). CSPP is a necessary document for any airport construction project that could have an impact on normal airport operations. This study also identified best industry practices for CSPP development due to the fact that there is no readily available source of information to identify the difference in CSPP requirements found between ICAO states which has left a challenge for engineering firms to face. This study highlighted that best practices practices in developing CSPP is found in a combination of US and UK practices. In the US, FAA requires a CSPP for each airfield construction project funded by the Airport Improvement Program (AIP) of the Passenger Facility Charge (PFC) or located on an airport certificated under Part 139.

FAA (2017) provides significant guidance for developing a CSPP for aiport construction projects. In this advisory, they introduced Safety and Risk Management (SRM) to the CSPP development process. Furthermore, to ensure that contractors fully understands the CSPP along with their responsibilities, FAA requires the contractor to produce a Safety Plan Compliance Document (SPCD) as part of final CSPP.

Jaroch (2020) analyzed a taxiway reconstruction project at Van Nuys project. The project was to reconstruction the 8000-foot-long asphalt Taxiway A and Taxiway B pavement including shoulders. The main challenge in the planning phase for this project was dividing the project into various phases to mitigate construction-related impact to the airport to ensure access for airport to and from the runways with the least impact to tenant operations. Each phase of construction was executed in the same manner, starting with shutting down the construction area, installation of lighted barricades, removal of airfield marking and signage leading into the work area, installing temporary lighting to maintain the electrical system for remaining active airfield areas, and demolishing the existing pavement and electrical system at the work area. After that, the contractor installs deep utilities, constructing the taxiway base material, installing in-pavement lighting conduit, placing the new asphalt pavement, installing edge light fixtures, signage, and tests the electrical system. Finally, the contractor completes the pavement marking of the new taxiway, removes the barricades, and opens the area up to aircraft operations. Once one phase is complete and access is restored, similar construction phase is then shut down and the process is repeated. The article highlighted one of the biggest challenges was faced in this project during early stage of construction of Taxiway B which was a heavy rain season, and their design team reacted quickly to re-sequence and combine certain phases of the project to compensate for the time lost due to initial weather delays.

2.3.2 Air traffic management

Herrero et al. (2005) proposed and analyzed two planning approaches for automatically optimize and find the best routes and sequences for airport operations to help airport ground controllers to improve surface operations and safety. This study addressed the airport global management of departure flights, moving aircrafts along taxiways between gate positions and runways, Two modified optimization algorithms, a time-space flow algorithm and a genetic algorithm, have been developed together to minimize the total ground delay. The study highlighted the significance in using simulation and decision support tools in helping airport controllers in their airport management efforts.

Castelli and Pellegrini (2011) analyzed the potential benefits and limitations of implementing collaborative decision making (CDM) process among airlines, airports, and air navigation service providers (ANSPs) in the framework of the European air traffic management (ATM) system. The goal of this proposed concept is to identify four dimensions (latitude, longitude, flight-level, and time) called target windows which are defined at specific transfer of responsibility areas. Two distinct Analytic Hierarchy Process (AHP) models were presented to evaluate the effect of the introduction of these winows in the planning and execution phases of a flight. The study analysis shows that the implementation of the new proposed protocol appears to be beneficial for airlines and ANSPS but not for airports.

Humbertson and Sinha (2012) described the technologies and tools that can be used by airport operation managers and air traffic management service providers to reduce the impact of irregular aircraft operations caused by significant weather events. This study also discusses the benefits of a shared situational awareness or common operating picture that could be achieved from proper implementation.

2.3.3 Information technologies and simulation tools

Li and Chen (2018) explored and described airport simulation technology that can help the civil aviation achieving scientific assessment and refined decision-making for airport planning, construction, and operating management. These simulation tools can be divided into four types: airside ground operating simulation, terminal area and airway airspace simulation, terminal building internal process simulation, and airport landside curbside traffic simulation. The first type focuses on analysing the operating efficiency of aircrafts in the runway-taxiway-area inside the airfield, and the evaluation of flights delay level, taxiing time, take-off and landing efficiency, and the ground operating capacity of an airport, such as Simmod simulation tool. The second type focuses on analysing the flight efficiency of aircrafts in the arrival and departure route network inside the terminal area and in the route network under airspace, and the evaluation of the terminal area airspace capacity. The third type focuses on analyzing the efficiency of arrival, departure, and transfer procedures in the terminal building. Finally, the fourth type focuses on the evaluation of the landside traffic efficiency in airport, curbside congestion, and the smoothness of traffic. This study highlighted the significance of implementing these simulation tools in airport planning, design, and operating phases to the optimization of airport construction plans and the improvement of airport operational management models.

Biancardo et al. (2020) presented the implementation of information and communication technology in airport construction projects. In this study, a Building Information Modeling (BIM) was adapted for an elevated walkway connecting the gate with the runway at one of airport construction projects. Revit software was used for the architectural/structural model, Robot Structural Analysis (RSA) for the analytical verification, and Navisworks for the 4D/5D model. The study highlights the benefits obtained from implementing BIM technology showing a reduction in construction times and costs. The same study discussed the help BIM can provide by overcoming typical inefficiencies of the traditional design method and conventional professional practices, allowing more integration between design and execution phases.

2.3.4 Limitations of available phasing models

Despite the significant contributions of the aforementioned research studies, they have limitations in optimizing the phasing plans of airport expansion projects as they are incapable of: (1) identifying optimal start dates of each phase and optimal activities start times for each phase of airport expansion projects; (2) determining optimal daily and weekly work plans for all airport expansion activities; (3) selecting optimal number of working shifts and shifts working hours for each construction day from a set of feasible alternatives; (4) quantifying, predicting, and minimizing the impact of construction activities on airport operations during the optimal planning of airport expansion projects; (5) measuring and minimizing the impact of air traffic data and airport operations on total construction cost throughout the entire duration of airport expansion projects; and (6) generating a set of optimal construction phasing plans that provide optimal trade-offs between minimizing the construction-related disruption in airport operations and minimizing the total construction cost. Accordingly, there is a need to develop a novel multi-objective model for optimizing the phasing plans of airport expansion projects that provides the capability of minimizing both construction-related disruptions in airport operations and construction cost.

2.4 Planning and Scheduling Models of Airport Expansion Projects

This section discusses a number of research studies were conducted that focused on: (1) planning of airport expansion and renovation projects; (2) analyzing the mutual interaction and impact between airport operations and construction activities in airport expansion and renovation projects; and (3) optimizing the scheduling and resource utilization of different types of construction projects.

2.4.1 Planning of airport expansion and renovation projects

Shami and Kanfani (1997) addressed the complicated characteristics of airport expansion and renovation projects and its challenges especially the interference between construction activities and facilities ongoing operations as these operations constrain the performance of construction from one side, and construction activities often cause disruption to airport operations on the side. This study outlined a new concept called the disturbance concept to develop a prototype decision support system to minimize the disturbance between construction project and airport operations. Shami and Kanfani (1997) developed a systematic decision support system (DSS) framework to identify, analyze, and evaluate the interrelationships between airport operation and construction management systems using the newly developed disturbance concept and total disturbance cost (TDC) model. These two components were linked in a database that was called the disturbance matrix. The DSS was developed to foster the TDC model and analyze the disturbance matrix. The authors integrated construction and operations scenarios using airport simulation tool (Simmod) and scheduling software (Primavera). The DSS then was used to assist management in selecting optimum scenarios based on a minimum disturbance cost. In this study, a real-life case study was analyzed to illustrate the capabilities of the developed model, and it highlighted that airports can accommodate construction without necessarily suffering heavy negative consequences and achieving a significant minimization in disturbance by combining improved actions in air traffic control and construction management. Also, the authors mentioned that the TDC model is invaluable in measuring airfield performance during construction and in resolving schedule criticality, liquidated damages, and work phasing.

Stewart (2001) presented practices used by GTAA to strike a balance between maintaining the same operational level of service and realistic construction methods and production by holding multiple meetings between airport authorities and construction managers to generate practical schedules to perform the work of airport construction projects. These practices generated a construction schedule that involves short shifted nighttime works and weekend hours. These practices also divided the work into various stages and sub-stages to ensure the minimal impact on airport operations and movement of aircrafts during the construction project. Although this schedule resulted in higher construction cost, it was considered a small price for the resulting increase in operational service and safety.

2.4.2 Airport operations and construction activities

Siow et al. (2002) developed a methodology to identify the critical construction phases to be analyzed, managed, and evaluated to minimize the construction impact. This study presented a new simulation tool, Terminal, Roadway, and Curbside Simulation tool (TRACS), to assist airport planners and decision makers in assessing and managing construction impact on airport operations. The authors highlighted in this study the efficiency and importance of using these tools for evaluating the performance of airport facilities and examining different what-if scenarios for airport planners and decision makers.

Khalafallah and El-Rayes (2006a) analyzed the proximity between airport operations and construction activities during the planning of construction site layout to minimize and eliminate all potential construction-related hazards to aviation safety. In this study, the authors developed a multi-objective optimization model for planning airport construction site layouts that is capable of minimizing construction-related hazards and minimizing site layout cost. This model is also capable of maximizing the control of hazardous construction debris near airport traffic areas, minimizing site layout costs including the travel cost of construction resources and the cost of debris control measures on airport sites, and satisfying all operational safety constrains required by the federal aviation administration.

In another study, Khalafallah and El-Rayes (2008) investigated another challenge caused by the proximitiy between airport operations and construction activities as airport expansion projects often require the presence of construction personnel, material, and equipment near airport secure area leading to an increase in the level of risk to airport security. In this study, the authors developed a multi-objective optimization model for planning airport construction site layout that is capable of minimizing construction-related security breaches while minimizing the site layout costs. This model is also capable of evaluating and maximizing construction-related security level in operating airports. Genetic Algorithm optimization technique was used in this model.

Alnasseri et al. (2013) presented a prototype for a theoretical framework for airport operators to implement in order to cope with an airport environment and enhance business operations when managing and controlling construction projects. This framework has integrated various existing theories associated with project strategies and strategic human resource management and it aims to achieve the framework that offers possible solutions for airport operators and project managers to implement when managing and controlling their construction projects.

Siewart and Le Bris (2015) presented real-life case studies to highlight the interrelationships between airport operations and construction activities, the safety concerns that resulted from this proximity between the two components, and best practices and recommendations to increase the safety. The authors mentioned that markings and lighting are the first safety nets due to their efficiency in dramatically reducing the risks, and they found that achieving and increasing safety and mitigating risks can be done in cheap, simple, and efficient means.

Hubbard et al. (2021) conducted a literature review on airfield infrastructure projects that usually are performed on active airfield which impose operational and human factors challenges for all users. This study focused on analyzing the impact of construction, data related to airfield safety, and presented a discussion of the human factors considerations and mitigation measures that may be appropriate. The same study highlighted the need for further study about the potential impact of airfield construction on airport operations and its safety. It also recommended future investigation for scheduling and contracting approaches other than timing construction activities to occur when air traffic volume is low.

2.4.3 Optimizing scheduling and resource utilization

El-Rayes and Jun (2009) developed a robust and practical optimization model that is capable of generating optimal and practical schedules that maximize the efficiency of resource utilization. This model incorporate two innovative resource leveling metrics to directly measure and minimize the negative impact of resource fluctuations on construction productivity and cost. The first metric quantifies the total amount of resources that need to be temporarily released during low demand period and rehired at a later stage during high demand periods, and the second measures the total number of idle nonproductive resource days that are caused by undesirable resource fluctuations. This study is useful to construction engineers and planners in their efforts to improve labor productivity and cost performance in construction projects.

In another study, Jun and El-Rayes (2010) investigated and analyzed construction projects that involves work in evening and night shifts, and developed a multi-objective optimization model for scheduling labor shifts in construction projects to minimize project duration, reduce cost, and minimize labor utilization in evening and night shifts. This study is useful to construction planners in their effort to optimize the utilization of multiple shifts in order to accelerate the delivery of projects while minimizing the negative impacts of evening and night shifts on construction productivity, safety, and cost.

Said and El-Rayes (2012) developed a new congested construction logistics planning (C2LP) system that optimize the utilization of interior building spaces by considering shifting some of the non-critical activities in order to generate sufficient interior space for storage areas. This model is designed to optimize two competing objectives of minimizing site logistic costs and minimizing project criticality. This study addresses the challenges that contractors face in planning material supply and site logistics due to the scarcity of construction site space.

Altuwaim and El-Rayes (2021) developed a novel multi-objective optimization model for repetitive construction projects that is capable of optimizing project duration, work interruption, and overtime use to address the challenges confronted in repetitive construction projects such as high rise building and highway construction as minimizing the duration of such projects usually requires interrupting the work continuity. This study provides a practical tool for construction planners to minimize project duration while minimizing crew work interruptions and the use of overtime hours.

In another related study, AlOtaibi et al. (2021) developed a model for optimizing the scheduling of renovation project for leased residential buildings to minimize total renovation cost. The model was applied on a cast study to illustrate its capabilities and achieved a 3.6%-4% reduction in total renovation cost in comparison with other available models and industry practices. This model is useful in providing support for construction planners who seek to minimize the total renovation cost of leased residential buildings.

2.4.4 Limitations of available planning and scheduling models

Despite the significant contributions of the aforementioned research studies, they have limitations in optimizing the planning of airport expansion and renovation projects as they are incapable of (1) identifying optimal project start date and optimal activity start times for airport expansion projects; (2) determining optimal daily and weekly work plans for all airport expansion activities; (3) selecting optimal working hours for each construction day from a set of feasible alternatives; (4) quantifying and minimizing the impact of construction activities on airport operations during the optimal planning of airport expansion projects; (5) measuring and minimizing the impact of air traffic data and airport operations on total construction cost throughout the entire duration of airport expansion projects; and (6) generating a set of optimal construction plans that provide optimal trade-offs between minimizing the construction-related disruption in airport operations and minimizing the total construction cost. Accordingly, there is a need to develop a novel multi-objective optimization model for the planning of airport expansion projects that provides the capability of minimizing both airport operation disruptions and construction cost.

2.5 Flights Taxi and Travel Times Prediction Models

This section discusses a number of related studies were conducted that focused on: (1) identifying and analyzing the interaction between construction activities and facilities functions during expansion and renovation projects; (2) estimating and predicting taxi and flight travel times using computational models; and (3) predicting flight delays using machine learning models.

2.5.1 Construction activities and facilities functions

Shami and Kanfani (1997) investigated and analyzed the interrelationship between construction activities and airport operations in his research to develop a decision support system to help airport and construction planners in selecting optimum construction/operations scenarios based on a minimum total disturbance cost. In this study, Simmod was used to assess the performance of the airport during the simulation of the built scenarios. This study aims to address the mutual impact between construction activities and airport operations and a case study was analyzed to illustrate the capabilities of this developed framework.

Yee et al. (2013) analyzed and investigated renovation projects of occupied building which are often confronted with challenges due to the interactions with buildings occupants and tenants. This study presented a formal representation of renovation planning information and reasoning methods that utilize the formal representation to identify occupant interactions automatically. The results of this study shows that the renovation planning ontology and reasoning methods enable planners to represent renovation planning information more thoroughly, and with increased detail, leading them to identify occupant interactions more accurately than traditional planning methods.

2.5.2 Taxi times prediction models

Legge and Levy (2008) analyzed the utilization of the Airport Surface Deterction Equipment, Model X (ASDE-X) surface surveillance data and compared them with the archived historical data and a dynamic real-time surface analysis to predict taxi-out times. Several methods for predicting taxi-out time were applied.

Balakrishna et al. (2008) presented their work in using reinforcement learning algorithm for estimating average taxi-out times in fifteen minute intervals of the day and at least fifteen minutes in advance of aircraft scheduled gate push-back time. The authors used a probabilistic framework of stochastic dynamic programming with a learning-based solution strategy and train the model on historic data collected from the Federal Aviation Administration's Aviation System Performance Metrics (ASPM). The model was tested on John F Kennedy International Airport ad the results showed a match between the actual average taxi-out times and predicted average taxi-out times within 5 minutes for about 65% of the time on an average across fifteen days.

Jordan et al. (2010) presented a new approach to taxi process modeling specifically intended to support the needs of the tower flight data manager (TFDM) development activity. A statistical learning method is used to extract key variables. The results shows that statistical learning techniques can be used to produce accurate, yet relatively simple models of aircraft taxi time.

Srivastsava (2011) presented a novel approach to build an adaptive taxi-out prediction model based on historical traffic database generated using the ASDE-X data. The model correlates taxi-out time and taxi-out delay to a set of explanatory variables. In this study, two prediction models were developed, one treats aircraft movement from starting location to the runway threshold uniformly while the other models aircraft time to get to the runway queue different from the wait time experienced by the aircraft while in the runway queue. Results from applying the models show a significant improvement in quality of predictions when compared with predictions available from FAA's Enhanced Traffic Management System (ETMS) or average taxi-out times for a flight.

Ravizza et al. (2013) combined both airport layout and historic taxi time information within a multiple linear regression analysis and identifying the most relevant factors affecting the variability of taxi times for both arrivals and departures. This combination of statistical approach and ground movement model was applied on two different airport and compared against previous results. The results showed high accuracy reaches to 99%.

Lee et al. (2015) presented the use of Linear Optimized Sequencing (LINOS), a discrete-event fast-time simulation tool, to predict taxi times and provide the estimates to the runway scheduler in real-time airport operations. The model accuracy was assessed using a data-driven analytical method using machine learning techniques. The results showed that LINOS could predict the taxi-out times as accurate as the Support Vector Machines method and better than the Linear Regression method and the Dead Reckoning method based on unimpeded taxi times.

In another study, Lee et al. (2016) presented applying machine learning techniques to actual traffic data at Charlotte Douglas International Airport for taxi-out time prediction. Surface surveillance data was first analyzed to find the key factors affecting aircraft taxi times. Various machine learning methods were used and the results showed that linear regression and random forest techniques provided the most accurate predictions in terms of root-mean-square errors.

Yin et al. (2018) applied machine learning techniques to predict the taxi-out time of departure aircraft at Shanghai Pudong International Airport. The key factors affecting taxi-out time and their correlations were revealed by exploring historical data. Extensive system of predictors was formulated for this machine learning approach based on a macroscopic network topology from an aggregate view. Three machine learning methods: linear regression (LR), support vector machines (SVM), and random forest (RF) were formulated using one-day and one-month training samples and applied to new test data to validate the prediction performance. The results on the model showed that the training RF model sing one-month sample significantly outperform other models in terms of prediction accuracy.

Lian et al. (2018) tested three conventional methods: generalized linear model, softmax regression model, and artificial neural network and two improved support vector regression (SVR) approaches based on swarm intelligence algorithm optimization and firefly algorithm. The results showed that the proposed two SVR approaches, especially the improved firefly algorithm optimization-based SVR method performed the best modelling measures and accuracy rate compared with the forecast models and it also achieved a better predictive performance when dealing with abnormal taxi-out time series.

Zhang et al. (2022) presented a data-driven method for predicting the arrival flight time by first extracting the features affecting arrival flight times. Then eight widely used models are developed to predict flight time. Finally, a case study was analyzed to verify the proposed method's effectiveness.

2.5.3 Flight delays machine learning prediction models

Gui et al. (2019) explored a broad scope of factors that influence the flight delay and compared several machine learning-based models in generalized flight delay prediction tasks. Data was collected by pre-processing automatic dependent surveillance-broadcast (ADS-B) messages and then integrated with other information, such as weather condition, flight schedule, and airport information. The prediction tasks consisted of classification tasks and regression tasks and the results showed that long short-term memory (LSTM) is capable of handling the obtained aviation sequence data but was confronted with over-fitting problem due to the limited database. Random forest-based model obtained higher prediction accuracy of 90.2% and overcame the overfitting problem.

Ye et al. (2020) presented a new method for predicting flight departure delays in airports by exploring supervised learning methods. Four popular supervised learning methods: multiple linear regression, a support vector machine, extremely randomized trees and LightGBM are investigated to improve the predictability and accuracy of the model. The model was trained using operational data from Nanjing Lukou International Airport and the results show that LightGBM model provides the brest result with 0.8655 accuracy rate with a 6.65 min mean absolute error which is 1.83 min less than results from previous research and models. This model helps in better understanding of delays interactions between time, flight plan and previous delay.

2.5.4 Limitations of available flights taxi and travel times prediction models

Despite the significant contributions of the aforementioned research studies, they have limitations in quantifying and predicting the construction impact on air traffic during airport expansion and renovation projects as they are incapable of: (1) estimating flights taxi and travel times during airport expansion projects; (2) quantifying the construction-related disruptions in airport operations; and (3) predicting the impact of construction activities on air traffic and flight travel times. Accordingly, there is a need to develop a machine learning model that is capable of estimating and predicting the impact of selected construction schedules on air traffic during the planning stage of airport expansion projects.

2.6 Site Layout Planning Models

As airports are required to stay minimally disrupted or fully functional during expansion projects, managing their construction site layout is challenging due to the proximity between construction activities and ongoing airport operations (Khalafallah and El-Rayes, 2006a). Airport expansion projects are executed in area-constrained sites that often causes: (1) disruption in airport operations due to the complexity of the airport expansion sites and the proximity of temporary facilities to airport ongoing operations (Alnasseri et al., 2013;

FAA, 2017; Shami and Kanafani, 1997); (2) construction delays and cost overruns due to the arrangements that need to be taken to compile with the FAA regulations and airport authorities (Khalafallah and El-Rayes, 2008; Shami and Kanafani, 1997); and (3) area constraints regulations that affect accelerating project delivery (Said and El-Rayes, 2013a).

To address the aforementioned challenges, a number of research studies were conducted to investigate various aspects of optimizing site layout planning, including: (1) quantifying the impact of facilities ongoing operations on construction activities (Alnasseri et al., 2013; Khalafallah and El-Rayes, 2006a; Khoury et al., 2006; Lopez et al., 2017; Shami and Kanafani, 1997); (2) optimizing site layout to minimize construction delay and cost (Abdelmohsen and El-Rayes, 2016; Calis and Yuksel, 2010; Easa and Hossain, 2008; Khalafallah and El-Rayes, 2004; Olugboyega and Wemimo, 2018; Sander et al., 2014; Xu and Li, 2012); and (3) optimizing site layout to accelerate delivery of projects (Bakry et al., 2014; Hinze, 2012; Hyari and El-Rayes, 2006; Ning et al., 2011; Said and El-Rayes, 2013a).

Despite the significant contributions of these studies, there is little or no reported research that considered (1) optimizing site layout of airport expansion projects to minimize the total disruption and cost of construction activities and airport operations; and (2) optimizing site layout to accelerate the delivery of project milestones in area-constrained construction sites that are in close proximity to ongoing airport operations. Thus, there is a pressing need for an advanced optimization model that is capable of optimizing construction site layout to simultaneously minimize disruptions in airport operations and accelerate the completion of project milestones.

The primary purpose of site layout planning is to allocate site space to resources so that they can be accessible and functional during construction (Zouein and Tommelein, 1999). Optimizing site layouts can assist in achieving multiple objectives such as minimizing resource transportation and facility relocation costs (Mawdesley et al., 2002; Tam et al., 2002; Zouein and Tommelein, 1999), improving site safety (Elbeltagi et al., 2004; Khalafallah and El-Rayes, 2004), and minimizing site security risks (Khalafallah and El-Rayes, 2008; Z. Li et al., 2015; Said and El-Rayes, 2012). Site layout models can also be static (one phase) or dynamic (multiple phases of construction). The following sections discuss several methodologies used in the literature to accomplish site layout planning tasks.

2.6.1 Heuristics

Zouein and Tommelein (1999) approached the problem of dynamic site layout planning with a combination of constraint satisfaction, heuristics and linear programming. The model objective is to minimize total cost, which is the sum of transportation and relocation costs. Resources are represented as rectangles in a two-dimensional space. The facility centroid, its dimensions, and its orientation identify the location of each facility. A series of hard constraints determine which positions are acceptable and soft constraints gauge the quality of the layout.

Resources are analyzed one at a time and a position is selected for each resource based upon two heuristics: (1) resources with the largest relocation weights; and (2) resources with the greatest interaction with other positioned resources. Tiebreaker heuristics are also identified, if required. A linear program is then used to minimize overall costs. The main limitation of the system is that layouts are selected chronologically; meaning earlier optimized layouts cannot be reanalyzed. As a result, the system cannot achieve global optimality.

Tam et al. (2002) analyzed a site layout-planning problem using nonstructural fuzzy decision support system (NSFDSS). NSDFSS consists of three steps: (1) decomposition, which is breaking the problem down in a hierarchal fashion; (2) conducting pairwise comparisons on a three-point scale (better, the same, or worse); and (3) synthesis of priorities, which combines decision criteria with weighting factors.

The authors claim that their method offers three advantages over the traditional analytical hierarchy process (AHP): (1) a simplified comparative rating scale (1, 0.5 and 0) in evaluating the relative importance of decision criteria; (2) built-in consistency checking by placing a greater level of reliability on higher rows and automatically resetting the values of lower rows if inconsistencies are found; and (3) elimination of consistency deviation by providing absolute consistency during evaluation. The data is then arranged in matrix form to display comparison and score assignment. Project managers can then use the priorities identified by the NSFDSS to aid in decision making. The authors reported two main limitations in this model: (1) decisions and comparisons are still not automated although the process is less labor intensive than AHP; and (2) quality of results is highly dependent on the knowledge and expertise of the project management team.

2.6.2 Genetic Algorithms

Mawdesley et al. (2002) utilized an augmented genetic algorithm to model the cost to move and position temporary facilities on a construction site over time. A user-defined grid system was established to create potential locations within site boundaries. Facilities are assumed to be rectangular and are represented by coordinates of two opposite corners. The model allows for user-defined minimum and maximum interfacility distances. There are three sources of costs considered in this model: (1) the cost to setup a facility; (2) the cost to remove a facility; and (3) the cost of transporting materials between locations.

Minimum travel distances can be calculated using either Manhattan (follows only axis-aligned directions) or Euclidean (straight line between two points) geometry. Additionally, the model allows for varying site conditions and can account for unequal transportation costs in north-south, south-north, east-west, and west-east directions. The authors identify two primary limitations of their model: (1) its sensitivity to the relative costs assigned to facility setup and material transport; and (2) modeling the dynamic nature of a project by considering the site layout to be correlated with the work phases.

Elbeltagi et al. (2004) developed a GA that was able to consider the effects of safety in dynamic layout planning. The model aimed to minimize distances between facilities for the purpose reducing resource travel costs, but only to the extent that it did not move facilities into unsafe zones around high-risk buildings. The authors adapted existing closeness relationships from Malakooti (1987) and introduced large negative values when safety concerns arose between two facilities. The model was built into Excel using macros, which allowed for linking to widely used scheduling software. Furthermore, model results can be exported to Geographical Information System (GIS) to automate site mapping.

While many other studies have investigated the optimization of construction site layout planning, considering the site layout of critical infrastructure projects as an objective has been limited to only a few studies, namely Khalafallah and El-Rayes (2008) and Said and El-Rayes (2012). The main limitation of these studies is that they only consider the security risk of human breaches, not the mutual disruption between construction activities and airport operations. The discussion of these papers in this section will focus on their facility layout component. Khalafallah and El-Rayes (2008) developed a multi-objective genetic algorithm capable of minimizing construction-related security breaches while keeping the site layout costs of airport expansion projects to a minimum.

The location of temporary facilities such as security fences, site offices and hazardous material storage facilities affect numerous aspects of this model including: (1) the response distances required by security personnel; (2) the buffer zone sizes between secure areas and temporary facilities; and (3) the travel costs of resources. The travel costs of resources are estimated based on the planned travel frequency of crews, the crew hourly cost rate, and the average speed of travel (El-Rayes and Khalafallah, 2005). In order to perform the optimization, project planners must provide the dimensions of each temporary facility, the available options for temporary fence placement, the location and dimension of each secure facility on the construction site and the recommended security response distances between secure areas. The output of the model includes identifying the optimal location of temporary facilities and the security fence and the optimal utilization of security control systems in order to achieve the aforementioned objectives.

Said and El-Rayes (2010) developed an automated multi-objective optimization framework, using genetic algorithm, to simultaneously minimize the site security risks and minimize the overall site costs associated with the construction of critical infrastructure projects. The main security threat in this model was the theft or destruction of classified materials located in a Sensitive Compartmented Facility (SCIF). The construction site was separated into three layers: (1) site fence; (2) site grounds; and (3) target fence. Additionally, multiple phases of construction were considered, potentially requiring the relocation of temporary facilities and construction materials. The model is designed to dynamically position all temporary facilities and relocate moveable facilities in each stage of the project. Facility location impacts the length of an attacker's intrusion path (which impacts the likelihood of a successful attack), the degree or amount of natural surveillance, and site layout costs, which are the sum of resource travel costs and facilities relocation costs.

Analogous to Zouein and Tommelein (1999), the facilities are represented by their centroid, dimensions and orientation. Four types of geometric constraints must be satisfied in order to successfully place a facility within the site boundary: 1) boundary; 2) overlap; 3) distance; and 4) zone constraints (El-Rayes and Said, 2009). The model generates an optimal combination of security measures and facility positions over multiple phases of construction to minimize site security risks and to minimize overall site costs.

2.7 New Technology Impact on Existing Airport Facilities

Airports are critical and secured areas, governments and airport's management make significant efforts to implement most recent reliable technologies and services to serve passengers in fastest and smoothest way to prevent any congestion and disturbance to occur at airports. This leads to more challenges that airports need to analyze and address, including; (1) the quick continuous development of technology; and (2) the need to upgrade existing facilities to implement and adapt these technologies.

Future airport expansion and construction costs are expected to be affected by new and emerging technologies, including (1) faster and cost-effective mass transit systems for airports such as hyperloop capsules and high-speed trains (Kumar and Khan, 2017; Park and Ha, 2006); and (2) autonomous vehicles and shared rides (Bansal and Kockelman, 2017; Fagnant and Kockelman, 2015; Henderson and Spencer, 2016; Philanthropies, 2017). These two emerging technologies are expected to reduce vehicle traffic and parking at airports in the next decades. Accordingly, strategic planning of airport expansion projects needs to analyze these evolving needs and develop long-term plans for transforming the use of under-utilized airport facilities such as roads and parking structures that occupy substantial areas at airports (Henderson and Spencer, 2016).

FAA requires airports to provide 1000 – 3300 parking spaces per million originating passengers or 1.5 times the number of peak hour passengers in a rate of 109-124 parked cars per acre (FAA, 1988). These airport parking facilities will be significantly under-utilized in the future as three out of four vehicles are expected to be autonomous by 2040 (Philanthropies, 2017). To adapt to the expected use of these new technologies at airports, decision makers must carefully analyze their predicted impact on existing facilities and develop an optimal transformation and upgrading plan for existing facilities at airports.

A number of significant research studies were conducted to investigate various aspects of new technologies and their future impact on existing infrastructure systems. These studies focused on (1) predicting the implementation of new technologies and their impact on existing infrastructure systems (Bansal and Kockelman, 2017; Davidson and Spinoulas, 2015; Fagnant and Kockelman, 2015; Gopalswamy and Rathinam, 2018; Henderson and Spencer, 2016; Litman, 2017; Philanthropies, 2017; Skarbek-Zabkin and Szczepanek, 2018; Tettamanti et al., 2016); and (2) upgrading and transforming transportation systems to adapt to these new technologies (Beiker, 2014; Brown et al., 2009; Cole, 2001; Farah et al., 2018; Fraedrich et al., 2019; Guerra, 2016; Pendyala, 2013).

Despite the significant contributions of these studies, there is little or no reported research that (1) considered the impact of these new technologies on existing airport facilities such as roads and parking structures; and (2) support airport decision makers in developing long term plans for gradual transformation of existing airport facilities to maximize the efficiency of their future utilization. Hence, there is a need for an innovative transformation-planning model for airport expansion projects that is capable of considering the impact of the aforementioned emerging technologies and generating long-term optimal plans for transforming the use of airport facilities that are expected to be under-utilized in the future in order to maximize the utilization and cost-effectiveness of all airport facilities.

The following sections present a comprehensive literature review of research studies on the new technology that are related to airport facilities and expansion projects sites, that focused on: (1) the future impact of these technology on existing facilities; and (2) transformation and upgrading plans for existing facilities.

2.7.1 Future Impact of New Technology on Existing Facilities

Philanthropies, B. (2017) analyzed the development of Autonomous Vehicles (AV) and predicted that 3 out of 4 cars in 2040 will be autonomous which means that cities need to be reshaped and planners have to reform the land use to adapt the future ubiquitous AVs. The AVs will be soon on the streets, this will lead to more challenges in different aspects including: (1) Laws; (2) Technology; (3) Integrated environment; and (4) Infrastructure. The following paragraphs provide a concise discussion of the challenges of these aspects. It should be noted that this analysis is still in its preliminary stage.

Law

Reconsideration of a broad range of legal guidelines and laws need to be taken into account in order to enable the general use of autonomous cars on public roads. Several challenges and difficulties will be on the way of implementing this new technology including defining who is responsible for traffic related problem and who is reliable for the accidents and injuries, other difficulties may be straightforward such as insurance and liability (Davidson and Spinoulas, 2015).

Technology

Autonomous Vehicles need to be supported with other technologies to provide the required service for AVs to be implemented safely on the roads. This parallel system needs to keep developing its features to get to the optimum level of protecting the safety of the people and the security of the system. Traffic system touches people lives directly and could cause significant loss of their lives if hackers succeeded in hacking the system. All these challenges lead the companies and the governments to specialize part of their budget to improve their preparations and arrangements in creating testing areas and cities to facilitate the adaption of the new future (Davidson and Spinoulas, 2015).

Integrated Environment

It's expected that the implementation of Autonomous vehicles to happen gradually. The partial implementation of adapting autonomous vehicles on our existing road network will impact the traffic efficiency and safety. This will raise many critical questions and serious concerns regarding the geometric road design, structural pavement features and design, and digital infrastructure (Farah et al., 2018).

Infrastructure

Farah et al. (2018) investigated the potential changes of existing infrastructure to hose the new technology in its best way. Cross sections and lane wideness will be reduced to increase the smoothness of the traffic and capacity of the roads. However, the pavement features and design would require to be investigated more carefully to determine the procedures of the emergency cases that requires pavement maintenance for example. On the other hand, parking spots will be reduced significantly due to the less need of long-time parking as vehicles would have the ability to drive back home on their own. This reduction would give more space to be utilized by the authorities in a different way (Henderson and Spencer, 2016).

Henderson and Spencer (2016) presented that Autonomous Vehicles will increase the unoccupied area of the building which would create opportunities for real estate developers and companies to invest and make a productive use of this extra space. AVs will still need some parking space for loading and unloading standing zones in addition to waiting spots for passengers or arriving with passengers. These changes need all associated parties with this technology to cooperate to set new comprehensive cities and facilities upgrading and transformation plans to create fully mature infrastructure that is capable of adapting the new system of transportation in the near future.

2.7.2 Transformation and Upgrading Plan for Existing Facilities

Development of new technologies and planning to transform and upgrade the infrastructure should follow parallel paths to go beyond all the barriers and to make the adoption of new technologies as smooth as possible. As all work being done together in the same time, problems can be solved and open the way to recommend new sets of policies, laws, transportation networks, and robust infrastructure (Cole, 2001; Fagnant and Kockelman, 2015; Guerra, 2016). Henderson and Spencer (2016) investigated the relation between the autonomous vehicles and commercial real estate to recommend some transformation and upgrading procedures for the existing infrastructure based on the predicted impact of this new technology on the current infrastructure and streets network. For example, Autonomous Vehicles will lead to a reduction in the width of streets' lanes and parking

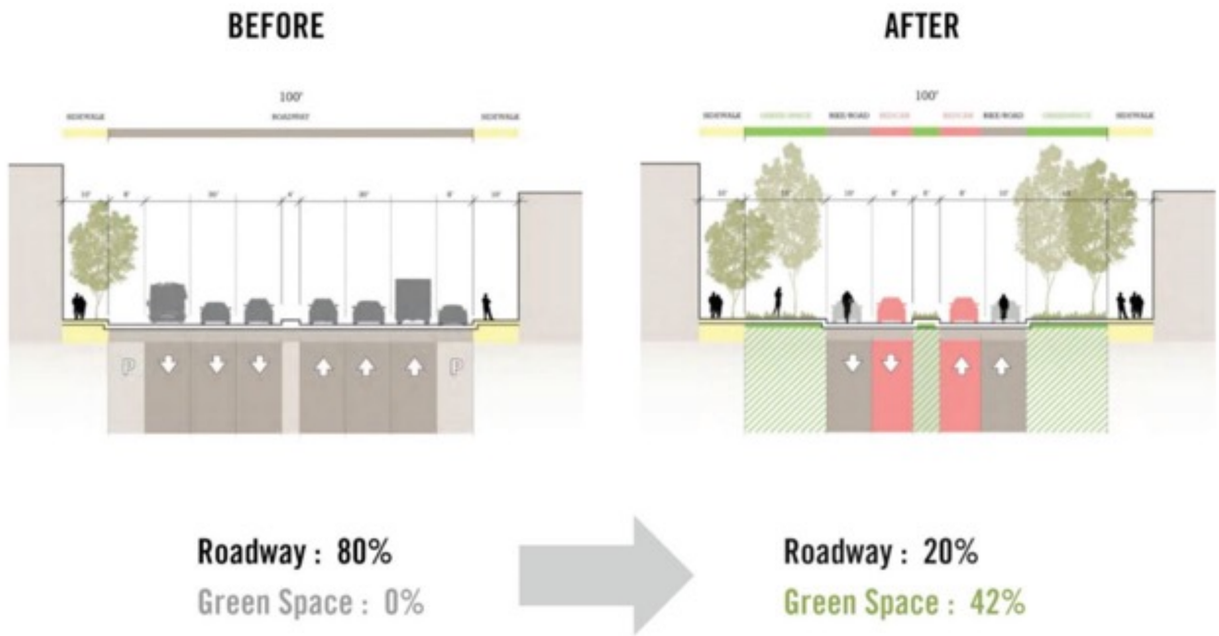

Fig. 2.5. Before and After AVs (Henderson and Spencer, 2016)

spots creating more space than can be used for different projects like increasing the green area in the roads to make the cities more sustainable and environment friendly or even creating more facilities to make the best utilization of this future extra areas.

Fig. 2.5 shows a suggested transformation of 19th Avenue in San Francisco before and after AVs. This change will decrease the specified areas for cars and utilize the extra space to increase green area and bicycle lane. While Fig. 2.6 presents an image of how to use the existing parking spots to build new facilities on the reduced parking area to increase the value and the utilization of the areas in the future. Suggestions and ideas are not limited and require additional studies to choose the best use to determine the best upgrading decisions and transformation plans.

Henderson and Spencer (2016) conducted a study that analyzes an existing building in Chicago consists of 12 parking floors and 30 office floors. This study shows that the present value of existing parking spots costs a loss of \$17,025,000 equal to -\$14,428 per spot. Assuming a 40% reduction in required parking, this leads to a valuation increase from

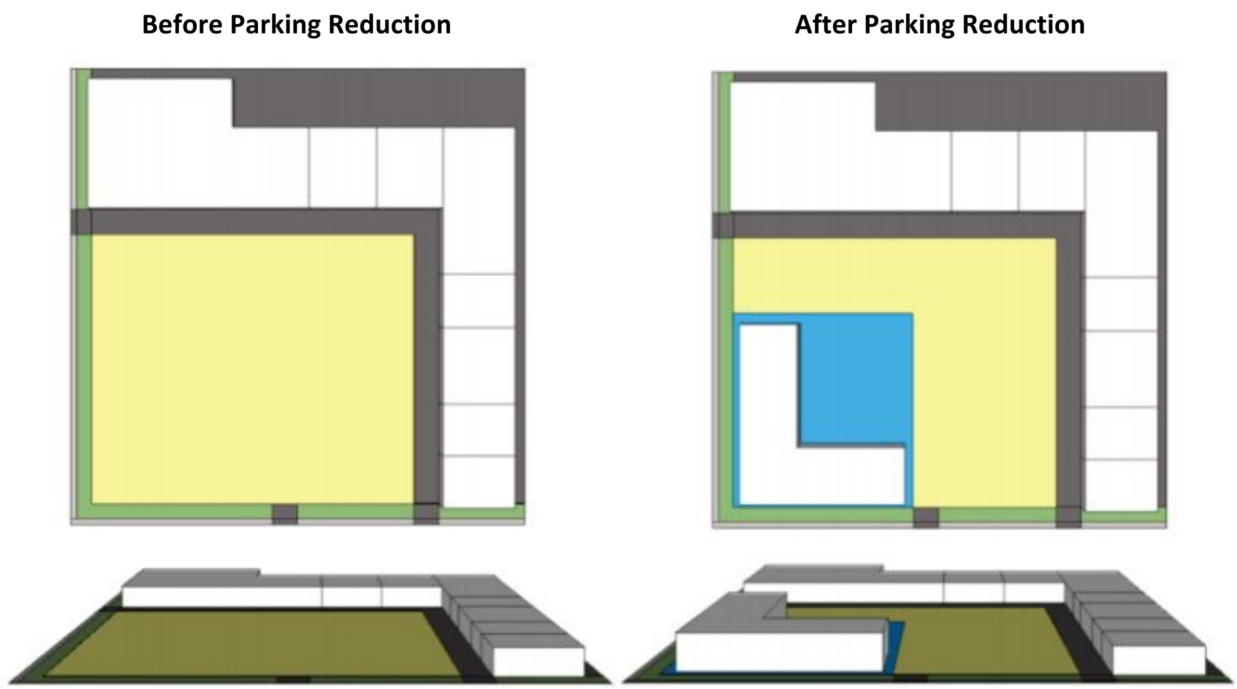

Fig. 2.6. Before and After Parking Reduction (Henderson and Spencer, 2016)

building an office building with the same volume and less parking achieving a present value of additional office space of $66,155,520 equal to $730 present value of each additional SF of Office Space, as shown in Tables 2.1 and 2.2.

Despite the significant contributions of these aforementioned studies, there is little or no reported research that considered (1) the impact of new technologies and transportation means on airport existing facilities; (2) optimizing a plan to perform a gradual transformation of airport existing facilities to future needed facilities and (3); a comprehensive guideline that can be adopted to transform and upgrade existing facilities to achieve the best present value and the maximum lifetime revenue. Hence, there is an urgent and pressing need for an innovative multi-objective transformation-planning model for airport expansion projects that is capable of setting the optimal plan to transform the future-unnecessary existing facilities to maximize the utilization of the area it occupies and to minimize the construction and life cycle costs.

In conclusion, bringing future into planning is a significant process to detect all the

Table 2.1. Chicago office building parking example (Henderson and Spencer, 2016)

Parking Requirements		Construction Costs	
Gross office space (SF)	600,000	Parking cost of construction ($/$SF$)	$200
Floor plate (size)	20,000	Office cost of construction	$350
Required number of floors	30	Total parking cost	$48,000,000
SF of space exempt from parking (SF)	10,000	Total building cost	$258,000,000
Ration (number of spaces/gross SF of office space)	0.002	Parking cost/total building cost (%)	19%
Total required parking spots	1180		
Parking Spot Parameters		Parking Garage Valuation	
Width (ft)	8	Parking space rent ($/month)	$125
Depth (ft)	18	Vacancy (%)	30%
Total area (SF)	144	Yearly parking revenue	$1,239,000
Garage efficiency (%)	75%	Parking rent annual growth rate (%)	2%
Required parking area	226,560	Discount rate (%)	6%
Number of parking levels	12	Present value of parking rent	$30,975,000
		Present value of parking	-$17,025,000
		Present value cost per spot	-$14,428

Table 2.2. Valuation increase from additional office space (Henderson and Spencer, 2016)

Reduction in required parking (%)	40%
Additional office space from parking reduction (SF)	90,624
Cost of extra office space (SF)	$31,718,400
Office rent ($/SF)	$60
Efficiency (%)	80%
Vacancy (%)	90%
Additional yearly office revenue	$3,914,957
Office rent annual growth rate (%)	2%
Office discount rate (%)	6%
Present value of additional office space	$66,155,520
Present value of each additional SF of office space	$730

possible challenges, find solutions for all predicted barriers, and set the best transformation plans and upgrading decisions to open the way to adopt new technologies with prepared robust infrastructure.

2.8 Multi-Objectives Optimization Techniques for Airport Expansion Projects

This section analyzes a number of available optimization techniques that are used for modeling multi-objectives optimization problems for addressing the unique challenges of airport expansion projects, including: (1) Weighted linear programming; (2) Meta-heuristic algorithms; and (3) Evolutionary (genetic) algorithms.

2.8.1 Weighted Linear Programming

A multi-objective problem can be solved by transforming it into a linear function using the weighted-sum method to formalize the problem in the form, minimize:

$$\sum_{i=1}^{k} w_i f_i\left(\bar{x}\right) \tag{2.1}$$

where k = number of objective functions, $f_i\left(\bar{x}\right)$ = scalar objective functions; and w_i = weighting coefficients representing the relative importance of the objectives.

In this method, it is generally assumed that all weighting coefficients are positive and the sum of the coefficients equal one (Coello, 1999). The two main advantages of this method over other optimization techniques are: (1) the ability to achieve a global optimum solution, as opposed to the sub-optimal solutions reached when using metaheuristic optimization methods, and (2) faster computational efficiency. The main disadvantage is the difficulty in determining the appropriate weighting coefficients when little is known about the problem or how the relative weights will affect the solution (Coello, 1999). To overcome this shortcoming, it is necessary to solve the same problem for many different values of w_i in order to generate the Pareto front (Caramia and Dell'Olmo, 2008).

The weighted-sum method can be employed in linear, integer or mixed-integer programming problems. A main limitation to linear programming is the requirement for all objective functions and constraints to be linear. Integer programming refers to decision variables that are non-continuous and non-fractions such as the number of personnel required to complete a task. Mixed-integer programming is when some decision variables require integers and others are continuous (Abdallah, 2014). These techniques have been used to solve many complex optimization problems in construction, including facility layout modeling (Foulds et al., 1998; Kim and Kim, 2000).

2.8.2 Nature-inspired Meta-heuristic Algorithms

Hard optimization problems can be defined as problems that cannot be solved by any deterministic method within a reasonable amount of time (Boussaid et al., 2013). Metaheuristics can be used to solve these hard optimization problems. Metaheuristics are "higher-level" heuristics, meaning that they are designed to approximately solve a wide range of optimization problems without having to deeply adapt to each specific scenario (Boussaid et al., 2013). Most metaheuristic algorithms are nature-inspired, seeking optimality by mimicking some physical, biological or ethological process. In a recent survey, Fister et al. (2013), identified more than 40 nature-inspired metaheuristic algorithms based upon such natural processes as migratory bird patterns (Eberhart and Kennedy, 1995), ant colony behaviors (Dorigo et al., 1996), bacterial foraging (Chu et al., 2008), firefly bioluminescence (Yang, 2009), slime mold life cycle (Monismith and Mayfield, 2008), cockroach infestation (Havens et al., 2008), mosquito host-seeking (Feng et al., 2009), and bat echolocation (Yang, 2010). This section will analyze the two most prevalent nature-inspired metaheuristic algorithms: particle swarm optimization and ant colony optimization.

Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based, stochastic optimization technique, inspired by the migratory patterns of birds attempting to reach an unknown destination (Zhou et al., 2011). PSO was originally developed by Eberhart and Kennedy (1995) and was later expanded to include multi-objective optimization by Moore and Chapman (1999). In PSO, each solution is a "bird" in the migrating flock. As the flock flies, the birds communicate with one another, identifying the bird in the best location. The rest of the flock then flies toward this bird and investigates their surrounding environment. This social behavior is repeated until the birds reach their destination. PSO successfully incorporates both intelligence and social interaction, combining local search, where the birds learn from their own experience, and global search, where the birds learn from the experience of others around them (Elbeltagi et al., 2005). PSO has been widely used in multi-objective optimization problems in construction, including modeling construction site layout (Ohmori et al., 2010; Rezazadeh et al., 2009; H. Zhang and Wang, 2008).

Ant Colony Optimization

Dorigo et al. (1996) developed ant colony optimization (ACO), a naturally inspired optimization technique that mimics the process of ants determining the shortest route between their nest and a food source (Elbeltagi et al., 2005). As ants travel, they deposit pheromone trails on the ground that are detected by other ants (Zhou et al., 2011). As the search for food begins, ants will randomly travel around all sides of an encountered obstacle, initially depositing equal concentrations of pheromones from the left and right direction. Ants with the shortest path to food will return to their nest following their original path, thus depositing more pheromones. Future ants will detect this greater concentration of pheromones and follow the established path from their nest to the food source (Elbeltagi et al., 2005). Over time, favored paths that are shorter and more efficient will emerge because of this positive feedback mechanism (Yang, 2010), as shown in Fig. 2.7. ACO has been effectively utilized to address many multi-objective optimization problems in

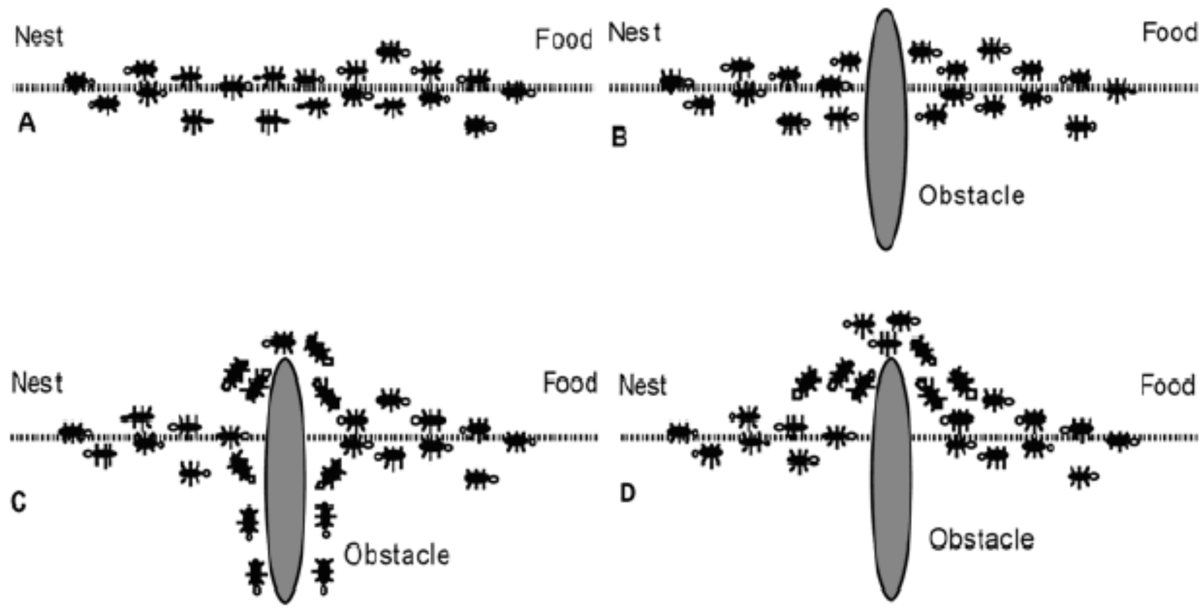

Fig. 2.7. Ant Colony Optimization (Yousefikhoshbakht et al., 2013)

construction, including construction site layout (Baykasoglu et al., 2006; Pour and Nosraty, 2006; Wong et al., 2010), and sustainability and building energy performance (Marzouk et al., 2012; Yuan et al., 2012). One limitation of ACO is that it can only be used in discrete problems (Elbeltagi et al., 2005).

2.8.3 Genetic Algorithm

Genetic algorithms, developed by John Holland in 1975, are search algorithms that mimic genetic operations based up Darwin's theory of natural selection (Goldberg, 1989). Genetic algorithms apply survival of the fittest to obtain near-optimum solutions by following a six-step process: (1) create a population of individual solutions (chromosomes); (2) calculate the value of the objective function(s) for each individual within the population; (3) assign a fitness value to each individual based upon the objective function(s); (4) perform reproduction with higher-fitness individuals having a higher probability of survival than individuals with lower fitness values; (5) create offspring by combining or varying the genotypes in the parent solutions through the processes of crossover and mutation;

(6) repeat steps 2-5 until termination conditions are satisfied (Weise et al., 2008).The structured randomness of genetic algorithms coupled with the inclusion of mutation to avoid local minima give genetic algorithms the ability to deal with complex problems and parallelism. Genetic Algorithm has been used successfully to address, formulate, and solve several types of optimization problems, whether the objective function is linear or nonlinear, static or dynamic, continuous or discontinuous, or even contains random noise (Yang, 2010). Genetic Algorithm is the most optimization tool used to address multi-objective optimization problems in construction engineering and management. Including: construction site layout planning (Elbeltagi et al., 2004; Khalafallah and El-Rayes, 2006b, 2008; Said and El-Rayes, 2010, 2013b).

2.9 Research Needs

This detailed literature review revealed that there is a pressing need for novel machine learning and optimization models for the planning of airport expansion projects that are capable of: (1) optimizing the planning of airport expansion projects to mitigate the impact of construction activities on airport operations, (2) quantifying the impact of airport construction activities and their phasing plans on flights ground movement time, and (3) grouping airport construction activities into phases and optimizing the scheduling of these phases to minimize construction-related airport disruptions while minimizing total construction cost. Moreover, this chapter studied and analyzed the capabilities and limitations of available models for optimizing the planning of airport expansion projects.

Chapter 3

Optimizing the Planning of Airport Expansion Projects

3.1 Introduction

This chapter presents the development of a novel multi-objective optimization model for the planning of airport expansion projects that provides the capability of minimizing both airport operation disruptions and construction cost. The developed model integrates a novel methodology that is capable of identifying an optimal project start time (ST), an optimal start time of each activity (ST_i), optimal working days per week (ND), and optimal working hours per day (NH).

The model optimization computations are performed using a novel methodology that integrates four main modules, as shown in Fig. 3.1: (1) simulation module that calculates and quantifies the impact of airport construction activities on air traffic and airport operations; (2) optimization module that searches for and identifies an optimal construction schedule that generates optimal trade-offs between the two important objectives of minimizing construction-related disruptions in airport operations and minimizing construction cost; (3) scheduling module that calculates the start and finish times of each activity in airport expansion projects; and (4) cost module that computes the total cost of construction-related disruptions in airport operations, and the total construction cost for each generated solution in the optimization module. The following sections provide a concise description of the

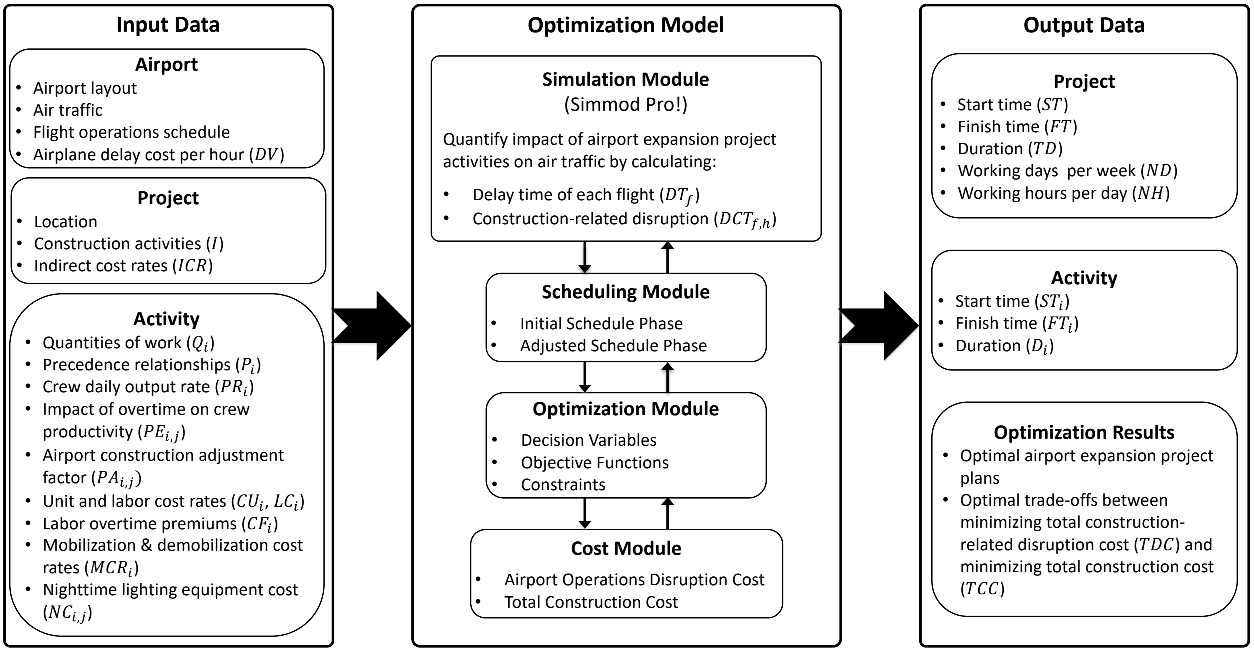

Fig. 3.1. Model development for airport expansion projects.

development and computations for each of these four modules.

3.2 Simulation Module

The main objective of this module is to calculate and quantify the impact of airport expansion activities on air traffic and flight delays. This module is designed to calculate the delay time encountered by all flights that are caused by airport construction activities. This is achieved using an air traffic operations simulation tool "Simmod Pro!" (ATAC, 2021). The analysis procedure in the present simulation module is organized in five main steps that are designed to (1) specify the layout of the airport, (2) define all related flight and airport operational data, (3) calculate flights ground movement time under normal conditions without construction activities, (4) calculate flights ground movement time during construction activities, and (5) calculate construction-related disruption cost based on the identified flight delays and the hourly cost rate of flight delays. This construction-related disruption cost is the output of this simulation module, and it will be used as input for the following modules, as shown in Fig. 3.1.

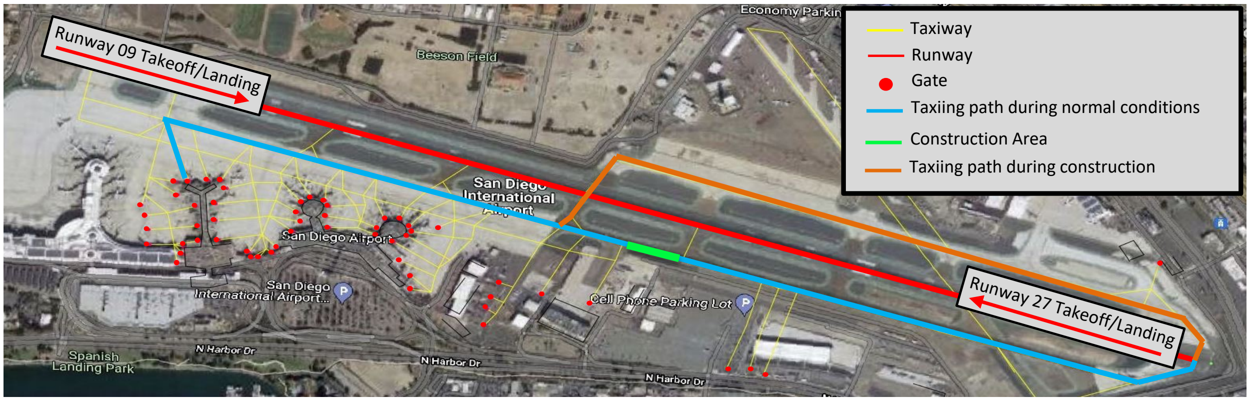

Fig. 3.2. Layout of San Diego International Airport in Simmod Pro!

3.2.1 Specify airport layout

In the first step, the layout of the airport is specified by modeling the airport taxiways and runways as a set of links that are connected by nodes, as shown in Fig. 3.2.

3.2.2 Define flight and airport operational data

This step specifies all related airport input data including flights schedule, flights origin and destination, airplanes type and size, arrival and departure gates, and airport runway, as shown in the sample dataset for San Diego Airport (SAN) in Table 3.1. The aircraft size is identified in this model based on FAA weight class criterion that classifies aircrafts in four main groups: (1) Super such as Airbus A388; (2) Heavy for aircrafts that are capable of takeoff weights of 300,000 pounds such as Boeing 747 and Airbus A340; (3) Large for aircrafts that are capable of takeoff weights more than 41,000 pounds and less than 300,000 pounds such as Boeing 737 and Airbus A320; and (4) Small for aircrafts that are capable of takeoff weights less than 41,000 pounds such as Cessna Caravan (FAA, 2019), as shown in Table 1. This input data is required by the software to simulate air traffic operations.

Table 3.1. Example flights information

Flight ID	Type	Time	Airplane Type	Airplane Size	Origin	Destination	Gate	Runway
2	Arrival	02:59	Cessna 208	Small	IPL	SAN	5	27
5	Departure	05:35	Boeing 738	Large	SAN	ORD	28	27
13	Arrival	06:14	Airbus 321	Large	PHX	SAN	31	27
195	Departure	11:22	DHC6	Small	SAN	NUC	4	27
381	Arrival	16:16	CRJ 700	Large	LAX	SAN	2	27
517	Departure	20:13	Boeing 737	Large	SAN	SFO	7	27

Table 3.2. Example flights ground movement time

		Normal Conditions			During Construction		
ID	Type	Landing Time (RT_f)	Gate Time (GT_f)	Ground Movement Time (MT_f) (hour)	Landing Time (CRT_f)	Gate Time (CGT_f)	Ground Movement Time (CMT_f) (hour)
2	Arrival	02:59	03:04	0.090	02:59	03:05	0.093
13	Arrival	06:14	06:21	0.124	06:14	06:22	0.131
381	Arrival	16:16	16:36	0.339	16:16	16:36	0.339
ID	Type	Gate Time (GT_f)	Take-off Time (RT_f)	Ground Movement Time (MT_f) (hour)	Gate Time (CGT_f)	Take-off Time (CRT_f)	Ground Movement Time (CMT_f) (hour)
5	Departure	05:35	05:37	0.021	05:35	05:42	0.115
195	Departure	11:22	11:34	0.203	11:22	11:35	0.206
517	Departure	20:13	20:22	0.158	20:13	20:23	0.171

3.2.3 Calculate flights ground movement time under normal conditions

In this step, the simulation tool is utilized to calculate the flight ground movement time under normal conditions from the gate to the runway for departure flights, and from the runway to the gate for arrival flights. The simulation tool is also used to generate a detailed report that calculates the flight ground movement time (MT_f) as the difference between gate departure/arrival time (GT_f) and take-off/landing time (RT_f) that includes taxiway and waiting times, as shown in Eq. (3.1) and Table 3.2.

$$MT_f = |GT_f - RT_f| \qquad \forall\, f \in \{1, \ldots, F\} \tag{3.1}$$

where MT_f= ground movement time of flight f during normal (non-construction) conditions; GT_f= gate departure/arrival time of flight f during normal conditions; and RT_f= take-off/landing time of flight f during normal conditions.

3.2.4 Calculate flights ground movement time under construction conditions

In this step, the locations of all construction activities are defined on the airport layout by removing their corresponding links from the airport model developed in the first step. This ensures that the simulation tool does not allow airplanes to use these links during construction activities, as shown in Fig. 3.2. Construction activities cause disruptions in air traffic operations because of their impact on increasing the length of taxiing paths and/or the waiting time on the taxiway. The simulation tool is then used to calculate the new flight ground movement time under construction conditions (CMT_f) using Eq. (3.2), as shown in Table 3.2.

$$CMT_f = |CGT_f - CRT_f| \qquad \forall\, f \in \{1, \ldots, F\} \tag{3.2}$$

where CMT_f= ground movement time of flight f due to closure of construction area; CGT_f= gate arrival/departure time of flight f due to closure of construction area; and CRT_f= landing/taking-off time of flight f due to closure of construction area.

3.2.5 Identify construction-related delays and disruptions cost

In this step, the construction-related delay $(DCT_{h,f})$ of each flight f at hour h due to closure of the construction area is calculated as the difference between the ground movement time under normal conditions (MT_f) and during construction (CMT_f) that were calculated in the previous steps, as shown in Eq. (3.3). This construction-related delay $(DCT_{h,f})$ is then used to estimate the disruption cost $(DCC_{h,f})$ for each flight that is caused by the closure of the construction site using Eq. (3.4). The model then estimates the hourly construction-related disruption cost by summing up the individual disruption costs of all flights during hour h, as shown in Eq. (3.5) . A sample of the performed calculations in Eqs. (3.3) – (3.5) is shown in Table 3.3. The model then repeats these calculations to estimate the hourly construction-related disruption cost (DCC_h) for each hour h. Table 3.4 shows an example of these estimated hourly construction-related disruption costs (DCC_h) due to the closure of a taxiway segment in San Diego International Airport on Tuesday November

Table 3.3. Example construction-related disruption costs during hour h

Flight ID (f)	Airplane Size	Cost of hour delay (DV)	Ground Movement Time (minutes): Normal condition (MT)	Ground Movement Time (minutes): Construction condition (CMT)	Disruption: Time (DCT) (minutes)	Disruption: Cost (DCC) ($)
2	SML	$1,400	5.40	5.58	0.18	4.20
5	SML	$1,400	1.26	6.90	5.64	131.60
13	LRG	$4,500	7.44	7.86	0.42	31.50
195	LRG	$4,500	12.18	12.36	0.18	13.50
318	LRG	$4,500	20.34	20.34	0.00	0.00
517	LRG	$4,500	9.48	10.26	0.78	58.50

Table 3.4. Example hourly construction-related disruption cost (DCC_h) in one day

Hour (h)	00:00	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00
DCC_h	0	0	4	4	0	248	2179	1409	742	356	156	6374
Hour (h)	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
DCC_h	767	369	1024	915	243	280	194	286	532	84	151	47

19th, 2019.

$$DCT_{h,f} = CMT_f - MT_f \tag{3.3}$$

where $DCT_{h,f}$= delay time in flight f due to closure of construction area during hour h.

$$DCC_{h,f} = DCT_{h,f} \times DV_f \tag{3.4}$$

$$DCC_h = \sum_{f=1}^{F} DCC_{h,f} \tag{3.5}$$

where $DCC_{h,f}$= cost of delay for flight f due to closure of construction area during hour h; and DV_f= delay cost rate for flight f in \$/hour that varies from \$1400/hour to \$4500/hour based on several factors such as size of aircraft (FAA, 2020b).

3.3 Optimization Module

The main purpose of this module is to search for and identify an optimal schedule for airport expansion projects that provides an optimal trade-off between the two important objectives of the developed model that focus on minimizing the cost of construction-related disruptions in airport operations and minimizing the total construction cost. The optimization module is developed in four steps that are designed to (1) identify all relevant decision variables; (2) formulate the optimization objective functions of minimizing the cost of the construction-related disruption in airport operations and minimizing the total construction cost; (3) model all related optimization constraints; and (4) execute the computations of the optimization model. The following subsections provide a concise description of these development steps of the optimization module.

3.3.1 Decision Variables

The purpose of this step is to identify all possible decision variables that affect the construction-related disruption cost in airport operations and the total construction cost. Accordingly, the identified decision variables in this model are project start time (ST), activities start time (ST_i), working hours per day (NH), and working days per week (ND), as shown in Fig. 1.2.

The first decision variable represents the selection of a project start time (ST) from a planner-specified range, as shown in Eq. (3.6). For example, a planner can specify that the earliest (ET) and latest (LT) project start times are January 2nd at 8:00 am and March 29th at 8:00 am, respectively. Accordingly, the model would search for an optimal project start time (ST) within these boundary limits, as shown in Eq. (3.6).

$$ET \leq ST \leq LT \tag{3.6}$$

where ET = earliest project start time, ST = project start time, and LT = latest project start time.

The second decision variable is activities start time (ST_i), which represents a selection from a set of feasible alternatives that ranges from the early start time of the activity to its late start time that can be calculated based on its free float time, as shown in Eqs. (3.7) and (3.8).

$$ES_i \leq ST_i \leq ES_i + FF_i \qquad \forall\, i \in \{1, \ldots, I\,\} \tag{3.7}$$

$$FF_i = \min(SST_i)\;-\;ES_i - D_i \qquad \forall\, i \in \{1, \ldots, I\,\} \tag{3.8}$$

where ES_i = early start of activity i; ST_i = selected start time of activity i; FF_i = free float of activity i; SST_i= successors start time of activity i; and D_i= duration of activity i.

The third decision variable represents the selection of the number of working days per week (ND) that can range from a minimum planner-specified number of days (MD) (e.g. 2 days per week) to a maximum of 7 days per week, as shown in Eqs. (3.9) and (3.10). Similarly, the fourth decision variable represents the selection of the number of working hours per day (NH) from a minimum (MNH) to a maximum (MXH) planner-specified number of hours, as shown in Eqs. (3.11) and (3.12).

$$MD \leq ND \leq 7 \tag{3.9}$$

$$0 < MD \leq 7 \tag{3.10}$$

$$MNH \leq NH \leq MXH \tag{3.11}$$

$$0 < MNH \leq MXH \leq 24 \tag{3.12}$$

where MD= minimum number of working days per week; ND= selected number of working days per week; MNH= minimum number of working hours per day; and NH= selected number of working hours per day; and MXH= maximum number of working hours per day.

3.3.2 Objective Functions

The present model is designed to generate optimal trade-offs between the two objective functions of: (1) minimizing the cost of construction-related disruption in airport operations (TDC); and (2) minimizing the total construction cost (TCC) of airport expansion project, as shown in Fig. 3.3.

Objective 1:

The first objective function is designed to minimize the cost of all construction-related disruptions (TDC) in airport operations, as shown in Eq. (3.13). TDC is calculated by summing up all construction-related disruption costs of all flights (f = 1 to F) caused by the closed construction area during all hours (h = ST to FT), as shown in Eq. (3.13).

$$Minimize\, TDC = Minimize \sum_{h=ST}^{FT} \sum_{f=1}^{F} DCC_{h,f} \tag{3.13}$$

where TDC= total construction-related disruption cost in \$, ST = project start time in hours, FT = project finish time in hours, and f = flight ID.

Objective 2:

The second objective function of the developed model is designed to minimize the total construction cost (TCC) of the airport expansion project, as shown in Eq. (3.14). TCC is calculated by summing up all its components including construction direct cost (CDC), indirect cost (CIC), mobilization cost (MC), and nighttime construction cost (NC), as shown in Eq. (3.14).

$$Minimize\, TCC = Minimize\, (CDC + CIC + MC + NC) \tag{3.14}$$

where TCC= total construction cost; CDC= construction direct cost; CIC= construction indirect cost; MC= mobilization cost; and NC= nighttime construction cost.

3.3.3 Optimization Constraints

The model is designed to comply with all related practical constraints including: (1) project completion time, (2) crew working time, and (3) job logic. First, the project completion time constraint is formulated to ensure that the project will be completed without

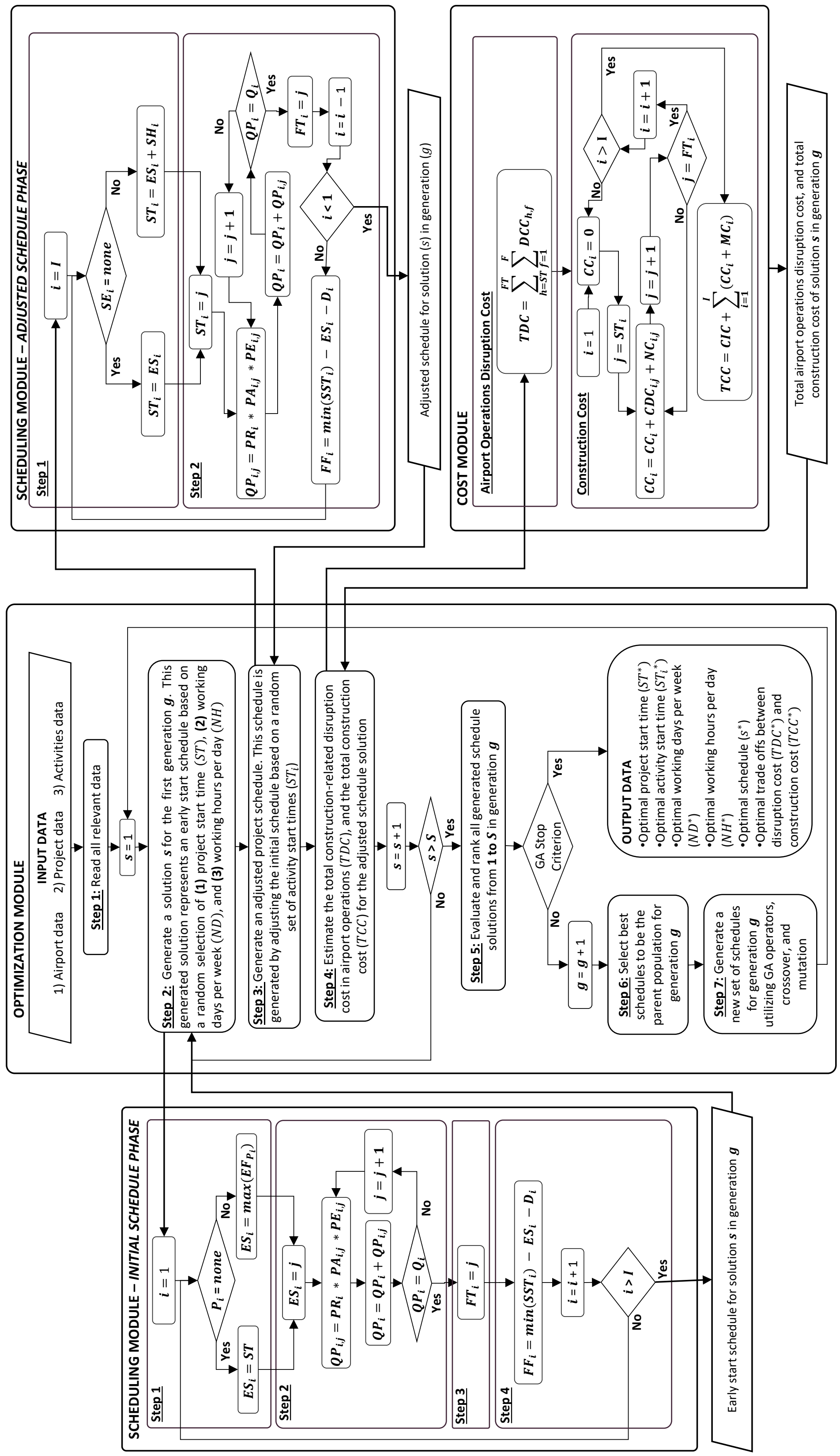

Fig. 3.3. Optimization model computations

delay within its early completion time. This is accomplished by guaranteeing that the planned start time (ST_i) of each activity i is within its float time to avoid causing a delay to successor activities beyond their float times, as shown in Eq. (3.7). Second, the crew working time constraint guarantees that the number of working days per week (ND) is greater than or equal the planner-specified minimum number of days (MD) and that it does not exceed 7 days per week, as shown in Eqs. (3.9) and (3.10). Similarly, this constraint ensures that the number of working hours per day (NH) ranges from a planner-specified minimum (MNH) to a maximum (MXH) number of hours, as shown in Eqs. (3.11) and (3.12). Third, the job logic constraint ensures that the planned start time of each activity (ST_i) is greater than or equal to the planned finish time of its predecessors, as shown in Eq. (3.15).

$$PFT_i \leq ST_i \qquad \forall\, i \in \{1, \ldots, I\ \} \tag{3.15}$$

where PFT_i = finish time of all predecessors of activity i

3.3.4 Optimization Computations

The model is designed to execute the optimization computations using multi-objective genetic algorithms due to their capabilities in (1) modeling nonlinear and discontinuous decision variables similar to those used in this model including project start date, activities start time, and working days per week; (2) searching for and identifying optimal solutions in problems with large search space within a reasonable computational time; and (3) successfully modeling similar scheduling, resource utilization, and construction optimization problems (Abdallah and El-Rayes, 2016; AlOtaibi et al., 2021; Altuwaim and El-Rayes, 2021; Hegazy and Wassef, 2001; Jun and El-Rayes, 2010; Khalafallah and El-Rayes, 2006a, 2006b, 2008; Long and Ohsato, 2009). The present model is implemented utilizing the nondominated sorting genetic algorithms II (NSGA-II) (Deb et al., 2002) and executed with the Distributed Evolutionary Algorithms (DEAP) (Fortin et al., 2012) toolbox for Python (vanRossum, 2017). As shown in Fig. 3.3, the optimization computations in this model are executed in seven main steps that are designed to:

1. Read all required project information including project data, activities data, and airport data, as shown in Fig. 3.1.

2. Generate an initial random set of early start schedules for the project $s = 1$ to S for the first generation $g = 1$. Each of these generated schedules represents an early start schedule based on a random selection for the aforementioned three decision variables: project start time (ST), working days per week (ND), and working hours per day (NH).

3. Generate a set of adjusted project schedules to evaluate the impact of delaying the start time of each activity beyond its earliest start time and within its free float. Each of these adjusted project schedules $s = 1$ to S is generated by adjusting each of the initial schedules generated in the previous step based on a random set of activity shift times (SH_i) using the integrated scheduling module in this model.

4. Estimate the total construction-related disruption cost in airport operations (TDC), and the total construction cost (TCC) for each adjusted schedule solution $s = 1$ to S in generation g using the cost module, as shown in Fig. 3.3.

5. Evaluate and rank all generated schedule solutions from 1 to S in the generation g and select the fittest schedules based on the aforementioned objective functions of total construction cost and construction-related disruption cost that were calculated in the previous step. End the optimization computations and generate its output data if the specified GA stopping criteria were satisfied. Otherwise, the model proceeds to steps 6 and 7.

6. Select the best solutions to be the parent population for the new generation $g = g + 1$.

7. Generate a new set of solutions for the new generation $g = g + 1$ utilizing GA operators, crossover, and mutation, as shown in Fig. 3.3.

3.4 Scheduling Module

The purpose of this module is to develop a practical schedule for all airport expansion construction activities (i = 1 to I). The calculations in this scheduling module are organized in two phases that are designed to (a) generate an initial early start schedule for airport expansion project, and (b) adjust the early start time of each activity to analyze and optimize the impact of delaying selected activities beyond their early start time on the optimization objective functions.

3.4.1 Phase 1: Initial Schedule Phase

This phase is designed to generate an initial early start schedule for airport expansion project based on planner-specified input data including: feasible range of project start times (ST), feasible range of working days per week (ND), feasible range of working hours per day (NH), construction activities (I), predecessors of each construction activity (P_i), activities quantity of work (Q_i), crew daily output rate of each activity (PR_i), airport construction adjustment factor $(PA_{i,j})$, and impact of overtime on crew productivity $(PE_{i,j})$, as shown in Fig. 3.1. This initial schedule will be used in the next phase to generate an adjusted schedule to analyze and optimize the impact of delaying selected activities beyond their early start time on the optimization objective functions.

This phase calculates the early start and finish times and the free float for each activity (i = 1 to I) using the following four steps, as shown in Fig. 3.3, as follows:

1. Calculate activity early start time (ES_i) for each activity (i = 1 to I) using one of the following two options:

    - For activity (i) that has no predecessor $(P_i = 0)$, ES_i is calculated as the selected project start time (ST) using Eq. (3.16).
    - For activity (i) that has predecessors $(P_i > 0)$, ES_i is calculated as the latest finish time of its predecessors using Eq. (3.17).

2. Calculate quantity of work $(QP_{i,j})$ performed in activity i in each hour j based on the crew output rate (PR_i), the impact of overtime on crew productivity $(PE_{i,j})$, and airport construction adjustment factor $(PA_{i,j})$ using Eq. (3.18). It should be noted that $PE_{i,j}$ represents the crew production efficiency that varies based on the number of working hours per day and number of working days per week, for example, if a crew works for 9 hours a day for 5 days a week, their productivity drops to 95% in the third week (RSMeans data, 2020). Similarly, $PA_{i,j}$ represents the encountered productivity loss during working at peak hours, evening times, and/or nighttimes, for example, the Mechanical Contractors Association of America (MCAA) estimates 20% loss in productivity for working during evening times (Kitchens, 1996).

3. Calculate early finish time (EF_i) of activity i based on its start time (ES_i) and duration (D_i) using Eq. (3.19). D_i is calculated as the total number of hours needed to complete the entire quantity of work (Q_i) considering that the quantity of work $(QP_{i,j})$ completed in each hour j may vary, as shown in Eq. (3.18).

4. Calculate free float (FF_i) of activity i using Eq. (3.20).

$$ES_i = ST \qquad \forall i \in I \; and \; P_i = 0 \tag{3.16}$$

$$ES_i = max(EF_{P_i}) \qquad \forall i \in I \; and \; P_i > 0 \tag{3.17}$$

$$QP_{i,j} = PR_i \; \times \; PA_{i,j} \; \times \; PE_{i,j} \quad \forall \; i \; \in I \;\; and \, \forall \; j \; \in (ES_i, \; \ldots, EF_i) \tag{3.18}$$

$$EF_i = ES_i + D_i \tag{3.19}$$

$$FF_i = min(SST_i) - ES_i - D_i \qquad \forall i \in I \tag{3.20}$$

where ES_i = early start of activity i in hours; EF_{P_i} = early finish time of predecessors of activity i in hours; $QP_{i,j}$ = performed quantity of work for activity i at working hour j in units of measurements; PR_i= crew hourly output rate of activity i in unit/hour; $PA_{i,j}$ = airport construction adjustment factor for activity i at working hour j that ranges from 0 to 1; $PE_{i,j}$ = impact of overtime on productivity for activity i at hour working hour j that ranges from 0

to 1; EF_i= early finish time of activity i in hours; Q_i = quantity of work of activity i in units of measurements such as CY for concrete; FF_i = activity free float in hours; SST_i = start time of successors of activity i in hours; and D_i = duration of activity i in hours.

3.4.2 Phase 2: Adjusted Schedule Phase

The main objective of this phase is to adjust the early start time of each activity to analyze and optimize the impact of delaying selected activities beyond their early start time on the optimization objective functions. This phase performs the adjustment calculations in two steps that are designed to delay the activity start time beyond its early start time and within its float, and calculate activity finish time, as shown in Fig. 3.3, as follows:

1. Calculate adjusted activity start time (ST_i) based on its early start time (ES_i) and shift time (SH_i) selected by the optimization module, as shown in Eq. (3.21).

2. Calculate finish time for activity i using Eq. (3.22) and recalculate the free float for its predecessors using Eq. (3.20) based on the adjusted start time of activity i.

$$ST_i = ES_i + SH_i \qquad \forall i \in I \quad where \quad 0 \leq SH_i \leq FF_i \tag{3.21}$$

$$FT_i = ST_i + D_i \tag{3.22}$$

where ST_i= adjusted start time of activity i in hours; FT_i = adjusted finish time of activity i in hours; and SH_i = shift time of activity i that ranges from 0 to activity free float time (FF_i).

3.5 Cost Module

The calculations in this module are organized in the following two submodules that are designed to compute (a) construction-related disruption cost in airport operations, and (b) total construction cost of the generated schedules in the previous module.

3.5.1 Airport Operations Disruption Cost

This submodule is designed to calculate construction-related disruption cost in airport operations (TDC). This cost is designed to account for all air traffic disruption cost that is caused by the closure of a construction area such as additional costs caused by longer taxiing time due to closure of a taxiway segment for construction and/or additional flight delay time caused by longer queues, as shown in Fig. 3.2. This is achieved by calculating all disruption costs in airport flights due to the construction closure during the project working hours using Eqs. (3.23) – (3.24).

$$TDC = \sum_{h=ST}^{FT} \sum_{f=1}^{F} DCC_{h,f} \tag{3.23}$$

$$DCC_{h,f} = DCT_{h,f} \times DV_f \tag{3.24}$$

where $DCC_{h,f}$ = cost of delay for flight f due to closure of construction area during working hour h in \$; $DCT_{h,f}$ = delay time (in hour) in flight f due to closure of construction area during hour h that is calculated using the aforementioned simulation module; and DV_f = delay cost rate for flight f in \$/hour that varies from \$1400/hour to \$4500/hour based on several factors such as aircraft size and number of passengers (FAA, 2020b).

3.5.2 Total Construction Cost

This submodule is designed to calculate all the components of the total construction cost that include construction direct cost (CDC), indirect cost (CIC), mobilization cost (MC), and nighttime construction cost (NC), as shown in Eq. (3.25).

$$TCC = CDC + CIC + MC + NC \tag{3.25}$$

First, the direct cost of airport expansion projects (CDC) is calculated in this module by summing up the direct cost of all activities in the project (i = 1 to I). The direct cost of each activity i is calculated by adding up all its hourly costs of construction crews and material over its entire duration, as shown in Eq. (3.26).

$$CDC = \sum_{i=1}^{I} \sum_{j=ST_i}^{FT_i} (QP_{i,j} \times (CU_i + (CF_{i,j} \times LC_i))) \tag{3.26}$$

where CDC = total construction direct cost in \$; CU_i= unit cost rate of activity i in \$/unit of measurement; $CF_{i,j}$= labor overtime premium rate of activity i at working hour j; and LC_i= labor cost rate of activity i in \$/unit of measurement.

Second, the project indirect cost (CIC) is calculated based on the project duration (TD) and the indirect cost rate (ICR) that accounts for all time-dependent costs, such as site supervision, site utilities, and office overhead, as shown in Eq. (3.27).

$$CIC = ICR \ \times \ TD \tag{3.27}$$

where ICR= indirect cost rate in \$/day; and TD = project duration in days

Third, the mobilization cost (MC) is calculated using Eq. (3.28) to account for all daily mobilization and demobilization costs that are often required to comply with airport operation regulations such as the daily cost of cleaning up and sweeping the airfield to meet the inspection standards and/or installing precast panels as a temporary pavement if the concrete could not be poured and cured in time to restore access for airport use (Delatte, 2006).

$$MC = \sum_{i=1}^{I} (MCR_i \times D_i) \tag{3.28}$$

where MCR_i= daily mobilization and demobilization cost rate of activity i in \$/day; and D_i = duration of activity i in days.

Fourth, nighttime construction cost (NC) is calculated to account for all additional costs incurred due to working during nighttime hours such as the ownership and operating cost

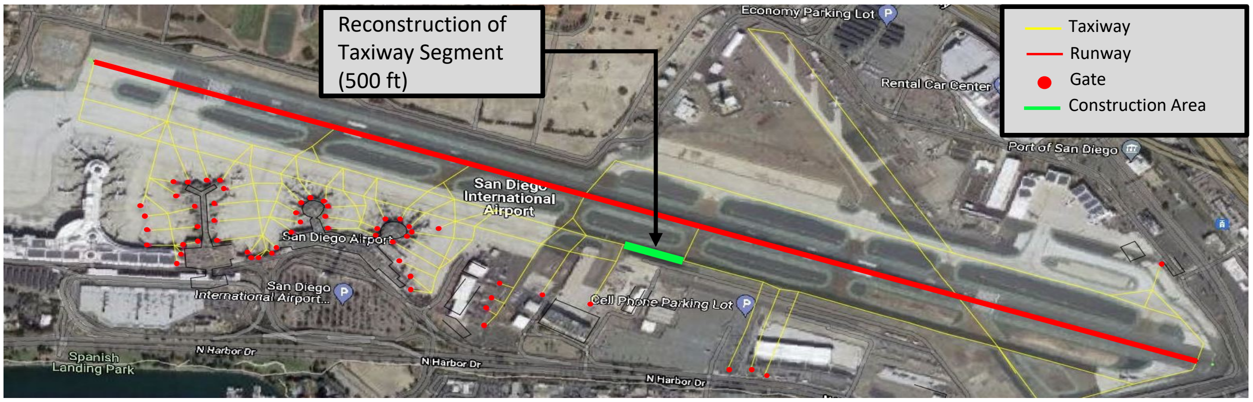

Fig. 3.4. Layout of San Diego International Airport (SAN) during construction in Simmod Pro!

of lighting equipment, as shown in Eq. (3.29).

$$NC = \sum_{i=1}^{I} \sum_{j=ST_i}^{FT_i} NC_{i,j} \tag{3.29}$$

where $NC_{i,j}$= nighttime construction cost of activity i at hour j in \$.

3.6 Case Study

The performance of the formulated optimization model is evaluated by analyzing a real-life case study to demonstrate the use of the model and highlight its capabilities in generating optimal tradeoffs between minimizing the cost of construction-related disruption in airport operations and total construction cost of airport expansion projects. The case study focuses on optimizing the construction planning of the relocation and reconstruction of a 500 ft-long segment of Taxiway B at San Diego International Airport, as shown in Fig. 3.4.

The input data for this case study consists of airport, project, and activity data, as shown in Fig. 3.1. First, the airport input data includes (a) airport layout, as shown in Fig. 3.4; (b) air traffic data; (c) flight operations schedule, as shown in Table 3.1; and (d) airplane delay cost per hour (DV) which is specified to be \$1400/hour for small aircrafts and \$4500/hour for large aircrafts. Second, the project input data includes (i) location which is specified to be San Diego, CA; (ii) a total of 22 construction activities that are grouped into six main work packages: demolish existing pavements and utilities, construct utilities and storm drainage system, site earthwork and grading, construct new concrete and asphalt pavements, construct airfield lighting and signage, and construct surface paint markings (San Diego county regional airport authority, 2021); and (iii) indirect cost rate that is specified to be 30% of the daily direct cost.

Third, the activity input data for this case study includes (1) predecessor activities (P_i), (2) quantity of work (Q_i), (3) crew daily output rates (PR_i), (4) unit cost rates (CU_i), as shown in Table 3.5; (5) impact of overtime on crew productivity ($PE_{i,j}$) that depends on the number of working hours per day and number of working days per week (RSMeans data, 2020); (6) airport construction adjustment factor ($PA_{i,j}$) that represents the impact of air traffic volumes and nighttime construction on crew productivity; (7) labor overtime premiums ($CF_{i,j}$) that was specified to be 150% of the regular rate; (8) mobilization and demobilization cost rate (MCR_i) which was specified to be 5% of the daily direct cost; and (9) nighttime construction cost ($NC_{i,j}$) that was specified to be 15% of the hourly direct cost.

The developed optimization model utilized the aforementioned input data to search for and generate an optimal reconstruction schedule that minimizes both construction-related disruption cost in airport operations and total construction cost. The genetic algorithm optimization computations for this case study were performed using the distributed evolutionary algorithm package (DEAP) in the Python programming platform (vanRossum, 2017). The GA search parameters utilized in this case study are the NSGA-II selection with a population size of 500, a mutation rate of 0.2, and a cross-over rate of 0.6. The optimization engine was set to terminate the optimization computations after a total of 2000 generations. The computational time for this case study was approximately 25 minutes using a personal laptop with 2 GHz Quad-Core Intel Core i5 Processor and 16 GB 3733 MHz LPDDR4X RAM.

Table 3.5. Input data of reconstruction activities and crews

Activity ID (i)	Construction Activities	Predecessors (P_i)	Quantity of work (Q_i)	Unit	Daily Output (PR_i) (unit/day)	Cost rate (CU_i) ($/unit)
A	Closing reconstruction area	-	1,800	LF	400	3.68
B	Installation of lighted barricades	-	180	EA	150	150
C	Removal of airfield marking	A, B	2,750	SF	500	1.61
D	Removal of signage	A, B	3	EA	5	689
E	Installation of temporary lighting	A, B	1	EA	8	10,000
F	Milling of asphalt pavement	C, D, E	22,000	SY	9000	0.92
G	Excavating down to subgrade	F	16,000	BCY	12500	0.35
H	Demolition of existing utilities	G	500	LF	800	1.15
I	Demolition of electrical system	G	500	LF	394	0.82
J	Removal of base soil	H, I	6,200	LCY	1080	2.06
K	Preparing the subgrade	J	22,000	SY	15000	0.12
L	Install deep utilities (duct bank)	K	500	LF	260	3.55
M	Placing base material	L	22,000	SY	4200	7.99
N	Compacting base material	M	22,000	SY	4200	7.99
O	Install conduit and base cans	N	500	LF	270	1.91
P	Install in-pavement lighting	O	10	EA	18.64	783
Q	Installation of asphalt pavement	P	22,000	SY	4520	14.68
R	Install in-pavement light fixtures	Q	10	EA	4	370
S	Install signage	Q	3	EA	5	996.65
T	Install a coat of pavement marking	Q	2,750	SF	4000	0.68
U	Remove the barricade	R, S, T	180	EA	250	25
V	Open the reconstruction area	U	1,800	LF	432	0.98

The optimization computations for this case study were executed using the aforementioned four modules (see Fig. 3.3). First, the simulation module was utilized to quantify the impact of the construction project on airport operations during the entire planned project duration to estimate airport operations disruption cost ($DCC_{h,f}$) that is used in the following modules. Second, the optimization module was used to search for and identify a set of optimal solutions for the four decision variables of project start time (ST), number of working days per week (ND), number of working hours per day (NH), and activity start time (ST_i). Third, the scheduling module was utilized to (a) generate an initial early start schedule for the case study using Eqs. (3.16) – (3.20), and (b) adjust the early start time of each activity to analyze and optimize the impact of delaying selected activities beyond their early start time on the optimization objective functions using Eqs. (3.21) and (3.22). Fourth, the cost module was used to estimate airport operation disruption cost and total construction cost for each of the generated solutions using Eqs. (3.23) – (3.29).

Upon completion of the aforementioned computations, the model generated 105 Pareto optimal solutions, where each represents a unique and optimal tradeoff between minimizing construction-related disruption cost in airport operations (TDC) and minimizing total construction cost (TCC), as shown in Fig. 3.5. A sample of these solutions along with their identified optimal project start time (ST), number of working days per week (ND), and number of working hours per day (NH) are summarized in Table 3.6. Furthermore, an example of the identified optimal activity start and finish times for one of the generated Pareto optimal solutions ($S90$) is shown in Table 3.7.

The generated 105 Pareto optimal solutions for this case study includes (1) a minimum airport operations disruption cost solution of \$750 ($S1$) with an associated maximum total construction cost of \$1,296,962, (2) a minimum total construction cost solution of \$800,344 ($S105$) with an associated maximum airport operations disruption cost of \$602,328, and (3) 103 additional Pareto optimal solutions that provide a wide range of optimal trade-offs between airport operations disruption cost and total construction cost, as shown in Fig. 3.5.

Table 3.6. Sample of Pareto optimal solutions

Sol. (S)	Number of days (ND)	Number of hours (NH)	Project Duration (TD) (days)	Project Start Time (ST)	Project Finish Time (FT)	Airport Disruption Cost (TDC)	Total Construction Cost (TCC)
1	6	5 (00 - 05)	109.2	November 23rd at 00:00	March 11th at 04:45	\$750	\$1,296,962
18	5	8 (21 - 05)	81.2	November 24th at 21:00	February 14th at 01:05	\$16,311	\$1,294,298
36	6	11 (17 - 04)	51.15	January 25th at 17:00	March 17th at 20:25	\$66,430	\$1,262,198
54	7	8 (16 - 00)	56.13	January 7th at 16:00	March 4th at 19:00	\$95,370	\$1,196,162
72	6	5 (16 - 21)	102.13	November 18th at 16:00	February 28th at 19:15	\$130,221	\$1,140,186
90	5	7 (13 - 20)	85.17	January 22nd at 13:00	April 17th at 17:05	\$196,254	\$998,849
105	5	8 (09 - 17)	78.1	April 1st at 09:00	June 18th at 11:00	\$602,328	\$800,344

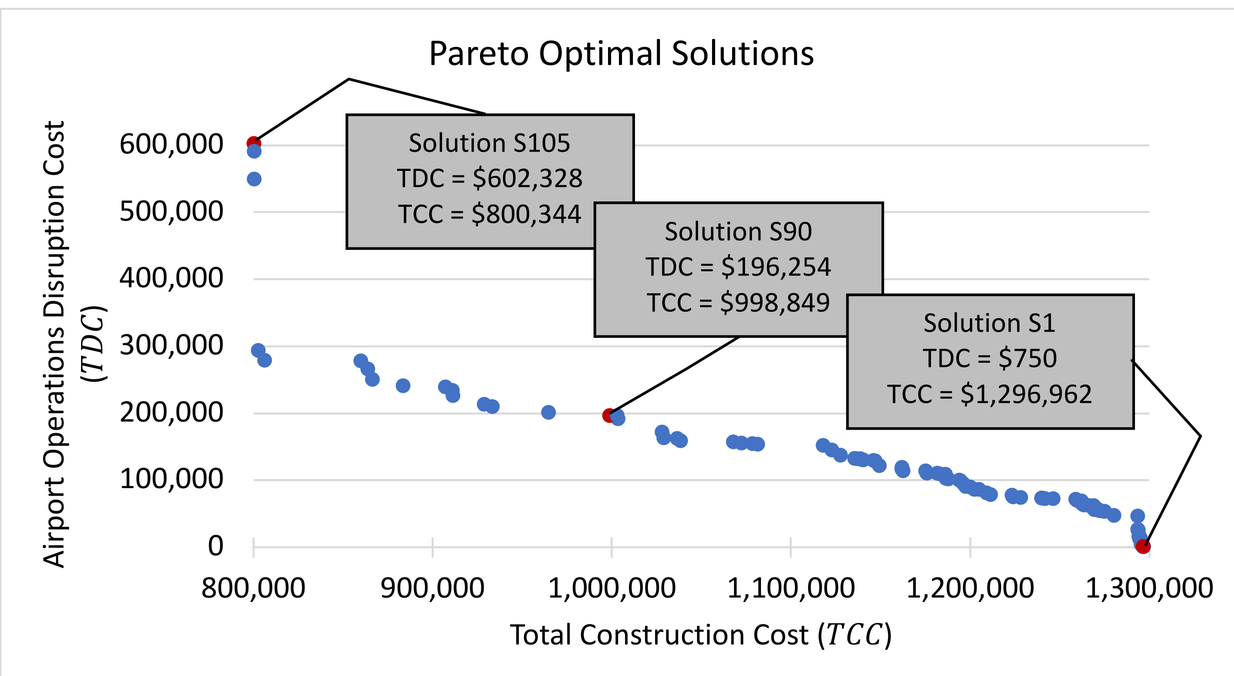

Fig. 3.5. Generated Pareto optimal solutions

Table 3.7. Optimal activity start and finish times for solution $S90$

Activity ID (i)	Activity Start Time (ST_i)	Activity Finish Time (FT_i)
A	January 22nd at 13:00	January 29th at 16:50
B	January 22nd at 14:00	January 23rd at 17:25
C	January 29th at 16:50	February 7th at 15:30
D	February 6th at 14:00	February 6th at 19:15
E	February 7th at 13:00	February 7th at 14:05
F	February 7th at 15:30	February 12th at 15:40
G	February 12th at 15:40	February 13th at 19:35
H	February 14th at 13:00	February 14th at 18:30
I	February 13th at 19:35	February 15th at 16:45
J	February 15th at 16:45	February 26th at 17:45
K	February 26th at 17:45	February 28th at 16:35
L	February 28th at 16:35	March 2nd at 19:20
M	March 2nd at 19:20	March 11th at 16:20
N	March 11th at 16:20	March 20th at 13:50
O	March 20th at 13:50	March 24th at 16:00
P	March 24th at 16:00	March 25th at 13:50
Q	March 25th at 13:50	April 4th at 14:55
R	April 4th at 14:55	April 9th at 15:55
S	April 4th at 16:00	April 5th at 14:25
T	April 4th at 17:00	April 5th at 16:10
U	April 9th at 15:55	April 10th at 15:20
V	April 10th at 15:20	April 17th at 17:05

On one end of the spectrum, optimal solution $S1$ provides minimum airport operations disruption cost (TDC) by scheduling the project to start and finish during the low air traffic season of San Diego Airport and planning the construction activities during nighttime hours that have the lowest air traffic. This is achieved by scheduling the project to start (ST) on Saturday November 23rd at midnight working 6 days per week ($ND = 6$) from Saturday to Thursday and 5 hours per day ($NH = 5$) from midnight to 5:00 am. However, this solution has the highest total construction cost due to the additional cost of nighttime construction and labor overtime premiums.

On the other end of the spectrum, optimal solution $S105$ provides minimum total construction cost (TCC) by scheduling the taxiway relocation activities during weekly working days and regular daytime hours. This solution scheduled the project to start (ST) on Monday April 1st at 9:00 am working 5 days per week ($ND = 5$) from Monday to Friday and 8 hours per day ($NH = 8$) from 9:00 to 17:00. This plan, however, causes the highest airport operational disruptions among the generated optimal solutions because it schedules the construction activities during high daily and hourly air traffic volumes. In addition to the aforementioned two extreme solutions, the model generated 103 other Pareto optimal solutions that enable planners to analyze and select the schedule that best meets their unique project requirements.

To verify the generated results of the optimization model, a brute-force computational analysis was executed to calculate airport disruption cost and total construction cost of all possible solutions for this case study and compare them to the model optimal results. The brute-force analysis was performed by identifying all combinations of all possible decision variables: (1) project start time (ST) from 1 to 8760, (2) activities shift time (SH_i) from 0 to FF_i, (3) working days per week (ND) from 5 to 7 days per week, and (4) working hours per day (NH) from 5 to 12 hours per day. A comparison between the results of all possible solutions and the generated optimal solutions by the model is illustrated in Fig. 3.6. This comparison confirms that the developed model was able to identify nondominated optimal

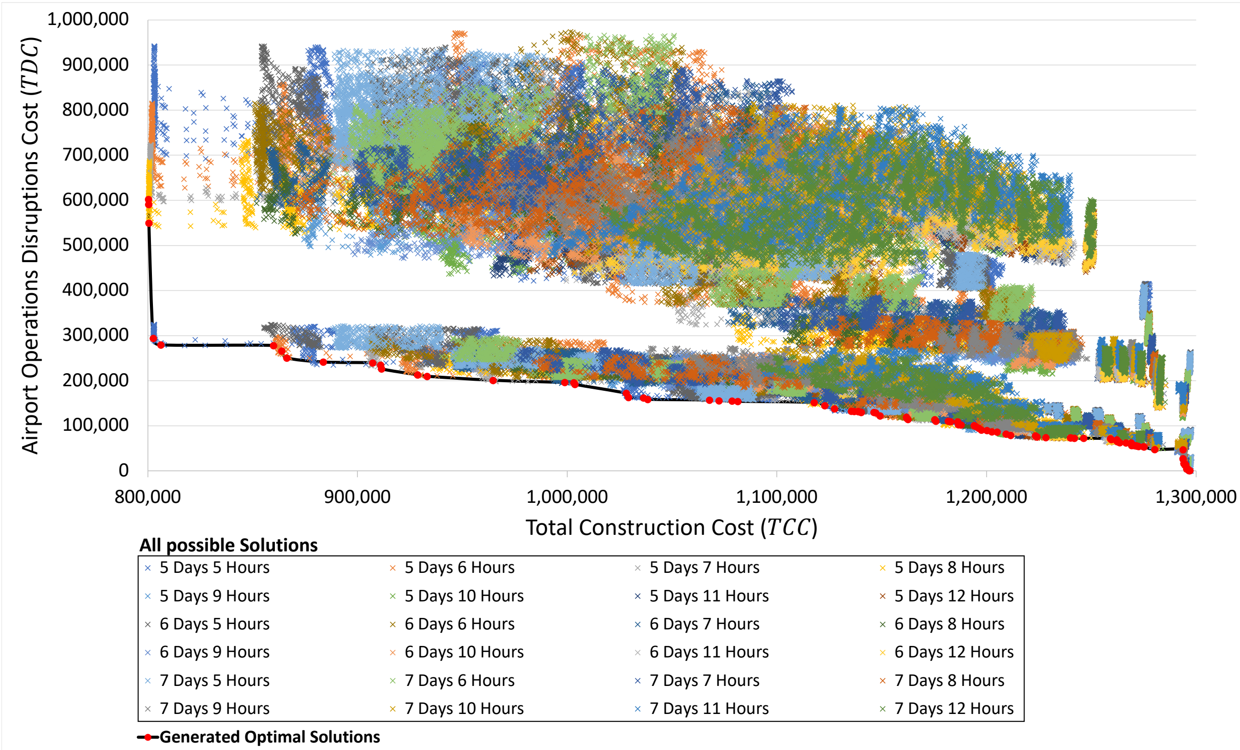

Fig. 3.6. Comparison of model results and all possible solutions

tradeoff solutions between minimizing airport operations disruption cost and minimizing total construction cost for this case study, as shown in in Fig. 3.6.

A sensitivity analysis was conducted to analyze the sensitivity of the generated results by the model to uncertainties and variations in its input parameters. This was achieved by varying the values of the model input parameters from -20% to 20% of their estimated values with an increment of 5%, as shown in Table 3.8. The input parameters considered in this sensitivity analysis are flights delay cost rate (DV_i), construction unit cost rate (CU_i), crew daily output rate (PR_i), and nighttime construction cost ($NC_{i,j}$). The sensitivity analysis evaluated the impact of the aforementioned variation in these four input parameters on the minimum and maximum values of the two optimization objective functions of the developed model, as shown in Table 3.8.

The results of the sensitivity analysis show that changes in these four input parameters had varying impacts on the two optimization objectives, as shown in Table 3.8. For example, changes in the flights delay cost rate (DV_i) input parameter caused comparable variations

Table 3.8. Sensitivity of model results to changes in input parameters

	Input Parameters															
	Flights Delay Cost Rate (DV_f)				Construction Unit Cost Rate (CU_i)				Crew Daily Output Rates (PR_i)				Nighttime Construction Cost ($NC_{i,j}$)			
Change in Parameters Values (%)	Change in Total Construction Cost (TCC) (%)		Change in Airport Disruptions Cost (TDC) (%)		Change in Total Construction Cost (TCC) (%)		Change in Airport Disruptions Cost (TDC) (%)		Change in Total Construction Cost (TCC) (%)		Change in Airport Disruptions Cost (TDC) (%)		Change in Total Construction Cost (TCC) (%)		Change in Airport Disruptions Cost (TDC) (%)	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
-20	0.0	0.0	-20.0	-26.5	-20.0	-20.0	0.4	-0.2	16.6	19.1	26.3	25.4	0.0	-1.5	0.2	0.2
-15	0.0	0.0	-15.1	-17.9	-15.0	-15.0	0.6	0.1	11.8	13.5	18.6	18.5	0.0	-1.0	0.0	0.0
-10	0.0	0.0	-10.0	-16.0	-10.0	-10.0	0.7	0.0	7.5	8.5	12.0	11.4	0.0	-0.8	0.2	-0.1
-5	0.0	0.1	-4.7	-3.9	-5.0	-5.0	0.1	0.2	3.5	4.0	5.4	5.5	0.1	-0.4	0.2	-0.3
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	4.9	3.0	5.1	5.0	-0.1	-0.1	-3.1	-3.7	-5.2	-5.3	0.0	-0.4	0.1	-0.2
10	0.0	0.0	9.9	8.0	10.1	10.0	-0.1	-0.3	-6.0	-6.9	-9.9	-10.3	0.0	-0.8	0.2	0.0
15	0.0	0.0	15.5	12.3	15.0	15.0	0.4	-0.3	-8.6	-9.9	-13.4	-14.0	0.0	-1.0	0.3	-0.1
20	0.0	0.0	21.0	17.4	20.0	20.0	-0.3	0.0	-11.0	-12.6	-17.2	-17.6	0.0	1.5	0.1	0.1

in airport operations disruption cost and had no impact on total construction cost (see Table 3.8 and Fig. 3.7) due to the direct relationship between this input parameter and airport operations disruption cost. On the other hand, changes in the construction unit cost rate (CU_i) input parameter caused comparable variation in total construction cost and had no impact on airport operations disruption cost due to the direct relationship between this input parameter and total construction cost. Changes in the crew daily output rate (PR_i), however, had a comparable impact on both airport operations disruption cost and total construction cost due to its direct relationship with the project duration that affects the aforementioned objective functions. On the contrary, changes in nighttime construction cost ($NC_{i,j}$) input parameter caused minimal variation in airport operations disruption cost and total construction cost for the solutions that involve nighttime construction work and had no impact on the total construction cost for the solutions that schedules the work during daytime hours, as shown in Table 3.8.

3.7 Conclusion

A novel multi-objective model was developed to support airport and construction planners in generating and analyzing optimal tradeoffs between minimizing the cost of construction-related disruption in airport operations and minimizing the total construction cost. The model is designed to optimize these two competing objective functions by generating a detailed construction plan of airport expansion projects. The developed

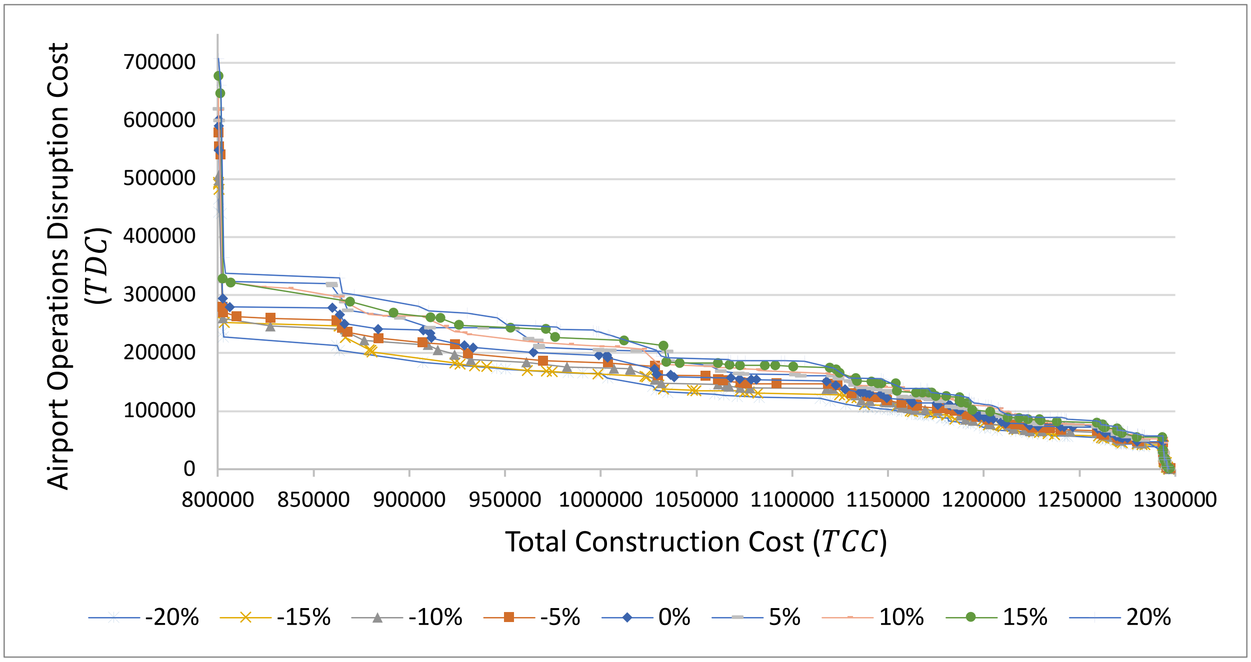

Fig. 3.7. Sensitivity of model results to variations in flights delay cost rate (DV_f)

model complies with all relevant practical constraints, including project completion time, crew working time, and job logic constraints. A case study was analyzed to illustrate the use of the model in identifying an optimal construction schedule for the relocation and reconstruction of a 500-ft long segment of Taxiway B at San Diego International Airport. In this case study, the model generated a set of 105 optimal tradeoff solutions, where each represents a unique and optimal tradeoff between the two optimization objectives of minimizing the cost of the construction-related disruption in airport operations and the total construction cost. At one extreme end of the generated tradeoff solutions, the model identified an optimal construction plan that provides the least airport operations disruption cost and the highest total construction cost. At the other end of the spectrum, the model identified another optimal construction plan that provides the least total construction cost and the highest airport operations disruption cost.

The results of the case study clearly illustrate the original contributions of the model to the body of knowledge including its novel methodologies for (1) identifying optimal start date and time for airport expansion projects and all their construction activities; (2) determining optimal daily and weekly work plans for all airport expansion activities; (3) selecting optimal daily working hours for all construction crews on the project; (4) quantifying and minimizing the impact of construction activities on airport operations; (5) analyzing and minimizing the impact of air traffic data and airport operations on total construction cost; and (6) generating a set of optimal construction plans that provide optimal trade-offs between minimizing the construction-related disruption in airport operations and minimizing the total construction cost. These novel capabilities are expected to support airport and construction planners in their efforts to identify an optimal schedule for airport expansion projects that minimizes the construction impact on ongoing airport operations while minimizing total construction cost.

Chapter 4

Predicting Construction Impact on Airport Operations

4.1 Introduction

The objective of this chapter is to present the development of a novel machine learning methodology that overcomes the limitations of existing related studies that stated earlier in the first chapter. The methodology can be used to develop robust machine learning models for predicting the impact of various construction phasing plans on flights ground movement time in any airport without the need for repetitive and time-consuming simulation computations. The methodology is designed to support airport and construction planners in their efforts to efficiently and accurately analyze and compare the impact of all feasible construction phasing plans on flights ground movement and airport operations.

The implementation of the machine learning methodology for predicting airport flights ground movement time is organized in four main stages: (1) data collection stage to gather all required airport data for training and testing the prediction model; (2) data preprocessing stage to identify, classify, transform, and split all predicted and predictor variables data into training and testing datasets; (3) model training stage to select the machine learning methods and fit each of them to the training dataset by adjusting its parameters to minimize the error; and (4) evaluation and validation stage to evaluate the performance of each selected method on the training dataset and validate its results by applying it on unseen

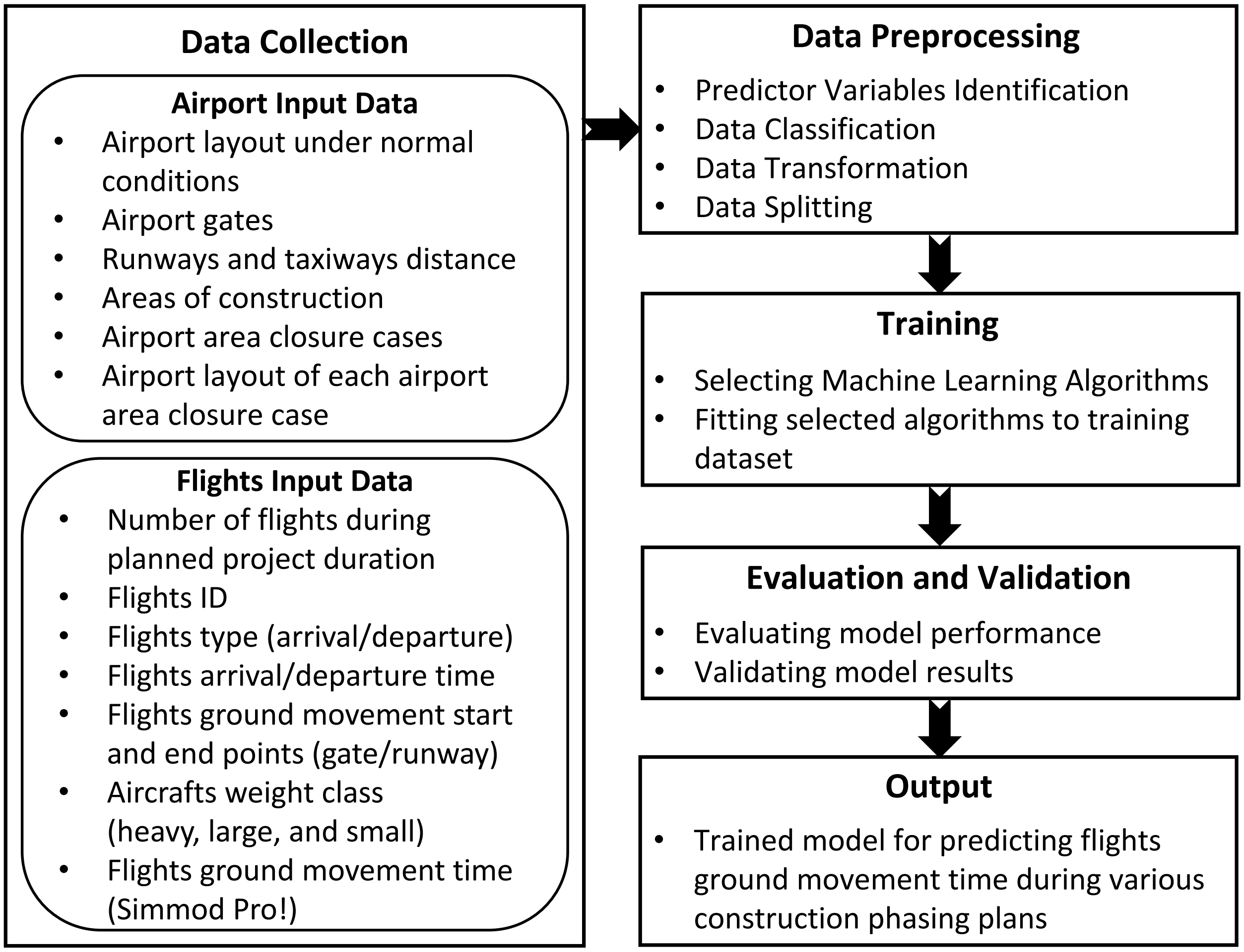

Fig. 4.1. Model development stages

testing dataset to verify its generalizability to make predictions on new unseen data, as shown in Fig. 4.1. The following sections provide a concise description of the development and computations of each of these four stages.

4.2 Data Collection

The primary purpose of this stage is to provide a dataset that the model can learn from. Machine learning algorithms learn from data by finding patterns that can be used to make predictions or decisions. This requires the collection and use of a large and diverse dataset that accurately represents the problem that the model is intended to solve. To illustrate the use of the proposed machine learning methodology, a large and diverse dataset is collected from a real-life airport expansion project that requires the relocation and reconstruction of 14 segments of a 5000 ft-long Taxiway B at San Diego International Airport (see Fig. 1.4). The procedure of data collection in this stage is organized in three main steps that are designed to: (1) gather all related airport and flights data, (2) develop a representative sample of various combinations of airport area closures that enables the model to capture the changes in flights ground movement time that are affected by varying area closures, and (3) calculate flights ground movement time during each of the specified area closures.

4.2.1 Gather airport and flights data

In the first step, the layout of San Diego International Airport is specified graphically by modeling the airport gates, taxiways, and runways as a set of links that are connected by nodes, as shown in Fig. 1.4 and Fig. 4.1. This step also specifies all related airport and flights data including flights schedule, flights origin and destination, aircrafts type and size, arrival and departure gates, and airport runways.

4.2.2 Develop a representative sample of airport area closures

In this step, a representative sample of various combinations of airport area closures was developed to enable the model to capture the changes in flights ground movement time during various area closures. As stated earlier, there are 16,383 possible combinations of airport area closures for the reconstruction of 14 segments of Taxiway-B in San Diego International Airport. To maximize computational efficiency, a representative sample of 100 possible airport area closures was developed that includes (1) fourteen possible combinations (cases 1 to 14) of single area closures, (2) one possible combination (case 100) that represents the concurrent closure of all fourteen areas, and (3) approximately 7 randomly generated combinations of concurrent area closures for each of the remaining area closure possibilities, as shown in Table 4.1.

Table 4.1. Representative sample of possible airport area closures

Number of closed areas	Number of cases	Case number	Concruurent airport area closures during construction
1	14	1	C1
		⋮	⋮
		14	C14
2	7	15	C5, C7
		⋮	⋮
		21	C6, C12
3	7	22	C4, C8, C13
		⋮	⋮
		28	C2, C7, C10
⋮	⋮	⋮	⋮
12	7	86	C1, C2, C3, C5, C7, C8, C9, C10, C11, C13 , C14
		⋮	⋮
		92	C2, C3, C5, C6, C7, C8, C9, C10, C11, C12, C13 , C14
13	7	93	C1, C2, C3, C4, C5, C6, C8, C9, C10, C11, C12, C13, C14
		⋮	⋮
		99	C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C14
14	14	100	C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C13, C14

Table 4.2. Sample of flights ground movement time

Flight ID	Flight type	Ground movement time (minutes)						
		Normal conditions	Airport area closure case					
			1	15	22	86	93	100
1	Arrival	1.512	2.419	1.619	1.512	1.512	2.339	2.563
110	Departure	10.819	16.456	12.725	11.606	14.411	15.506	16.456
200	Arrival	3.665	4.212	3.832	3.965	4.132	4.432	4.732
300	Departure	13.730	18.166	15.503	14.503	17.065	16.885	18.711
410	Arrival	2.535	3.667	2.535	2.535	3.346	3.457	3.685
515	Departure	7.259	7.771	7.671	7.716	8.018	8.006	9.680

4.2.3 Calculate flights ground movement time

In this step, the ground movement time of all airport flights is calculated for each of the 100 possible airport area closures that were generated in the previous step using an FAA-validated air traffic simulation tool called Simmod Pro (ATAC, 2021; FAA, 2004). Each of these 100 simulation runs was performed in three main substeps that are designed to: (1) define airport layout including all its revised nodes and links to account for all airport area closures during construction, (2) specify all flight and airport data, and (3) calculate flights ground movement time during construction. In this step, a total of 53,900 flights ground movement times were calculated using Simmod Pro to analyze the impact of the aforementioned 100 alternative airport area closures (see Table 4.1) on the ground movement time for each of the 539 daily arriving and departing flights at San Diego International Airport. A sample of these calculated flights ground movement time by Simmod Pro for various airport area closures is shown in Table 4.2.

4.3 Data Preprocessing

The main objective of this stage is to preprocess the raw data that was collected in the previous stage to ensure its quality and reliability. This is achieved by conducting (1) predictor variables identification to select and calculate all predictor variables that have an impact on flights ground movement time; (2) data classification to group predictor variables based on their types such as categorical and numerical variables; (3) data transformation to encode categorical variables and normalize numerical variables to improve the performance of the machine learning models; and (4) data splitting to divide the transformed data into training and testing datasets, as shown in Fig. 4.2.

First, the predictor variables in the developed models were identified based on those reported by existing studies (Lee et al. 2016) to have an impact on flights ground movement time: (1) flight type, (2) flight ID, (3) aircraft weight class, (4) assigned gate and runway, (5) flight arrival/departure time, (6) airport area closure case, and (7) flights ground movement distance. The first six variables in this list are readily available data in most airports while the last variable (flights ground movement distance) needs to be calculated using graph algorithms such as Dijkstra's algorithm (Dijkstra, 1959), as shown in Fig. 4.2. This flights ground movement distance depends on the aircraft taxi path that changes based on the assigned gate and runway of the flight and the dynamic layout of the airport that also changes based on the location of the closed area for construction. To automate the calculation of the distance, Dijkstra's algorithm is utilized to calculate the distance of the shortest path between the flight assigned gate and runway based on the airport area closure case (Dijkstra, 1959). This is achieved by defining the airport layout under construction as nodes and weighted links where the weight represents the distance of the corresponding taxiway segment. The links that represent the construction areas of the airport area closure case are removed to quantify the impact of its closure on the flight ground movement distance using the Dijkstra's shortest path algorithm, as shown in Fig. 4.2.

Second, the aforementioned seven predictor variables were then classified in two groups based on their types: (1) categorical variables such as flights type, flights ID, aircrafts weight class, assigned gates and runways, and airport area closure cases; and (2) numerical variables such as flights arrival/departure times and flights ground movement distance, as

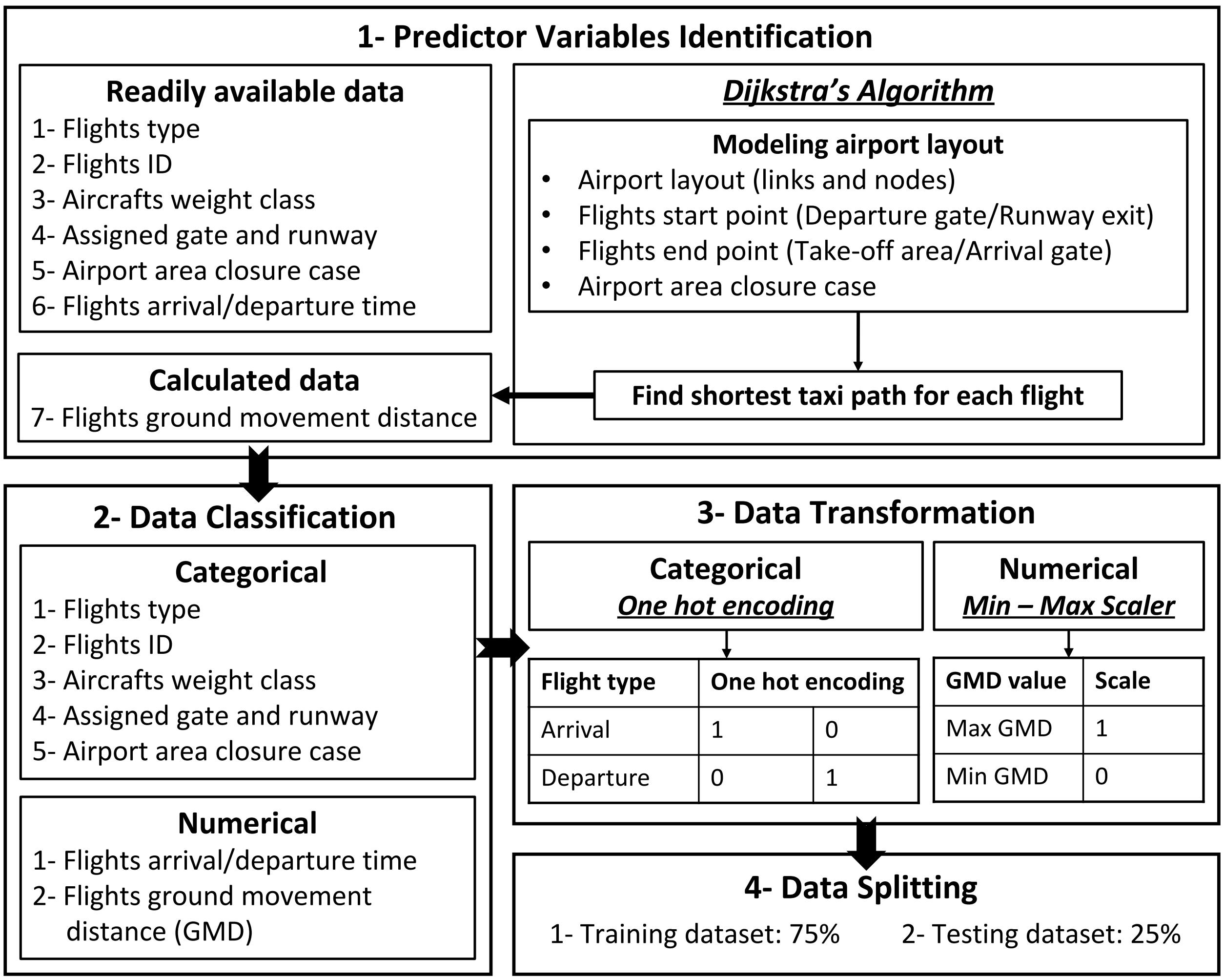

Fig. 4.2. Data preprocessing

Table 4.3. Training and testing datasets

Dataset	Data size	Average ground movement time (minutes)	Standard deviation (minutes)
Training	40425	6.1432	4.6519
Test	13475	6.0880	4.6141
Total	53900	6.1294	4.6425

shown in Fig. 4.2.

Third, each of these categorical and numerical variables were transformed to improve the performance of the machine learning models. The categorical variables were transformed using one hot encoding method to represent each categorical variable as a binary vector that consists of several elements equal to the categories that the data variable has (Daly et al., 2016), as shown in Fig. 4.2. For example, the flight type variable is encoded as a binary vector of two elements where an arrival flight is encoded as [1, 0] and a departure flight is encoded as [0, 1]. All other categorical variables were encoded using a similar procedure. The numerical variables were transformed using min-max normalization technique to scale the values of these variables to a range between 0 and 1, as shown in Fig. 4.2. This normalization is often used to minimize the risk of one feature dominating the others, which may occur if the features have very different ranges of values (Pedregosa et al., 2011).

Fourth, the transformed data were then split into training and testing datasets that include 75% and 25% of the entire dataset of 53,900 flights, respectively, as shown in Table 4.3. The training dataset will be used to train the machine learning models and evaluate their performance, while the testing dataset will be used to validate their performance on unseen data.

4.4 Training

The purpose of the training stage is to develop and compare the performance of five machine learning models that can be used to predict and quantify the impact of various airport area closures on flights ground movement time. These five prediction models were developed using five machine learning algorithms that are widely used for similar domain problems such as predicting travel time for both cars and aircrafts on the ground (Lee et al., 2016) (1) Multilayer Perceptron Neural Networks (MLP), (2) Ridge Regression (RR), (3) k-Nearest Neighbors (kNN), (4) Random Forest Regressor (RFR), and (5) Support Vector Machines (SVM). Each of these models was developed using the aforementioned training dataset.

The first model was developed using Multilayer Perceptron Neural Networks (MLP) algorithm which is inspired by biological neural networks and suitable for civil engineering problems (Attalla and Hegazy, 2003; Chakraborty and Elzarka, 2019). This model comprised of an input layer, hidden layers, and an output layer, with the numeric weights for training in the connections (Rosenblatt, 1961). The developed MLP model consists of 1024 nodes in the input layer where their input and output mapped by a rectified linear unit ($ReLU$) activation function, two hidden layers with 128 and 4 nodes with a $ReLU$ activation function, and one node in the output layer with a linear function, as shown in Fig. 4.3 and Fig. 4.4. The model is built and trained with 200 epochs and batch size of 8. The second model was developed using Ridge Regression (RR) which is a simple statistical prediction method that performs regression on past observations with regulated linear coefficients (Hilt and Seegrist, 1977). The third model was developed using k-Nearest Neighbors (kNN) algorithm which is a non-parametric method used for classification and regression that uses the k^{th} closest training examples in the feature space to predict the property values of the output (Cover and Hart, 1967). The number of nearest neighbors in the developed model was specified to be 3 (k value = 3), as shown in Fig. 4.3.

The fourth model was developed using Random Forest Regressor (RFR) which is a learning method for regression that constructs a multitude of decision trees at training time and returns the mean or average prediction of the individual trees (Ho, 1998). This model was made up of 50 individual small trees (estimators), as shown in Fig. 4.3. The

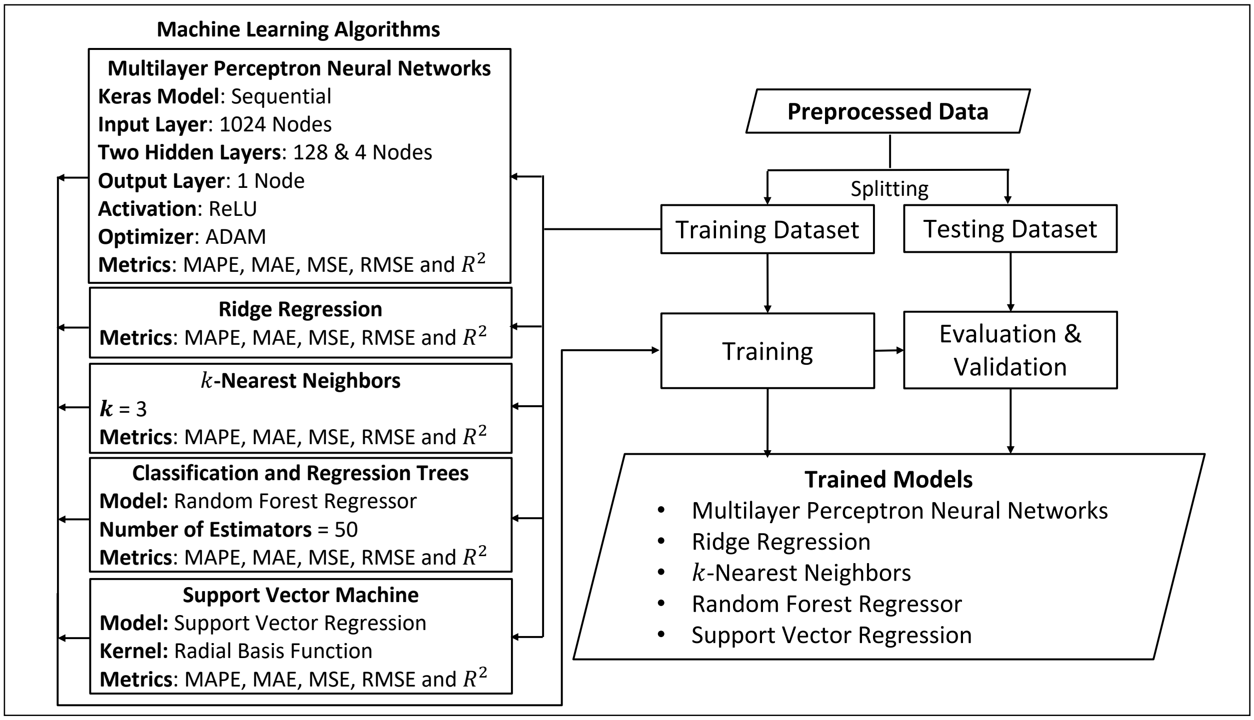

Fig. 4.3. Model training framework

fifth model was developed using Support Vector Machines (SVM) that solves classification problems by mapping the training data from the input space into a higher dimensional feature space via a kernel function (Cortes and Vapnik, 1995). The SVM method can be applied to ground movement time prediction problems using an algorithm called Support Vector Regression (SVR). For this SVR model, the Radial Basis Function (RBF) was used as the kernel function for regression, as shown in Fig. 4.3. The five aforementioned machine learning algorithms were implemented in Python (vanRossum, 2017) using Keras library (Chollet et al., 2015) for the first neural networks model, and scikit-learn library (Pedregosa et al., 2011) for the remaining four models

The selected hyperparameters for each of the five developed models were tuned using the randomized search method from scikit-learn library (Pedregosa et al., 2011). This commonly used method involves specifying a range or a set of values for each hyperparameter and then trying randomly selected sets of combinations to search for and identify an optimal set of hyperparameters for each developed model.

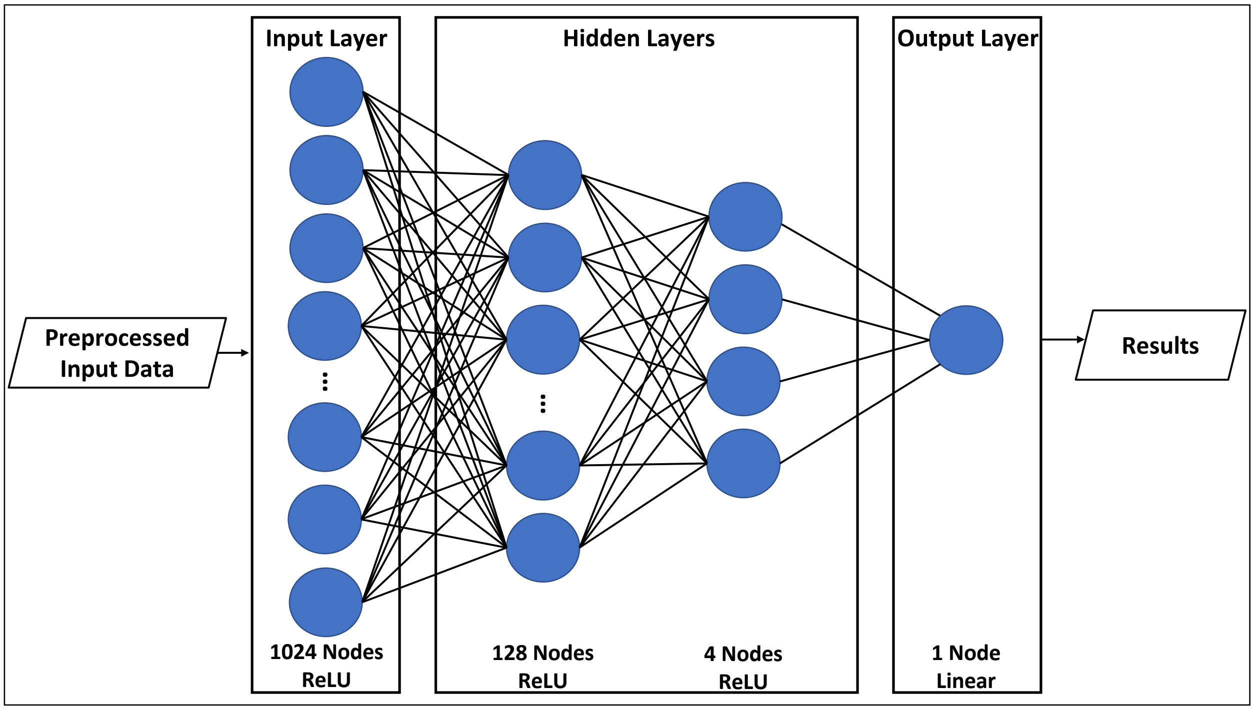

Fig. 4.4. Graphical representation of developed multilayer perceptron neural networks model

The performance of the aforementioned five machine learning models was measured using five different metrics: (1) mean absolute percentage error ($MAPE$) which is the average of the absolute difference between the predicted and true values divided by the true value, as shown in Eq. (4.1); (2) mean absolute error (MAE) which is calculated by summing up the absolute differences between the predicted and true values and divided by the number of predictions, as shown in Eq. (4.2); (3) mean squared error (MSE) which is the average squared difference between the predicted and true values, as shown in Eq. (4.3); (4) root mean squared error ($RMSE$) which is the square root of MSE, as shown in Eq. (4.4); and (5) coefficient of determination (R^2) which is a measure of how well a statistical model fits the data, and is calculated as the square of the correlation between the predicted and true values, as shown in Eq. (4.5).

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|P_i - A_i|}{A_i} \times 100\%}{n} \tag{4.1}$$

$$MAE = \frac{\sum_{i=1}^{n} |P_i - A_i|}{n} \tag{4.2}$$

$$MSE = \frac{\sum_{i=1}^{n} (P_i - A_i)^2}{n} \tag{4.3}$$

$$RMSE = \sqrt{MSE} \tag{4.4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (A_i - P_i)^2}{\sum_{i=1}^{n} (A_i - \bar{A})^2} \tag{4.5}$$

where P_i = predicted value of the i^{th} observation; A_i = true value of the i^{th} observation; n = number of observations in the dataset; and $\bar{A}$ = the mean of true values.

4.5 Evaluation and Validation

The main objective of this stage is to (1) evaluate the performance of each developed model using the training dataset, (2) validate its results using the testing dataset by comparing its predicted values to the true values in the testing dataset that was never seen before by the model, (3) analyze the distribution of prediction errors over multiple windows to provide additional insight into the performance of the developed models, and (4) conduct cross-validation analysis to evaluate the generalizability of the aforementioned models.

First, the performance of each of the developed models was evaluated using the training dataset and the aforementioned metrics. The outcome of this evaluation shows that the MLP and RFR models provided the highest performance while the kNN and RR models provided the lowest performance among the developed models. The MLP and RFR models provided the lowest (a) mean absolute percentage error ($MAPE$) of 0.57% and 1.29%, and (b) mean absolute error (MAE) of 0.039 and 0.076 minutes of flights ground movement time, respectively, as shown in Table 4.4. On the other hand, the kNN and RR

Table 4.4. Performance of developed models

Model	Dataset	Performance Metrics: Mean Absolute Percentage Error	Mean Absolute Error	Mean Squared Error	Root Mean Squared Error	Coefficient of Determination (R^2)	Training Time (Seconds)
Multilayer Perceptron Neural Network (MLP)	Training	0.5739%	0.0393	0.0134	0.1156	99.9382%	3321.18
	Test	2.2268%	0.1275	0.1681	0.4100	99.2104%	
Ridge Regression	Training	8.9014%	0.4377	0.7038	0.8389	96.7476%	0.81
	Test	9.3342%	0.4503	0.7374	0.8587	96.5359%	
k-Nearest Neighbors (kNN)	Training	5.7540%	0.3822	1.0591	1.0291	95.1060%	4.03
	Test	9.5441%	0.6255	2.2771	1.5090	89.3032%	
Random Forest Regressor (CART)	Training	1.2849%	0.0764	0.0476	0.2182	99.7799%	263.59
	Test	3.6125%	0.2063	0.3343	0.5782	98.4294%	
Support Vector Regression (SVM)	Training	4.7800%	0.2718	0.6899	0.8306	96.8117%	3630.86
	Test	5.8454%	0.3224	0.7874	0.8873	96.3014%	

models provided the highest (a) $MAPE$ of 5.75% and 8.90%, and (b) MAE of 0.382 and 0.438 minutes of flights ground movement time, respectively, as shown in Table 4.4.

Second, the results of the developed models were validated using the testing dataset by comparing their predicted values to the true values. The results of this validation analysis show that the MLP and RFR models provided the highest performance while the kNN and RR models provided the lowest performance among the developed models. The MLP and RFR models provided the lowest (a) mean absolute percentage error ($MAPE$) of 2.23% and 3.61%, and (b) mean absolute error (MAE) of 0.128 and 0.206 minutes of flights ground movement time, respectively, as shown in Table 4.4 and Fig. 4.5. On the other hand, the kNN and RR models provided the highest (a) $MAPE$ of 9.54% and 9.33%, and (b) MAE of 0.626 and 0.45 minutes of flights ground movement time, respectively, as shown in Table 4.4 and Fig. 4.5.

The outperformance of the MLP model compared to the other four developed models can be attributed to its reported capability of handling complex relationships in datasets and ability to abstract and capture non-linear relationships through a combination of linear transformations and non-linear activation functions (Sarker, 2021). Similarly, the RFR model is a tree-based ensemble method that can capture non-linear relationships in

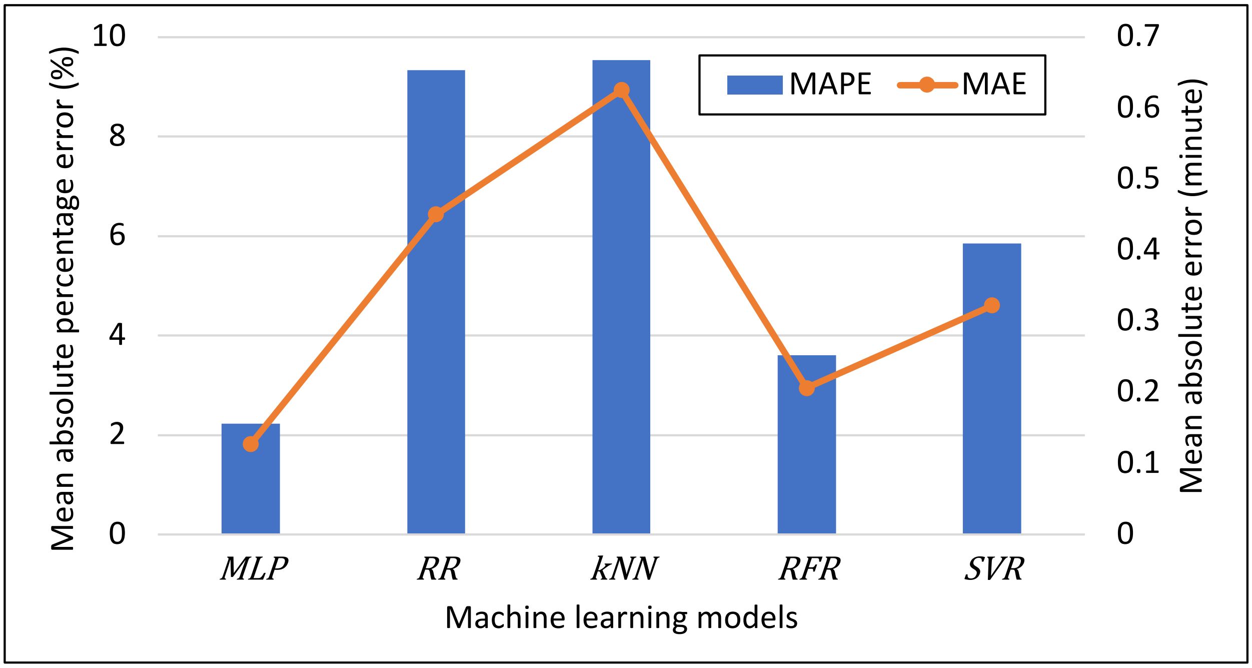

Fig. 4.5. Performance of developed models using testing dataset

the data and handle interactions between variables (Breiman, 2001). Additionally, the SVR model with RBF kernel can capture non-linear relationships between the input and output variables, but it may have not performed better than the MLP and RFR models in this study due to the high dimensionality and complexity of the non-linear relationship in data (Cai et al., 2016). However, the SVR model can perform better if more advanced optimization techniques were used for hyperparameters tuning or if low-dimensional and small dataset were available (Cai et al., 2016). On the other hand, the kNN and Ridge Regression Models are linear models and are limited in their ability to effectively capture complex non-linear relationships as the other three developed models (Pedregosa et al., 2011; Shi and Liu, 2018).

Third, the distribution of prediction errors was analyzed over multiple windows to provide additional insight into the performance of the machine learning models beyond what can be gleaned from the performance metrics. For example, a performance metric, such as MSE, can provide an overall measure of error but may not reveal more subtle patterns in the data such as heteroscedasticity (i.e., non-constant variance of errors) or autocorrelation in

Table 4.5. Percentage of predicted flights ground movement time over multiple error windows

Model	Error windows				
	+/- 1-second	+/- 5-second	+/- 30-second	+/- 1-minute	+/- 5-minute
Multilayer Perceptron Neural Network (MLP)	44.96%	73.51%	94.52%	97.38%	99.92%
Ridge Regression (RR)	3.25%	16.42%	79.71%	89.55%	99.58%
k-Nearest Neighbors (kNN)	43.66%	55.62%	74.75%	81.87%	97.74%
Random Forest Regressor (RFR)	51.03%	67.98%	88.73%	94.15%	99.84%
Support Vector Regression (SVR)	8.95%	44.43%	87.62%	92.31%	99.26%

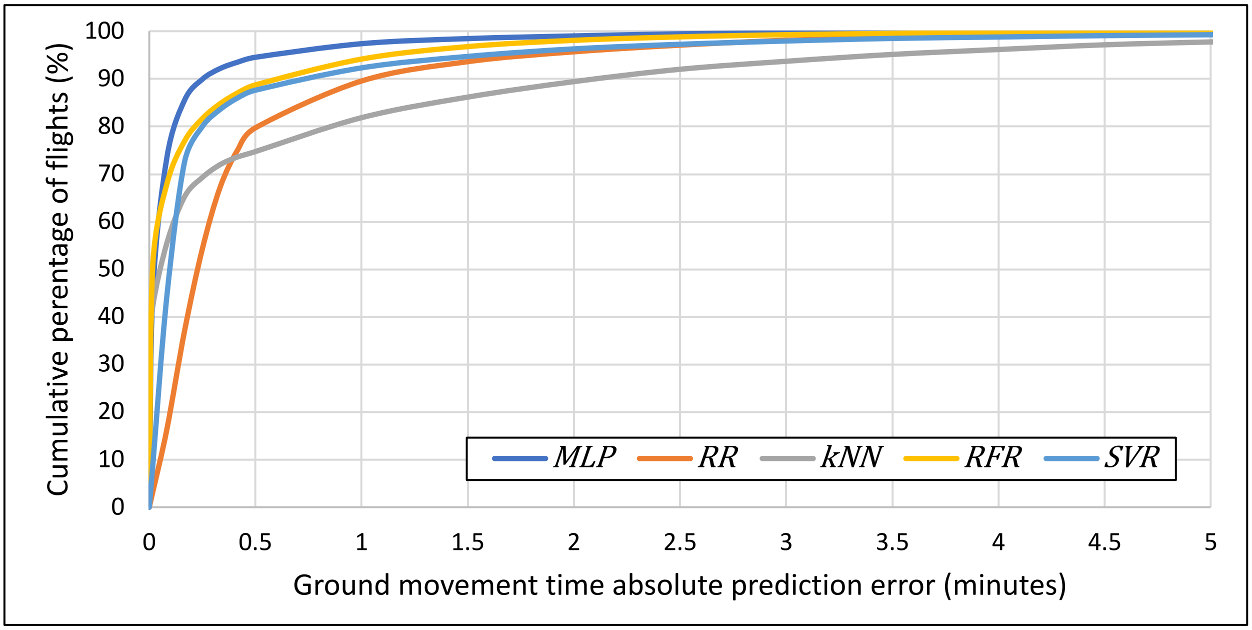

Fig. 4.6. Prediction error distribution for developed machine learning models

the errors. By analyzing the distribution of errors over multiple windows, it is possible to detect these patterns and gain a deeper understanding of how the model is performing. Accordingly, the percentage of predicted flight ground movement times that fell within each error window for the testing dataset was calculated and analyzed, as shown in Table 4.5 and Fig. 4.6. The error windows were defined as ranges of deviation from the true ground movement time. For example, the first error window of -1 to +1 second includes all predictions that were within 1 second of the true flight ground movement time. The results of this analysis indicate that the MLP and RFR models provided the best performance as 94.52% and 88.73% of their predictions were within +/- 30 seconds of the true flights ground movement time, respectively (see Table 4.5 and Fig. 4.6).

Table 4.6. Percentage of flights within multiple absolute percentage error windows

Model	Absolute percentage error windows				
	1%	5%	10%	50%	100%
Multilayer Perceptron Neural Network (MLP)	69.45%	92.63%	96.30%	99.52%	99.89%
Ridge Regression (RR)	10.01%	45.99%	72.65%	98.56%	99.61%
k-Nearest Neighbors (kNN)	48.28%	67.65%	77.54%	95.71%	98.97%
Random Forest Regressor (RFR)	61.30%	84.35%	91.72%	99.18%	99.70%
Support Vector Regression (SVR)	24.57%	76.54%	89.77%	98.66%	99.56%

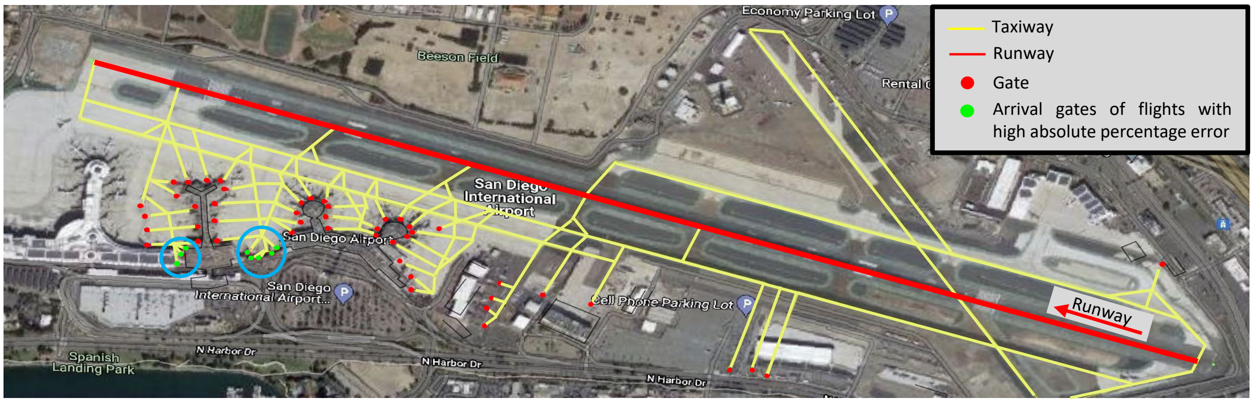

Fig. 4.7. Arrival gates of flights with high absolute percentage error

Furthermore, the distribution of prediction errors was analyzed over multiple absolute percentage error windows (see Table 4.6) to investigate predicted flights ground movement time with an absolute percentage error of more than 100%. The MLP model was able to predict the ground movement times of 99.89% of the flights in the testing dataset with an absolute percentage error less than 100%, as shown in Table 4.6. The remaining 0.11% of the flights (15 flights) with an absolute percentage error of more than 100% were found to be arrival flights using small aircrafts with short ground movement times of approximately one minute and their assigned arrival gates were in a specific location of the airport, as highlighted in Fig. 4.7. Additionally, these flights were found to account for 85% to 100% of the flights with the highest absolute percentage error when predicted by the other four developed models. This analysis shows that the developed prediction models may not be able to capture the unique characteristics of arrival flights that use small aircrafts and assigned to the highlighted gates in Fig. 4.7 when their ground movement times are short.

Fourth, a cross-validation was conducted to evaluate the generalizability of the five developed machine learning models. Cross-validation is a resampling procedure used to evaluate the model's ability to generalize to unseen data (Pedregosa et al., 2011). The cross-validation analysis in this stage was conducted using the widely used k-fold procedure (Pedregosa et al., 2011). This was achieved by dividing the training dataset into k folds that are used to train and test the model in k iterations, as shown in Fig. 4.8. In each of these iterations, a machine learning model was developed and tested in three steps that were designed to (1) train the model using $k-1$ subsets of the training dataset that are represented by blue boxes in Fig. 4.8, (2) test the developed model using the remaining subset of the training dataset that is represented by the yellow box in Fig. 4.8, and (3) calculate the model prediction error. These three steps were repeated for each iteration k, as shown in Fig. 4.8 and Table 4.7. The results of this cross-validation analysis confirm the generalizability of the five developed machine learning models as they all performed consistently in each iteration, as shown in Table 4.7. For example, the $MAPE$ of the developed MLP model in the five iterations of this cross-validation analysis were all consistent ranging from 2.29% to 2.50% with an average of 2.40%, as shown in Table 4.7. This average $MAPE$ of the cross-validation analysis (2.40%) is also very close to that of the aforementioned validation analysis (2.23%) that was calculated using the testing dataset. The remaining four machine learning models had similar consistent performance in the cross-validation analysis, as shown in Table 4.7. This confirms the generalizability of the developed five machine learning models. The results also confirm that MLP model outperformed the remaining four developed machine learning models in all five performance evaluation metrics, as shown in Table 4.7. The overall results of this evaluation and validation stage clearly illustrate the high accuracy that can be achieved by the five developed models, especially the MLP and RFR models that had an accuracy of 97.77% and 96.39% in predicting the impact of airport area closures on flights ground movement time.

Table 4.7. Cross-validation results

Model	Performance Metric	Cross Validation Score					Mean	Standard Deviation
		Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5		
Multilayer Perceptron Neural Networks (MLP)	Mean Absolute Percentage Error ($MAPE$)	2.45%	2.29%	2.35%	2.50%	2.42%	2.40%	0.07%
	Mean Absolute Error (MAE)	0.1434	0.1346	0.1401	0.1358	0.1423	0.1392	0.0035
	Mean Squared Error (MSE)	0.1924	0.1604	0.1797	0.1778	0.1815	0.1784	0.0103
	Coefficient of Determination (R^2)	99.09%	99.22%	99.15%	99.20%	99.15%	99.16%	0.04%
Ridge Regression (RR)	Mean Absolute Percentage Error ($MAPE$)	9.32%	9.15%	9.20%	9.04%	9.18%	9.18%	0.09%
	Mean Absolute Error (MAE)	0.4583	0.4359	0.4479	0.4454	0.4543	0.4483	0.0077
	Mean Squared Error (MSE)	0.7636	0.6917	0.7027	0.7432	0.7838	0.7370	0.0351
	Coefficient of Determination (R^2)	96.53%	96.68%	96.72%	96.58%	96.44%	96.59%	0.10%
k-Nearest Neighbors (kNN)	Mean Absolute Percentage Error ($MAPE$)	9.69%	9.79%	9.52%	9.84%	9.77%	9.72%	0.11%
	Mean Absolute Error (MAE)	0.6755	0.6524	0.6633	0.6630	0.6882	0.6685	0.0123
	Mean Squared Error (MSE)	2.6038	2.3905	2.5491	2.5335	2.7361	2.5626	0.1118
	Coefficient of Determination (R^2)	88.18%	88.52%	88.12%	88.35%	87.60%	88.16%	0.31%
Random Forest Regressor (RFR)	Mean Absolute Percentage Error ($MAPE$)	3.89%	3.73%	3.75%	3.87%	3.77%	3.80%	0.06%
	Mean Absolute Error (MAE)	0.2355	0.2214	0.2300	0.2276	0.2295	0.2288	0.0046
	Mean Squared Error (MSE)	0.4310	0.3588	0.4146	0.3639	0.3999	0.3936	0.0282
	Coefficient of Determination (R^2)	98.09%	98.33%	98.06%	98.39%	98.20%	98.21%	0.12%
Support Vector Regression (SVR)	Mean Absolute Percentage Error ($MAPE$)	6.23%	5.61%	5.73%	5.99%	6.17%	5.94%	0.24%
	Mean Absolute Error (MAE)	0.3575	0.3220	0.3379	0.3435	0.3616	0.3445	0.0142
	Mean Squared Error (MSE)	0.9465	0.7426	0.8027	0.8857	0.9949	0.8745	0.0920
	Coefficient of Determination (R^2)	95.70%	96.43%	96.26%	95.92%	95.49%	95.96%	0.34%

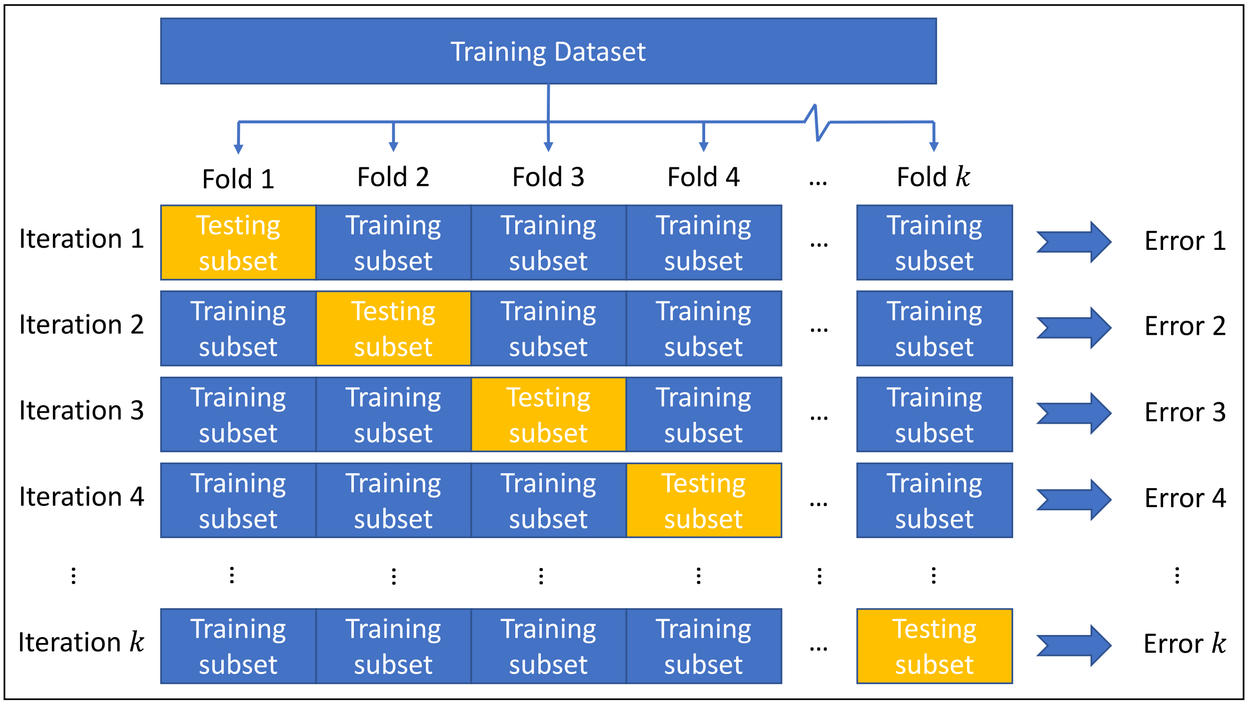

Fig. 4.8. Cross-validation framework

4.6 Case Study

The performance of the developed machine learning models was evaluated by analyzing a real-life case study. This analysis highlights the capabilities of the developed models in quantifying the impact of alternative construction phasing plans on flights ground movement time during airport expansion projects without the need for repetitive and time-consuming simulations. The case study focuses on an airport expansion project that requires the relocation and reconstruction of 14 segments of a 5000 ft-long Taxiway B at San Diego International Airport (San Diego county regional airport authority, 2021), as shown in Fig. 1.4. For this case study, airport and construction planners need to consider the impact of three alternative construction phasing plans on flights ground movement time during the reconstruction of the 5000 ft-long taxiways. These three alternative construction phasing plans include concurrent, sequential, and overlapping closures of all 14 areas, as shown in option I, II, and III in Fig. 4.9. All work for all phases in these three construction phasing plans were scheduled to take place 5 days per week from Monday to Friday working 8

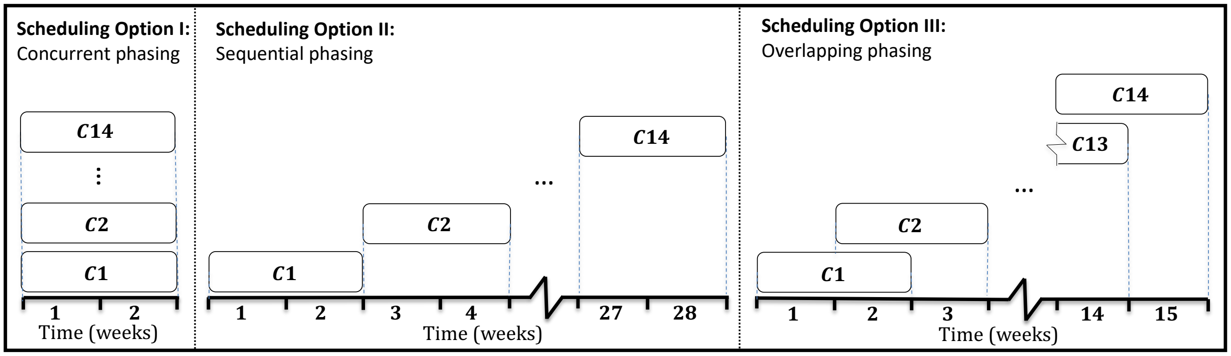

Fig. 4.9. Construction phasing plans

hours per day from 9:00 to 17:00.

The developed multilayer perceptron neural networks model (MLP) was used to support airport planners in assessing and predicting the impact of the aforementioned three alternative construction phasing plans on flights ground movement time without the need for time-consuming simulations. For each alternative phasing plan, the MLP model was used to predict ground movement time of all flights that are scheduled during the airport expansion project. For each flight, the difference between its predicted ground movement time during construction and normal conditions was then used to calculate its construction-related delay. This delay accounts for all construction-related disruption such as additional flights taxi time due to longer taxi path and queues caused by the closure of taxiway segments during construction. For each of the three alternative construction phasing plans, these calculated delays for all affected flights were then analyzed to calculate (1) the total number of delayed flights; (2) the total delays of all affected flights in minutes and hours; and (3) the number of flights with construction-related delays that are greater than 10%, 30%, . . . , 500% of regular flight ground movement time during normal conditions with no construction; and, as shown in Table 4.8. This analysis illustrates that option I that schedules all construction phases concurrently was the least disruptive construction phasing plan among the three considered alternatives in this case study. Option I resulted in (1) the least total number of delayed flights of 1,878; (2) the least total delays in ground movement time of 47.9 hours for all of the 1,878 flights that were delayed during

Table 4.8. Impact of construction phasing plans on flights ground movement time

Construction phasing plan	Total delayed flights	Total delay	Number of flights with delays more than X% of normal ground movement time								
			10%	30%	50%	70%	100%	150%	200%	300%	500%
Option I concurrent	1,878	2,879 mins (47.9 hours)	1,429	1,193	986	815	648	436	306	137	21
Option II sequential	12,580	4,319 mins (71.9 hours)	6,441	4,202	2,730	1,824	1,208	579	226	101	50
Option III overlapping	7,391	3,488 mins (58.1 hours)	4,945	3,356	2,409	1,648	1,160	599	362	214	37

construction; and (3) the least number of flights that suffer varying levels of delays, as shown in Table 4.8.

The results of the case study clearly illustrate the capability of the model to efficiently and accurately predict the impact of alternative construction phasing plans on the total number of delayed flights and their total delays in minutes and hours without the need for performing repetitive and time-consuming runs using air traffic simulation tools. This can lead to significant saving in the computational time and effort required to analyze the impact of alternative construction phasing plans on flights ground movement time during airport expansion projects. As stated earlier, there are 16,383 possible combinations of airport area closures for this case study and analyzing even a very small subset of these possible combinations using air traffic simulation tools requires at least 15 minutes per simulation run for each alternative airport area closure. To overcome this limitation, the developed prediction models require less than a second to accurately calculate and predict the impact of any airport area closure alternative on flights ground movement time, as shown in the three analyzed construction phasing plans in this case study.

4.7 Conclusion

A novel machine learning methodology was developed to enable construction planners to accurately analyze the impact of feasible construction phasing plans on flights ground movement time without the need for repetitive and time-consuming simulation computations.

This methodology can be used to develop machine learning models for predicting the impact of airport area closures on air traffic during airport expansion projects. The methodology implementation is organized in four main stages: (1) data collection stage to gather all required airport data for training and testing the prediction models; (2) data preprocessing stage to identify, classify, transform, and split all predicted and predictor variables data into training and testing datasets; (3) model training stage to select the machine learning methods and fit each of them to the training dataset; and (4) evaluation and validation stage to evaluate the performance of each selected method and validate its results. The methodology was used to develop and compare the performance of five machine learning models using multilayer perceptron neural networks (MLP), ridge regression (RR), k-nearest neighbors (kNN), random forest regressor (RFR), and support vector regression (SVR). The performance of each of these developed models was evaluated using five evaluation metrics: mean absolute percentage error ($MAPE$), mean absolute error (MAE), mean squared error (MSE), root mean squared error ($RMSE$), and coefficient of determination (R^2). This performance evaluation showed that the developed multilayer perceptron neural networks model outperformed the other models in all performance metrics as it provided the lowest $MAPE$ of 2.23% and MAE of 0.128 minutes.

A real-life case study of an airport expansion project was analyzed to illustrate the use of the developed methodology. This case study required the relocation and reconstruction of a 5000 ft-long Taxiway B of San Diego International Airport. Three alternative construction phasing plans were analyzed and their impact on flights ground movement time was predicted using the developed multilayer perceptron neural networks model. The case study results illustrate the capability of the model in predicting the impact of alternative construction phasing plans on flights ground movement time during airport expansion projects efficiently and accurately without the need for repetitive and time-consuming simulation computations.

The original contributions of the developed novel machine learning methodology include (1) development of five machine learning models for accurately and efficiently quantifying the impact of construction-related airport area closures and flights ground movement operations on flights ground movement time; (2) comparison of the performance and accuracy of multilayer perceptron neural networks model, ridge regression, k-nearest neighbors, random forest regressor, and support vector regression in predicting flights ground movement time during airport expansion projects; and (3) efficient and reliable assessment of the impact of alternative construction phasing plans on airport operations without the need for repetitive and time-consuming simulation computations. These original contributions and novel capabilities are expected to support airport and construction planners in their efforts to efficiently and accurately analyze and compare the impact of feasible construction phasing plans on airport operations in order to identify the least disruptive phasing plan that minimizes total number of delayed flights and total delays of all affected flights.

Chapter 5

Optimizing the Phasing Plans of Airport Expansion Projects

5.1 Introduction

The objective of this chapter is to develop a novel methodology for optimizing the phasing plans of airport expansion project that overcomes the aforementioned limitations of existing research studies and identifies optimal daily and hourly work plans for all construction activities in order to minimize both airport operation disruptions and total construction cost. The methodology is designed to enable airport and construction planners to identify all optimal planning decisions including: optimal start time of each construction phase (PS_p), optimal start time of each activity in each phase ($AS_{p,i}$), optimal working days per week for each phase (WD_p), optimal number of shifts per day for each phase (WS_p), optimal working hours per shift ($WH_{p,ws}$), and optimal lag time between shifts ($lag_{p,ws}$), as shown in Fig. 5.1. The developed methodology integrates (1) the machine learning model that was developed in the previous chapter to predict the impact of construction phasing plans on flights ground movement time during airport expansion projects without the need for repetitive and time-consuming simulations, and (2) a multi-objective optimization model to generate optimal tradeoff between minimizing airport operations disruption cost and total construction cost, as shown Fig. 5.1. The following sections provide a concise description of the development and computations of the optimization model.

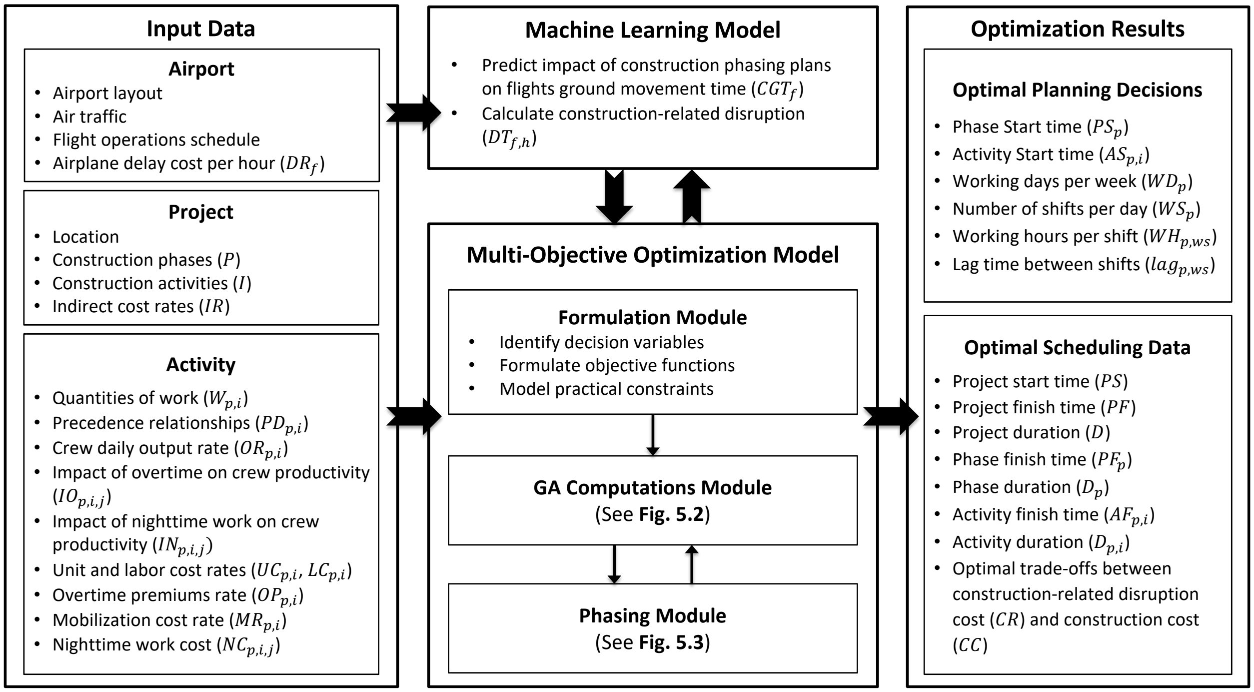

Fig. 5.1. Methodology for optimizing airport construction phasing plans.

5.2 Multi-Objective Optimization Module

The main objective of this model is to generate optimal construction phasing plans that provide optimal trade-offs between minimizing construction-related disruption cost and total construction cost. The development of the multi-objective optimization model is performed in three main modules: formulation, GA computations, and phasing modules that are discussed in the following sections.

5.3 Formulation Module

The formulation module is designed to (1) identify all relevant decision variables that include phases start time (PS_p), start time of each activity in each phase ($AS_{p,i}$), working days per week for each phase (WD_p), number of shifts per day for each phase (WS_p), working hours per shift ($WH_{p,ws}$), and lag times between shifts ($lag_{p,ws}$), as shown in Fig. 1.6; (2) formulate the optimization objective functions for minimizing construction-related disruption cost and minimizing total construction cost, as shown in Eqs. (5.1) and (5.2); and (3) model all related optimization constraints including phases start time, crew working time, and job logic, as shown in the illustrated example of activities A,B, and C in Fig. 5.3.

$$Minimize\ CR = Minimize \sum_{h=PS}^{PF} \sum_{f=1}^{F} CR_{h,f} \tag{5.1}$$

where CR= total construction-related disruption cost in \$, PS = project start time in hours, PF = project finish time in hours, and f = flight ID.

$$Minimize\ CC = Minimize\ (CD + CI + CM + CN) \tag{5.2}$$

where CC= total construction cost; CD= construction direct cost; CI= construction indirect cost; CM= mobilization cost; and CN= nighttime construction cost.

5.4 GA Computations Module

The optimization computations of the formulated multi-objective model are executed using multi-objective genetic algorithms due to their capabilities in (1) dealing with the nonlinear and discontinuous decision variables and constraints of the formulated model including phases and activities start time; and (2) identifying optimal solutions for similar problems with large search space in a reasonable computational time (Abdallah and El-Rayes, 2016; Al-Ghzawi and El-Rayes, 2023; AlOtaibi et al., 2021; Altuwaim and El-Rayes, 2021; Hegazy and Wassef, 2001; Jun and El-Rayes, 2010; Khalafallah and El-Rayes, 2006a, 2006b, 2008; Said and El-Rayes, 2010).

The optimization computations are accomplished in five main steps (see Fig. 5.2) that are designed to (1) generate a new population of randomly selected construction phasing plans $s = 1$ to S for the first generation $g = 1$ using the phasing module, as shown in Fig. 5.2; (2) quantify the impact of each phasing plan on flights ground movement time

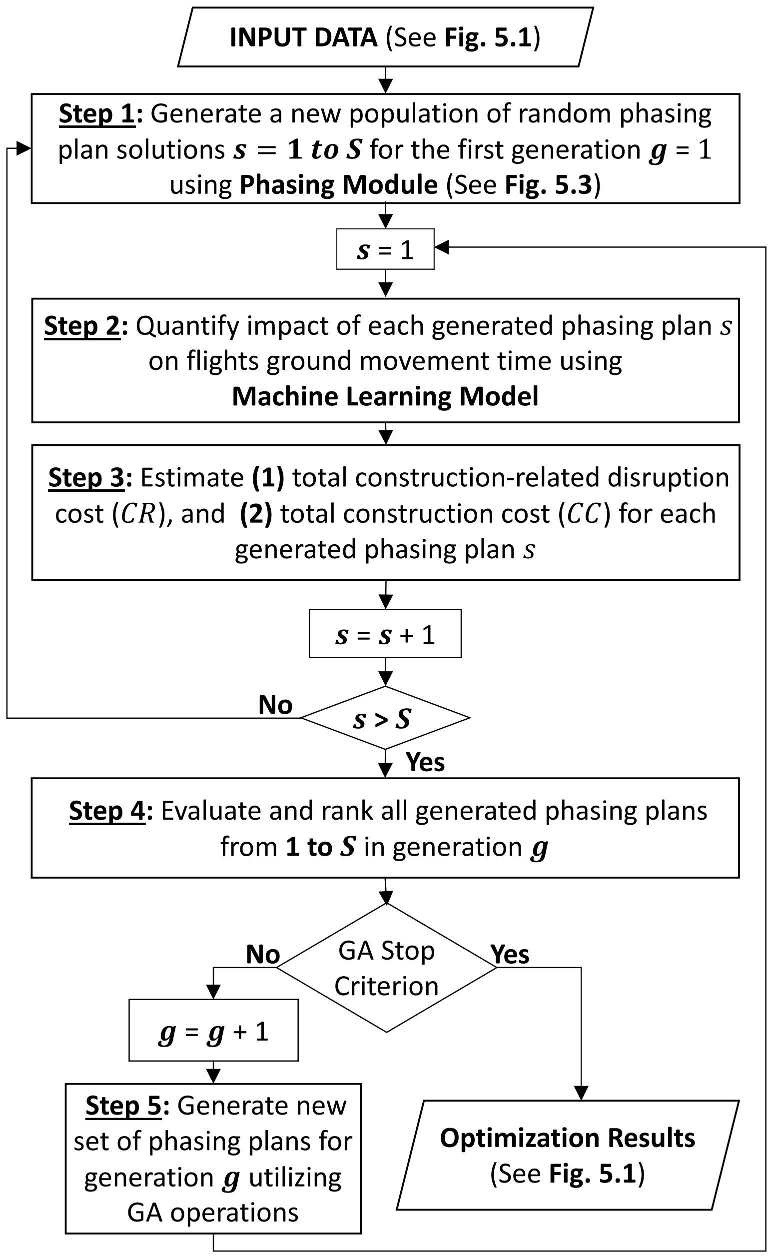

Fig. 5.2. Genetic algorithms computations module

using the developed machine learning model; (3) estimate the total construction-related disruption cost in airport operations (CR), and the total construction cost (CC) for each phasing plan using Eqs. (5.1) and (5.2); (4) evaluate and rank all generated solutions from 1 to S in generation g; and (5) perform GA operations of selection, mutation, and crossover to generate a new set of phasing plans for the new generation $g = g + 1$, as shown in Fig. 5.2. The optimization computations are terminated when the GA stopping criteria are satisfied and then the model generates its optimization results (See Fig. 5.1).

5.5 Phasing Module

The purpose of this module is to generate a practical phasing plan for each solution s generated by the GA optimization module that specifies the start and finish times of each construction phase and its activities, as shown in Fig. 5.3 To ensure practicality, this module is designed to ensure that generated phasing plans comply with all relevant constraints including phases start time, crew working time, and job logic. To accomplish this, the computations in this module are performed in six steps (see Fig. 5.3) that are designed to:

1. Calculate early start time ($AES_{p,i}$) of all activities that have no predecessor ($PD_{p,i} = 0$) based on GA selected phase start time (PS_p).

2. Calculate the required duration in working hours of all activities i in each phase p ($D_{p,i}$) based on activity quantity of work ($W_{p,i}$), crew output rate ($OR_{p,i}$), impact of scheduled overtime ($IO_{p,i,j}$) and nighttime work ($IN_{p,i,j}$) on the productivity of construction crews, as shown in step 2 in Fig. 5.3. $IO_{p,i,j}$ represents the impact of overtime use on the productivity of construction crews. For example, the production efficiency of a crew working 10 hours per day and 6 days per week was reported to be 85% based on an analysis of historical crew productivity data (RSMeans data, 2020). Similarly, $IN_{p,i,j}$ represents the impact of working during nighttime hours on the productivity of construction crews. For example, the Mechanical Contractors Association of America

Table 5.1. San Diego International Airport taxiway segments length

Phase	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Length (ft)	500	300	200	550	350	225	425	275	200	200	350	500	225	700

(MCAA) reported that the productivity of crews working during nighttime hours is approximately 70% of those achieved during regular working hours (Kitchens, 1996).

3. Schedule the early start ($AES_{p,i}$) and early finish ($AEF_{p,i}$) times of all activities in each phase based on the outcomes the previous two steps.

4. Calculate the early start time ($AES_{p,i}$) of all remaining activities that have predecessors ($PD_{p,i} > 0$) in each phase and repeat steps 2 and 3.

5. Calculate the free float of all activities in each phase ($FR_{p,i}$), as shown in Fig. 5.3.

6. Identify scheduled start time of all activities in each phase ($AS_{p,i}$) based on GA selections for this decision variable that are constrained by the activity free float (see Fig. 5.3) to prevent extending the project duration beyond its early completion time. This enables the model to consider and optimize the impact of alternative activity start times on minimizing construction-related disruption cost and total construction cost.

5.6 Case Study

The performance of the formulated multi-objective optimization model is evaluated by analyzing a real-life case study to demonstrate the use of the model and highlight its capabilities in generating construction phasing plans that provide optimal tradeoffs between minimizing the cost of construction-related disruption in airport operations and total construction cost of airport expansion projects. The case study focuses on optimizing the construction phasing plan for an airport expansion project that requires the relocation and reconstruction of 14 segments of a 5000 ft-long Taxiway B at San Diego International Airport, as shown in Fig. 5.4 and Table 5.1.

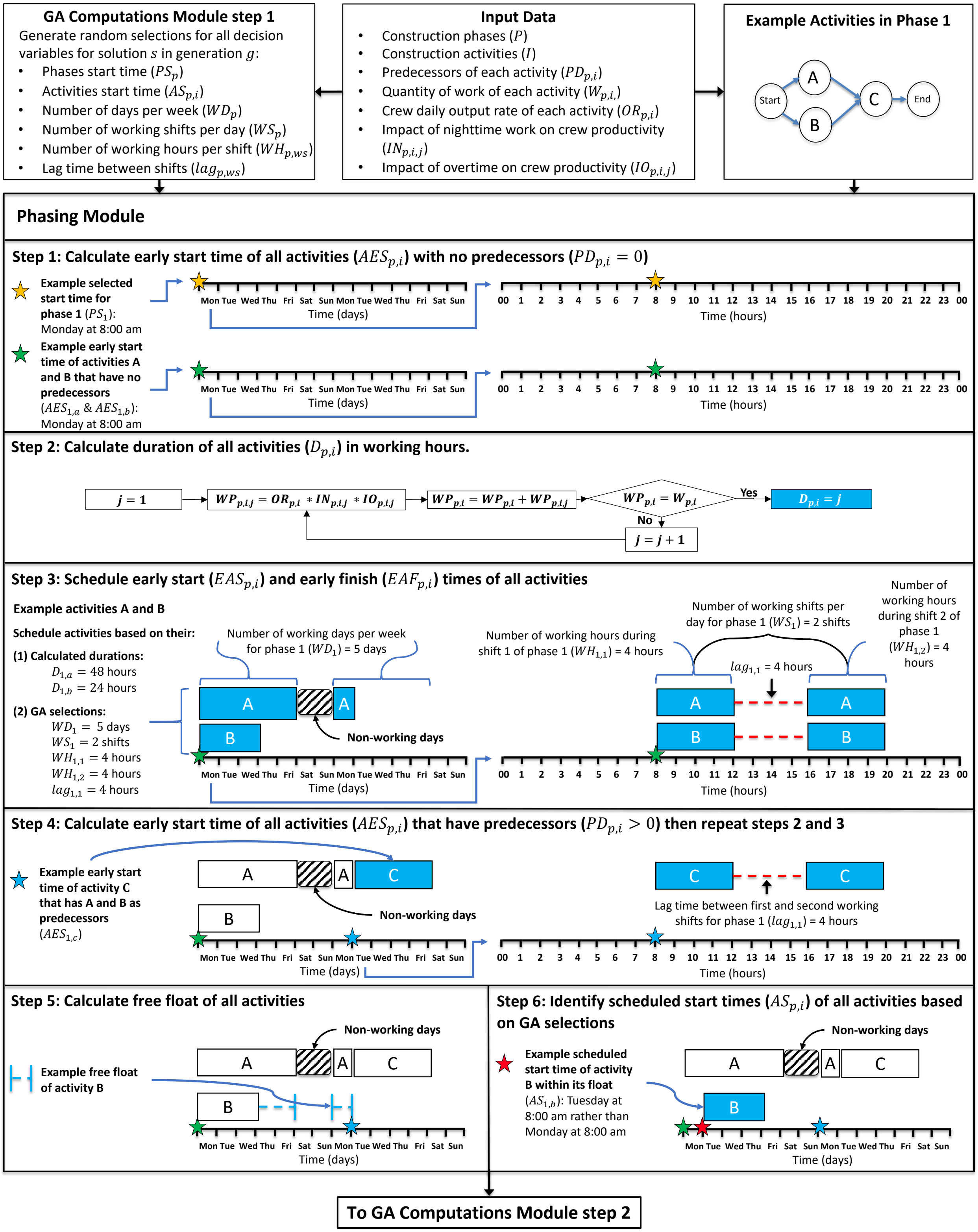

Fig. 5.3. Phasing module computations.

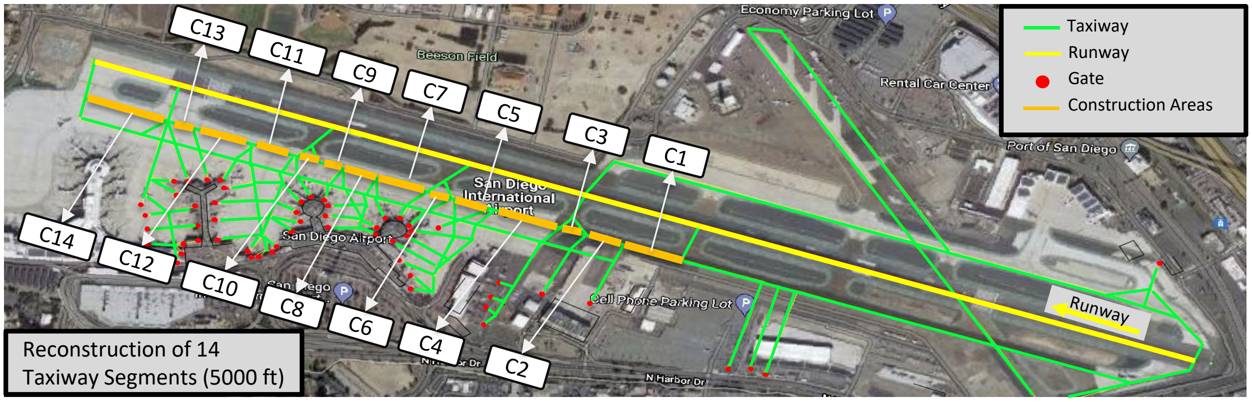

Fig. 5.4. Layout of San Diego International Airport (SAN) in Simmod Pro!

The input data for this case study (see Fig. 5.1) includes (1) airport layout as shown in Fig. 5.4; (2) air traffic data such as flight types and their assigned gates and runways; (3) flight operations schedule such as arrival/departure time; (4) aircraft delay cost rate (DR_f) that depends on aircraft weight class and was specified to be \$1,500, \$3,000, and \$4,500 per hour for small, large and heavy aircrafts, respectively (FAA, 2020b); (5) all construction activities for each of the 14 phases, as shown in Table 5.2 (San Diego county regional airport authority, 2021); (6) construction indirect cost rate that was specified to be 25% of the construction direct cost; (7) predecessor activities ($PD_{p,i}$); (8) quantity of work ($W_{p,i}$); (9) crew daily output rates ($OR_{p,i}$); (10) unit cost rates ($UC_{p,i}$), as shown in Table 5.2; (11) impact of overtime on crew productivity ($IO_{p,i,j}$); (12) impact of nighttime work on crew productivity ($IN_{p,i,j}$); (13) labor overtime premiums ($OP_{p,i,j}$) that was specified to be 200% of the regular rate; (14) mobilization cost rate ($MR_{p,i}$) which was specified to be 3% of construction direct cost; and (15) nighttime construction cost ($NC_{p,i,j}$) such as nighttime lighting equipment cost that was specified to be 10% of construction direct cost.

The aforementioned airport layout, air traffic data, and flight operations schedule were utilized to develop a machine learning model that provides the capability of predicting flights ground movement time during construction without the need for repetitive and time-consuming simulations. To develop this model, the layout of San Diego International Airport and all its related input data were specified in Simmod Pro, as shown in Fig. 5.4. Simmod

Table 5.2. Input data of phase $C8$ reconstruction activities and crews

Activity ID (i)	Construction Activities	Predecessors ($PD_{p,i}$)	Quantity of work ($W_{p,i}$)	Unit	Daily Output ($OR_{p,i}$) (unit/day)	Cost rate ($UC_{p,i}$) ($/unit)
1	Close construction site	-	1350	LF	400	3.78
2	Install lighted barricades	-	100	EA	150	145
3	Remove airfield markings	1, 2	1512.5	SF	500	2.81
4	Remove signage	1, 2	2	EA	5	539
5	Install temporary lighting	1, 2	1	EA	8	9,430
6	Mill asphalt pavement	3, 4, 5	12000	SY	9,000	0.87
7	Excavate to subgrade	6	9000	BCY	12,500	0.42
8	Demolish existing utilities	7	275	LF	800	1.27
9	Demolish electrical system	7	275	LF	394	0.79
10	Remove base soil	8, 9	3400	LCY	1,080	2.16
11	Prepare subgrade	10	12000	SY	15,000	0.15
12	Install duct banks	11	275	LF	260	3.46
13	Place base material	12	12000	SY	4,200	8.01
14	Compact base material	13	12000	SY	4,200	7.99
15	Install conduit and base cans	14	275	LF	270	1.91
16	Install in-pavement lighting	15	5	EA	18.64	784
17	Install asphalt pavement	16	12000	SY	4,520	13.68
18	Install in-pavement light fixtures	17	5	EA	4	362
19	Install signage	17	2	EA	5	980
20	Install pavement marking	17	1512.5	SF	4,000	0.68
21	Remove lighted barricades	18, 19, 20	100	EA	250	27
22	Restore construction site	21	1350	LF	432	1

Pro was then utilized to calculate the ground movement times for all flight under normal (GT_f) and construction (CGT_f) conditions. This resulted in creating a training dataset of 40,425 flights and a testing dataset of 13,475 flights that were used in training and testing the machine learning model as described earlier. The machine learning model was developed using Multilayer Perceptron Neural Networks (MLP) in Python (vanRossum, 2017) and executed using Keras library (Chollet et al., 2015), and its performance was validated using mean absolute percentage error ($MAPE$) and mean absolute error (MAE). The results show that the MLP model provided $MAPE$ of 2.23% and MAE of 0.128 minutes which indicate that the average accuracy of the developed MLP model was approximately 97.77%.

The aforementioned MLP model was then combined with the developed multi-objective optimization model to search for and generate an optimal reconstruction phasing plan that minimizes both construction-related disruption cost in airport operations and total construction cost, as shown in Fig. 5.1. The genetic algorithm optimization computations for this case study were performed using the distributed evolutionary algorithm package ($DEAP$) in the Python programming platform (vanRossum, 2017). The GA search parameters utilized in this case study are the $NSGA-II$ selection with a population size of 512, a mutation rate of 0.6, and a cross-over rate of 0.2. The optimization engine was set to terminate the optimization computations after a total of 20,000 generations or when the set of the Pareto optimal solutions do not change for 200 consecutive generations. The computational time for this case study was approximately 32 hours when the engine terminated after 5,270 generations using a personal laptop with 2 GHz Quad-Core Intel Core i5 Processor and 16 GB 3733 MHz LPDDR4X RAM.

Upon completion of the aforementioned computations, the model generated 150 Pareto optimal solutions, where each represents a unique phasing plan that provides an optimal tradeoff between minimizing construction-related disruption cost in airport operations (CR) and minimizing total construction cost (CC), as shown in Fig. 5.5. A sample of these

Table 5.3. Sample of Pareto optimal solutions

Sol. (S)	Project Start Time (PS)	Project Finish Time (PF)	Airport Disruption Cost (CC)	Total Construction Cost (CR)
1	Saturday, January 19th at 00:00	Saturday, January 4th at 02:12	\$1,005	\$13,350,668
26	Thursday, March 7th at 23:00	Sunday, February 16th at 23:15	\$25,369	\$13,121,845
52	Monday, March 25th at 00:00	Saturday, March 4th at 12:42	\$57,409	\$12,493,477
71	Sunday, February 10th at 12:00	Monday, March 2nd at 00:28	\$116,591	\$11,553,746
103	Tuesday, January 29th at 10:00	Wednesday, April 8th at 01:27	\$171,554	\$10,370,702
126	Monday, February 4th at 09:00	Wednesday, March 18th at 23:58	\$351,298	\$8,731,728
150	Monday, January 21st at 08:00	Tuesday, December 24th at 13:48	\$879,791	\$8,233,435

phasing plans along with their project start time (PS), project finish time (PF), airport disruption cost (CR), and total construction cost time (CC) are summarized in Table 5.3.

The generated 150 Pareto optimal solutions for this case study includes (1) a minimum airport operations disruption cost solution of \$1,005 ($S1$) with an associated maximum total construction cost of \$13,350,668; (2) a minimum total construction cost solution of \$8,233,435 ($S150$) with an associated maximum airport operations disruption cost of \$879,791; and (3) 148 additional Pareto optimal solutions that provide a wide range of optimal trade-offs between airport operations disruption cost and total construction cost, as shown in Fig. 5.5.

On one end, optimal solution $S1$ provides minimum airport operations disruption cost (CR) by scheduling the construction activities during nighttime hours that have very limited or no air traffic to avoid disrupting airport operations during high air traffic hours. This is achieved by planning the work of all phases to be 5 days per week (WD = 5) from Saturday to Wednesday by working in 1 shift per day (WS = 1) for 5 hours (WH = 5) from

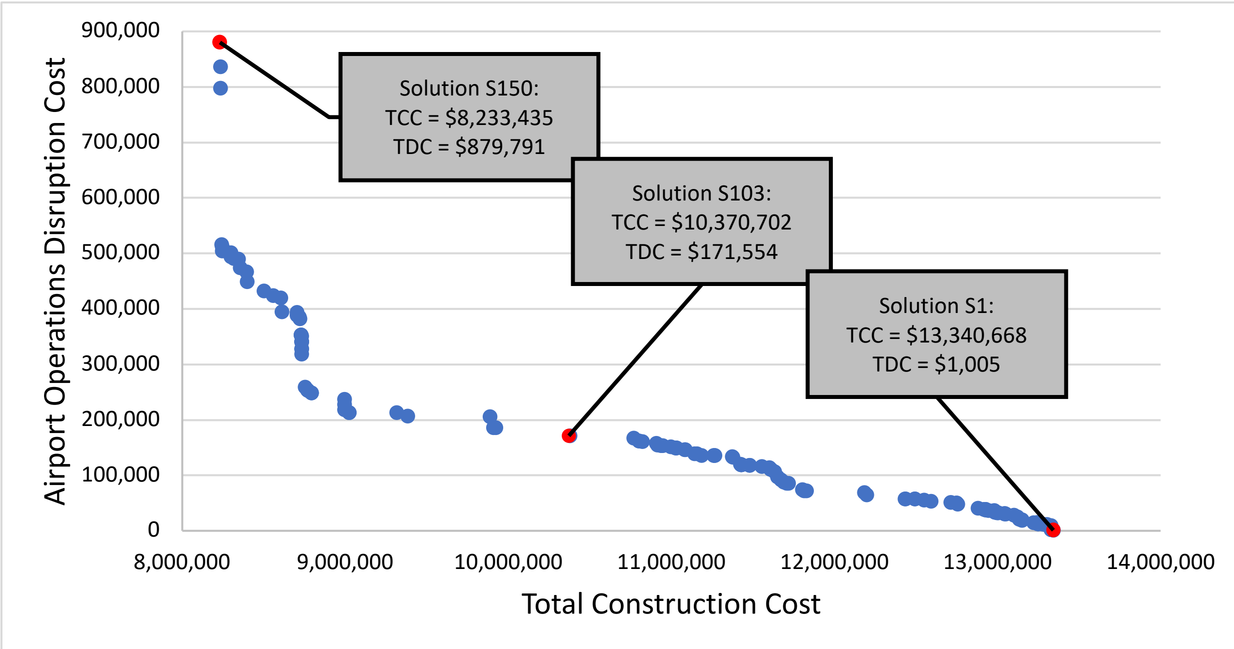

Fig. 5.5. Generated Pareto optimal solutions

midnight to 5:00 am when there is very limited number of flights, as shown in Table 5.4. However, this solution has the highest total construction cost among the generated optimal solutions due to the additional cost of nighttime construction and labor overtime premiums. A detailed phasing plan of this solution including the identified optimal phases start time (PS_p), activities start time ($AS_{p,i}$) number of working days per week for each phase (WD_p), number of working shifts per day for each phase (WS_p), and number of working hours per shift ($WH_{p,ws}$) are summarized in Table 5.4, Table 5.5, and Fig. 5.6. Furthermore, the integrated models generated optimal schedule of each construction phase at different levels of details including daily schedule and hourly work plans, as shown in the example in Fig. 5.7.

On the other end, optimal solution $S150$ provides minimum total construction cost (CC) by scheduling the taxiway relocation activities during weekly working days and regular daytime hours to avoid labor overtime premium costs and related productivity losses. This solution scheduled the work for all phases to be 5 days per week (WD = 5) from Monday to Friday by working in 1 shift per day (WS = 1) for 8 hours (WH = 8) from 8:00 to 16:00 or

Table 5.4. Optimal phasing plan for solution $S1$

Construction (Phase p)	Start Time Order	Number of Days per Week (WD_p)	Number of Shifts per Day (WS_p)	Number of Hours per Shift ($WH_{p,ws}$)	Phase Start Time (PS_p)	Phase Finish Time (PF_p)
C1	4	5	1	5	Saturday, March 16th at 00:00	Sunday, July 28th at 2:45
C2	11	5	1	5	Saturday, August 3rd at 00:00	Sunday, October 27th at 3:18
C3	3	5	1	5	Saturday, February 23rd at 00:00	Tuesday, April 23rd at 00:18
C4	6	5	1	5	Saturday, May 11th at 00:00	Monday, October 7th at 1:15
C5	11	5	1	5	Saturday, August 3rd at 00:00	Saturday, November 9th at 3:58
C6	1	5	1	5	Saturday, January 19th at 00:00	Monday, March 25th at 00:32
C7	9	5	1	5	Saturday, June 15th at 00:00	Wednesday, October 9th at 2:12
C8	14	5	1	5	Saturday, October 19th at 00:00	Saturday, January 4th at 2:11
C9	5	5	1	5	Saturday, April 27th at 00:00	Tuesday, June 25th at 2:12
C10	1	5	1	5	Saturday, January 19th at 00:00	Monday, March 18th at 3:09
C11	6	5	1	5	Saturday, May 11th at 00:00	Sunday, August 18th at 2:15
C12	8	5	1	5	Saturday, June 1st at 00:00	Monday, October 14th at 12:54
C13	13	5	1	5	Saturday, August 24th at 00:00	Tuesday, October 29th at 1:09
C14	10	5	1	5	Saturday, June 22nd at 00:00	Tuesday, December 24th at 3:36

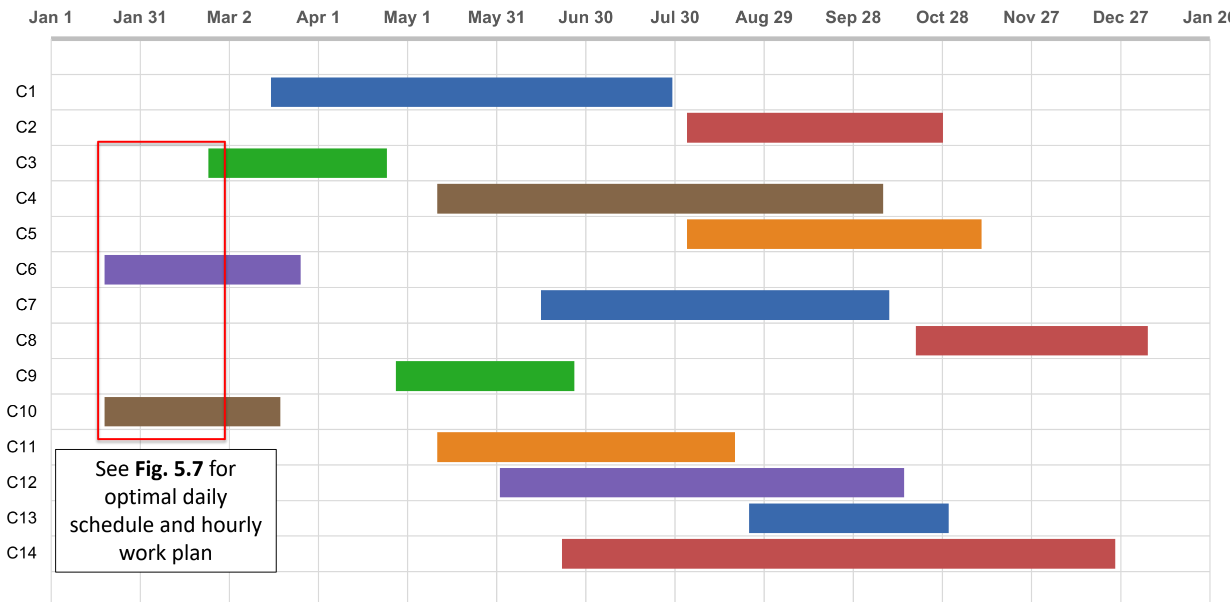

Fig. 5.6. Optimal schedule of all construction phases in solution $S1$

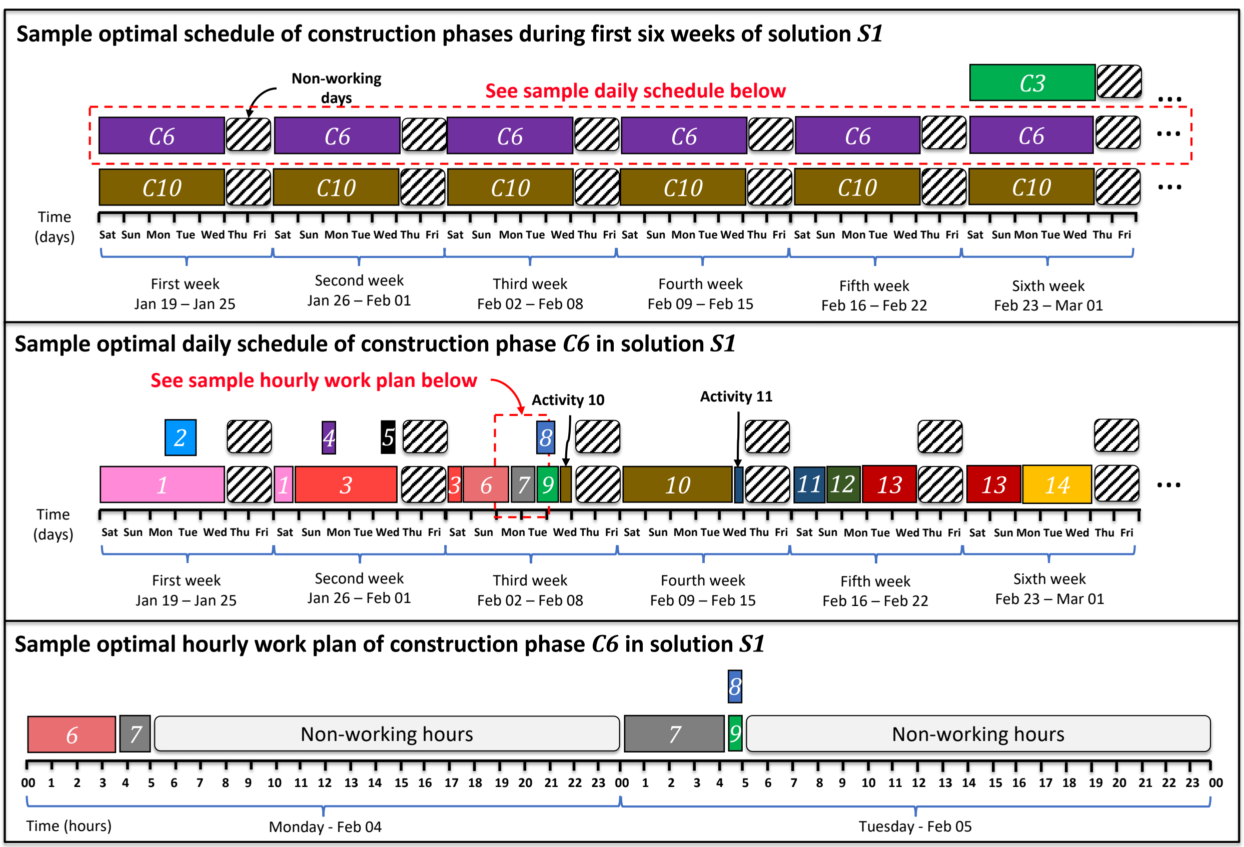

Fig. 5.7. Optimal daily schedule and hourly work plan of phase $C6$ in solution $S1$

Table 5.5. Optimal activity start and finish times of phase $C1$ in solution $S1$

Activity ID (i)	Activity Start Time ($AS_{1,i}$)	Activity Finish Time ($AF_{1,i}$)
1	Saturday, March 16th at 00:00	Tuesday, March 26th at 3:43
2	Sunday, March 17th at 1:00	Tuesday, March 19th at 2:45
3	Tuesday March 26th at 3:43	Wednesday, April 10th at 2:10
4	Saturday, April 6th at 2:00	Sunday, April 7th at 2:40
5	Tuesday, April 9th at 2:00	Tuesday, April 9th at 3:12
6	Wednesday, April 10th at 2:10	Wednesday, April 17th at 00:55
7	Wednesday, April 17th at 00:55	Sunday, April 21st at 3:14
8	Monday, April 22nd at 4:00	Wednesday, April 24th at 00:07
9	Sunday, April 21st at 3:14	Wednesday, April 24th at 00:41
10	Wednesday, April 24th at 00:41	Saturday, May 11th at 1:35
11	Saturday, May 11th at 1:35	Tuesday, May 14th at 00:47
12	Tuesday, May 14th at 00:47	Sunday, May 19th at 4:28
13	Sunday, May 19th at 4:28	Monday, June 3rd at 00:19
14	Monday, June 3rd at 00:19	Monday, June 17th at 2:01
15	Monday, June 17th at 2:01	Sunday, June 23rd at 00:24
16	Sunday, June 23rd at 00:24	Monday, June 24th at 00:45
17	Monday, June 24th at 00:45	Sunday, July 7th at 4:05
18	Sunday, July 7th at 4:05	Sunday, July 14th at 4:02
19	Monday, July 8th at 3:00	Tuesday, July 9th at 4:03
20	Monday, July 8th at 1:00	Tuesday, July 9th at 2:55
21	Sunday, July 14th at 4:02	Tuesday, July 16th at 1:13
22	Tuesday, July 16th at 1:13	Sunday, July 28th at 2:45

Table 5.6. Optimal phasing plan for solution 150

Construction Phase (p)	Start Time Order	Number of Days per Week (WD_p)	Number of Shifts per Day (WS_p)	Number of Hours per Shift ($WH_{p,ws}$)	Phase Start Time (PS_p)	Project Finish Time (PF_p)
C1	5	5	1	8	Monday, April 1st at 8:00	Tuesday, June 18th at 14:24
C2	4	5	1	8	Monday, March 25th at 9:00	Monday, May 13th at 14:51
C3	13	5	1	8	Monday, October 28th at 9:00	Friday, November 29th at 15:41
C4	7	5	1	8	Monday, June 10th at 9:00	Thursday, September 5th at 12:12
C5	6	5	1	8	Monday, May 13th at 9:00	Tuesday, July 9th at 13:43
C6	11	5	1	8	Monday, October 7th at 9:00	Wednesday, November 13th at 15:45
C7	3	5	1	8	Monday, February 18th at 8:00	Thursday, April 25th at 13:27
C8	10	5	1	8	Monday, July 29th at 8:00	Thursday, September 12th at 13:03
C9	1	5	1	8	Monday, January 21st at 8:00	Friday, February 22nd at 14:09
C10	9	5	1	8	Monday, July 22nd at 8:00	Tuesday, August 27th at 10:43
C11	11	5	1	8	Monday, October 7th at 9:00	Monday, December 2nd at 15:26
C12	8	5	1	8	Monday, July 8th at 9:00	Wednesday, September 25th at 11:03
C13	14	5	1	8	Monday, November 18th at 8:00	Tuesday, December 24th at 13:48
C14	2	5	1	8	Monday, January 21st at 9:00	Wednesday, May 8th at 10:41

from 9:00 to 17:00 to minimize the additional costs of overtime and nighttime premiums, as shown in Table 5.6. This plan, however, causes the highest airport operational disruptions among the generated optimal solutions because it schedules the construction activities during high daily and hourly air traffic volumes. A detailed phasing plan of this solution is summarized in Table 5.6 and in Fig. 5.8. In addition to the aforementioned solutions, the developed methodology was capable of generating 148 other Pareto optimal solutions (phasing plans) that enable airport planners and construction managers to analyze and select the plan that best meets their unique project requirements.

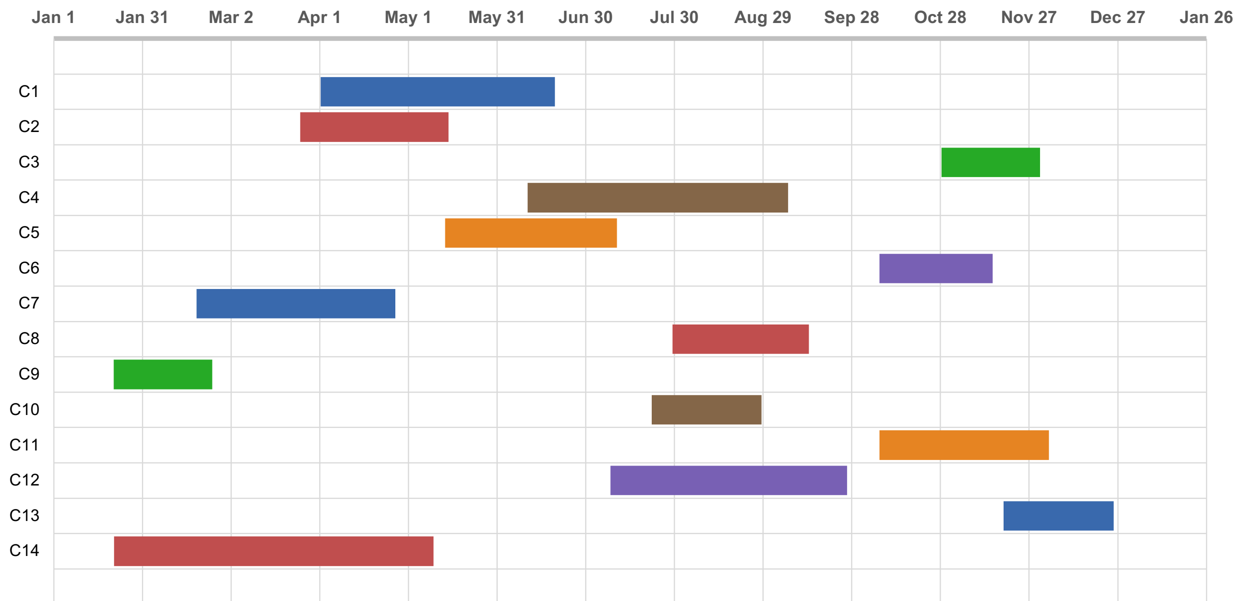

Fig. 5.8. Optimal schedule of all construction phases in solution $S150$

5.7 Discussion

To verify the generated results by the developed methodology and its machine learning model, the construction-related disruption costs of the aforementioned two extreme optimal solutions ($S1$ and $S150$) and a third intermediate solution ($S103$) were compared to those calculated using an FAA verified air traffic simulation tool (Simmod Pro). To enable this comparison, the construction closure scenarios of each of these three optimal solutions ($S1$, $S103$, and $S150$) were modeled in Simmod Pro to calculate their flights ground movement time during normal and construction conditions. The difference between flights ground movement time during normal and construction conditions was then used to calculate the construction-related disruption cost for each of the generated optimal solutions, as shown in Table 5.7. These construction-related disruption costs calculated based on the simulation results provided by Simmod Pro were then compared to those generated by the developed optimization methodology for the three optimal solutions ($S1$,$S103$, and $S150$). This comparison illustrates that the difference between the construction-related disruption cost calculated by the developed methodology and the simulation software was only 1.82%,

Table 5.7. Validation of developed machine learning model

Solution (s)	Calculated construction-related disruption cost (CR) based on Machine Learning Model	Simulation Model (Simmod Pro)	Difference (%)
$S1$	$1,005	$987	1.82%
$S103$	$171,554	$174,313	-1.58%
$S150$	$879,791	$862,214	2.04%

-1.58% and 2.04% for optimal solutions $S1$, $S103$, and $S150$, respectively as shown in Table 5.7. These results confirm the validity of the developed optimization methodology and its machine learning model and their reliability in predicting the impact of alternative construction phasing plans on flights ground movement time without the need for repetitive and time-consuming simulations.

5.8 Conclusion

A novel methodology was developed to optimize the scheduling of construction phasing plans during airport expansion projects. The developed methodology integrates (1) machine learning model to predict the impact of construction phasing plans on flights ground movement time during airport expansion projects without the need for repetitive and time-consuming simulations, and (2) multi-objective optimization model to generate optimal construction phasing plans that provide optimal trade-offs between minimizing airport operations disruption cost and total construction cost. A case study was analyzed to illustrate the use of the methodology in identifying optimal construction phasing plans for the reconstruction of 14 phases for a 5000 ft-long Taxiway B at San Diego International Airport. The integrated models generated a set of 150 optimal tradeoff solutions for this case study, where each represents a unique and optimal tradeoff between minimizing the cost of the construction-related disruption in airport operations and the total construction cost. The results of the case study clearly illustrate the original contributions of the methodology to the body of knowledge in (1) identifying optimal construction phasing plans including the start dates and times of each phase and activity; (2) determining optimal schedule of each construction phase at different levels of details including daily schedule and hourly work plans; (3) quantifying and minimizing the impact of construction phasing plans on flights ground movement time using machine learning; and (4) generating a set of optimal phasing plans that provide optimal trade-offs between minimizing airport operations disruption cost and minimizing total construction cost.

Chapter 6

Conclusion

6.1 Summary

The present research study focused on optimizing the planning of airport expansion projects in order to minimize both airport operations disruption cost and total construction cost. The new research development of this study include: (1) a novel optimization model for the planning of airport expansion projects that is capable of minimizing both airport operations disruptions cost and total construction cost; (2) an innovative machine learning methodology that can be used to create robust machine learning models for predicting the impact of alternative airport area closures on flights ground movement time in any airport without the need for repetitive and time-consuming simulation computations; and (3) a novel methodology for optimizing the phasing plans of airport expansion project that identifies optimal daily and hourly work plans for all construction activities in order to minimize both airport operation disruptions and total construction cost.

First, a novel planning and scheduling model was developed for optimizing the planning of airport expansion projects that provides the capability of minimizing both airport operations disruption cost and total construction cost. The model computations were performed in four main modules: (1) simulation module that calculates and quantifies the impact of airport construction activities on airport operations; (2) multi-objective genetic algorithms optimization module that identifies an optimal schedule for airport expansion projects; (3) scheduling module that calculates the start and finish times of each construction activity; and (4) cost module that computes the total cost of construction-related disruptions in airport operations and the total construction cost. A real-life case study of an airport expansion project is analyzed to illustrate the use of the model and highlight its unique capabilities. The results of the case study clearly illustrate the original contributions of the developed model and its novel capabilities that are expected to support airport and construction planners in their efforts to identify optimal construction schedule for airport expansion projects.

Second, an innovative machine learning methodology was developed to enable airport and construction planners quantifying the impact of various construction phasing plans on flights ground movement time during airport expansion project. The methodology implementation is organized in four main stages: data collection, data preprocessing, model training, and evaluation and validation stage. The methodology is used to develop five machine learning models using multilayer perceptron neural networks, ridge regression, k-nearest neighbors, random forest regressor, and support vector regression and their performance is compared and evaluated using five evaluation metrics. A real-life case study of an airport expansion project is analyzed to illustrate the use of the developed methodology and highlight its original contributions that are expected to support airport and construction planners in their efforts to efficiently and accurately analyze and compare the impact of feasible construction phasing plans on airport operations in order to identify the least disruptive phasing plan that minimizes total number of delayed flights and total flight delays.

Third, a novel methodology was developed to optimize the phasing plans of airport expansion projects and provides the capability of minimizing both airport operation disruptions and total construction cost. The developed methodology integrates a machine learning model to predict the impact of construction phasing plans on flights ground movement time during airport expansion projects without the need for repetitive and time-consuming simulations, and a multi-objective optimization model to generate optimal construction phasing plans that provide optimal trade-offs between minimizing airport operations disruption cost and total construction cost. A real-life case study was analyzed to illustrate the use of the methodology in identifying optimal construction phasing plans for the relocation and reconstruction of an airport Taxiway. The results of the case study clearly illustrate the original contributions of the developed models that are expected to support airport and construction planners in identifying optimal construction phasing plans to improve the functional performance of airports during expansion projects while minimizing their total construction cost.

6.2 Research Contributions

This section highlights the main contributions of this research study to the body of knowledge that include:

1. Novel methodology for measuring and quantifying construction-related delays in flights ground movement time during airport expansion projects and their associated costs.
2. Original machine learning methodology for predicting the impact of various phasing plans on flights ground movement time during construction of airport expansion projects.
3. Innovative model for optimizing the planning of airport expansion projects that provides optimal tradeoffs between minimizing construction-related disruptions in airport operations and minimizing total construction costs.
4. Novel model for optimizing airport construction phasing plans that generates optimal schedules for all airport construction phases at different levels of details including daily and hourly work plans.

6.3 Research Impact

The aforementioned research developments and contributions are expected to have significant and broad impacts on the current practices for planning airport expansion projects. They have a strong potential to enable construction and airport planners to generate optimal plans that are capable of: (1) accurately and efficiently predicting the impact of airport area closures on flights ground movement time during construction; (2) minimizing construction-related air traffic disruptions for airports that need to remain operational during expansion projects; and (3) minimizing total construction cost of airport expansion projects.

6.4 Future Research Work

While the present study fully achieved its research objectives, additional research areas have been identified to expand and build upon the completed research work. Future related research areas can focus on: (1) expanding the developed models to consider related construction planning risks including those caused by weather, site conditions, and labor productivity uncertainties; and (2) considering the impact of emerging transportation technologies such as autonomous vehicles on the effectiveness and use of existing airport facilities such as parking lots.

6.4.1 Planning of airport expansion projects under uncertainty

The developed models in this research study provide the capability of analyzing and minimizing the disruptive impact of construction activities on airport operations and air traffic and minimizing total construction cost of airport expansion projects. These developed models can be expanded to consider the impact of uncertainty in weather, site conditions, and labor productivity that are often encountered in airport expansion projects. To address this challenge, the formulation of the developed models can be expanded to (1) utilize historical weather data to account for and model the impact of weather on the planning of airport expansion projects; and (2) model uncertainties associated with the production rates of construction crews and their deployment dates through the use of Monte-Carlo simulation. These expansions are expected to provide much-needed support for airport planners and enable them to consider the impact of uncertainty during the planning of airport expansion projects.

6.4.2 Impact of emerging transportation technologies on the use of existing airport facilities

Future airport expansion and construction costs are expected to be affected by new and emerging technologies, including (1) faster and cost-effective mass transit systems for airports such as hyperloop capsules and high-speed trains (Kumar and Khan, 2017; Park and Ha, 2006); and (2) autonomous vehicles and shared rides (Bansal and Kockelman, 2017; Fagnant and Kockelman, 2015; Henderson and Spencer, 2016; Philanthropies, 2017). These two emerging technologies are expected to reduce vehicle traffic and parking use at airports in the next decades. For example, FAA requires airports to provide 1000 – 3300 parking spaces per million originating passengers or 1.5 times the number of peak hour passengers in a rate of 109-124 parked cars per acre (FAA, 1988). These airport parking facilities will be significantly under-utilized in the future as three out of four vehicles are expected to be autonomous by 2040 (Philanthropies, 2017). This expected reduction in the use of current airport facilities creates challenges in the strategic planning of airport expansion projects. Accordingly, there is a need to consider and optimize the impact of the aforementioned emerging technologies in order to generate long-term optimal plans for transforming the use of airport facilities that are expected to be under-utilized in the future.

References

Abdallah, M. (2014). *Optimizing the selection of sustainability measures for existing buildings*. University of Illinois at Urbana-Champaign.

Abdallah, M., & El-Rayes, K. (2016). Multiobjective optimization model for maximizing sustainability of existing buildings. *Journal of Management in Engineering*, *32*(4), 04016003. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000425

Abdelmohsen, A. Z., & El-Rayes, K. (2016). Optimal trade-offs between construction cost and traffic delay for highway work zones. *Journal of Construction Engineering and Management*, *142*(7), 05016004.

ACI-NA. (2021). Building the runway to economic growth. *Airport Council International – North America (ACI-NA)*. https://airportscouncil.org/wp-content/uploads/2021/03/2021ACINAInfrastructureNeedsStudy.pdf

Al-Ghzawi, M., & El-Rayes, K. (2023). Optimizing the planning of airport airside expansion projects to minimize air traffic disruptions and construction cost. *Journal of Construction Engineering and Management*, *149*(4), 04023013. https://doi.org/10.1061/JCEMD4/COENG-12893

Alnasseri, N., Osborne, A., & Steel, G. (2013). Managing and controlling airport construction projects: A strategic management framework for operators. *Journal of Advanced Management Science Vol*, *1*(3). https://doi.org/10.12720/joams.1.3.317-320

AlOtaibi, M., El-Rayes, K., & Altuwaim, A. (2021). Optimizing the renovation scheduling of leased residential buildings to minimize total project cost. *Journal of Construction Engineering and Management*, *147*(7), 04021074. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002063

Altuwaim, A., & El-Rayes, K. (2021). Multiobjective optimization model for planning repetitive construction projects. *Journal of Construction Engineering and Management*, *147*(7), 04021072. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002063

ASCE. (2021). 2021 infrastructure report card. *American Society of Civil Engineers (ASCE)*. https://infrastructurereportcard.org/wp-content/uploads/2020/12/Aviation-2021.pdf

Ashford, N. J., Mumayiz, S., & Wright, P. H. (2011). *Airport engineering: Planning, design, and development of 21st century airports*. John Wiley & Sons.

ATAC. (2021). Simmod PRO!®. *ATAC Corporation*. https://www.atac.com/simmod-pro/

Attalla, M., & Hegazy, T. (2003). Predicting cost deviation in reconstruction projects: Artificial neural networks versus regression. *Journal of construction engineering and management*, *129*(4), 405–411.

Bakry, I., Moselhi, O., & Zayed, T. (2014). Optimized acceleration of repetitive construction projects. *Automation in construction*, *39*, 145–151.

Balakrishna, P., Ganesan, R., Sherry, L., & Levy, B. S. (2008). Estimating taxi-out times with a reinforcement learning algorithm. *2008 IEEE/AIAA 27th Digital Avionics Systems Conference*, 3–D.

Bansal, P., & Kockelman, K. M. (2017). Forecasting americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, *95*, 49–63.

Baykasoglu, A., Dereli, T., & Sabuncu, I. (2006). An ant colony algorithm for solving budget constrained and unconstrained dynamic facility layout problems. *Omega*, *34*(4), 385–396.

Beiker, S. (2014). History and status of automated driving in the united states. *Road Vehicle Automation*, 61–70.

Biancardo, S. A., Viscione, N., Oreto, C., Veropalumbo, R., & Abbondati, F. (2020). Bim approach for modeling airports terminal expansion. *Infrastructures*, *5*(5), 41.

Boussaid, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *Information sciences*, *237*, 82–117.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5–32.

Brinkley, L. (2017). Construction at SFO to cause weekend flight delays, cancellations. *ABC7 News*. https://abc7news.com/travel/construction-at-sfo-to-cause-weekend-flight-delays-cancellations/1912722/

Brown, J. R., Morris, E. A., & Taylor, B. D. (2009). Planning for cars in cities: Planners, engineers, and freeways in the 20th century. *Journal of the American Planning Association*, *75*(2), 161–177.

Bureau of Transportation Statistics. (2022a). Airline on-time performance and causes of flight delays. *U.S. Department of Transportation*. https://www.bts.dot.gov/explore-topics-and-geography/topics/airline-time-performance-and-causes-flight-delays

Bureau of Transportation Statistics. (2022b). Airline on-time statistics and delay causes. *U.S. Department of Transportation*. https://www.transtats.bts.gov/OT_Delay/ot_delaycause1.asp?6B2r=FE&20=E

Bureau of Transportation Statistics. (2021). Number of u.s. airports. *Bureau of Transportation Statistics, U.S. Department of Transportation*. https://www.bts.gov/content/number-us-airportsa

Cai, X., Qiu, H., Gao, L., Yang, P., & Shao, X. (2016). An enhanced rbf-hdmr integrated with an adaptive sampling method for approximating high dimensional problems in engineering design. *Structural and Multidisciplinary Optimization*, *53*, 1209–1229.

Calis, G., & Yuksel, O. (2010). A comparative study for layout planning of temporary construction facilities: Optimization by using ant colony algorithms. *Proceedings of the 13th International Conference on Computing in Civil and Building Engineering, Nottingham, UK*, 267.

Caramia, M., & Dell'Olmo, P. (2008). *Multi-objective management in freight logistics*. Springer.

Castelli, L., & Pellegrini, P. (2011). An ahp analysis of air traffic management with target windows. *Journal of Air Transport Management*, *17*(2), 68–73.

Chakraborty, D., & Elzarka, H. (2019). Advanced machine learning techniques for building performance simulation: A comparative analysis. *Journal of Building Performance Simulation*, *12*(2), 193–207.

Chollet, F., et al. (2015). *Keras*. https://github.com/fchollet/keras

Chu, Y., Mi, H., Liao, H., Ji, Z., & Wu, Q. (2008). A fast bacterial swarming algorithm for high-dimensional function optimization. *2008 IEEE congress on evolutionary computation (ieee world congress on computational intelligence)*, 3135–3140.

Coello, C. A. (1999). A comprehensive survey of evolutionary-based multiobjective optimization techniques. *Knowledge and Information systems*, *1*(3), 269–308.

Cole, S. (2001). Dare to dream: Bringing futures into planning. *Journal of the american Planning association*, *67*(4), 372–383.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning*, *20*, 273–297.

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *IEEE transactions on information theory*, *13*(1), 21–27.

Daly, A., Dekker, T., & Hess, S. (2016). Dummy coding vs effects coding for categorical variables: Clarifications and extensions. *Journal of choice modelling*, *21*, 36–41.

Davidson, P., & Spinoulas, A. (2015). Autonomous vehicles: What could this mean for the future of transport. *Australian Institute of Traffic Planning and Management (AITPM) National Conference, Brisbane, Queensland*.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Delatte, N. (2006). *Concrete pavement design, construction, and performance.* ((1st ed.)). CRC Press. https://doi.org/10.1201/9781482288483

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, *1*(1), 269–271.

Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant system: Optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *26*(1), 29–41.

Dubey, N. (2020). *Construction safety and phasing plans: Good practices at airports* (Doctoral dissertation). Michigan State University.

Easa, S. M., & Hossain, K. M. A. (2008). New mathematical optimization model for construction site layout. *Journal of construction engineering and management*, *134*(8), 653–662.

Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. *MHS'95. Proceedings of the sixth international symposium on micro machine and human science*, 39–43.

Elbeltagi, E., Hegazy, T., & Eldosouky, A. (2004). Dynamic layout of construction temporary facilities considering safety. *Journal of construction engineering and management*, *130*(4), 534–541.

Elbeltagi, E., Hegazy, T., & Grierson, D. (2005). Comparison among five evolutionary-based optimization algorithms. *Advanced engineering informatics*, *19*(1), 43–53.

El-Rayes, K., & Jun, D. H. (2009). Optimizing resource leveling in construction projects. *Journal of Construction Engineering and Management*, *135*(11), 1172–1180. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000097

El-Rayes, K., & Khalafallah, A. (2005). Trade-off between safety and cost in planning construction site layouts. *Journal of construction engineering and management*, *131*(11), 1186–1195.

El-Rayes, K., & Said, H. (2009). Dynamic site layout planning using approximate dynamic programming. *Journal of computing in civil engineering*, *23*(2), 119–127.

FAA. (2021). Air traffic by the numbers. *Federal Aviation Administration (FAA)*. https://www.faa.gov/air_traffic/by_the_numbers/

FAA. (2020a). National plan of integrated airport systems (NPIAS) 2021-2025. *Federal Aviation Administration (FAA)*. https://www.faa.gov/airports/planning_capacity/npias/current/media/NPIAS-2021-2025-Narrative.pdf

FAA. (2017). Operational safety on airports during construction. *Federal Aviation Administration (FAA)*. https://www.faa.gov/documentLibrary/media/Advisory_Circular/150-5370-2G.pdf

FAA. (2022). Q1-2022 airport construction impact report. *Federal Aviation Administration (FAA)*. https://www.faa.gov/sites/faa.gov/files/2022-01/Q1_2022_508_Airport_Construction_Impact_Report.pdf

FAA. (1988). Planning and design guidelines for airport terminal facilities – advisory circular no.150/5360-13 chg:1. *Federal Aviation Administration (FAA)*. https://www.faa.gov/documentLibrary/media/advisory_circular/150-5360-13/150_5360_13_part4.pdf

FAA. (2019). Aircraft type designators. *Federal Aviation Administration (FAA)*. https://www.faa.gov/documentLibrary/media/Order/2019-10-10%5C_Order%5C_JO%5C_7360.1E%5C_Aircraft%5C_Type%5C_Designators%5C_FINAL.pdf

FAA. (2020b). Facts about the FAA and air traffic control. *Federal Aviation Administration (FAA)*. https://www.faa.gov/newsroom/facts-about-faa-and-air-traffic-control

FAA. (2004). Capability assessment of various fast-time simulation models and tools with analysis concerns. *Federal Aviation Administration (FAA)*. https://www.tc.faa.gov/acb300/ap5%5C_workshops/documents/AP9%5C_MS%5C_TIM%5C_Paper%5C_Final%5C_101504.pdf

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181.

Farah, H., Erkens, S. M., Alkim, T., & Arem, B. v. (2018). Infrastructure for automated and connected driving: State of the art and future research directions. *Road vehicle automation 4*, 187–197.

Feng, X., Lau, F., & Gao, D. (2009). A new bio-inspired approach to the traveling salesman problem. *International Conference on Complex Sciences*, 1310–1321.

Fister Jr, I., Yang, X.-S., Fister, I., Brest, J., & Fister, D. (2013). A brief review of nature-inspired algorithms for optimization. *arXiv preprint arXiv:1307.4186*.

Fortin, F.-A., Rainville, F.-M. D., Gardner, M.-A., Parizeau, M., & Gagné, C. (2012). DEAP: Evolutionary algorithms made easy. *Journal of Machine Learning Research*, *13*(70), 2171–2175. http://jmlr.org/papers/v13/fortin12a.html

Foulds, L. R., Hamacher, H. W., & Wilson, J. M. (1998). Integer programming approaches to facilities layout models with forbidden areas. *Annals of Operations Research*, *81*, 405–418.

Fraedrich, E., Heinrichs, D., Bahamonde-Birke, F. J., & Cyganski, R. (2019). Autonomous driving, the built environment and policy implications. *Transportation research part A: policy and practice*, *122*, 162–172.

Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. addison. *Reading*.

Gopalswamy, S., & Rathinam, S. (2018). Infrastructure enabled autonomy: A distributed intelligence architecture for autonomous vehicles. *2018 IEEE Intelligent Vehicles Symposium (IV)*, 986–992. https://doi.org/10.1109/IVS.2018.8500436

Guerra, E. (2016). Planning for cars that drive themselves: Metropolitan planning organizations, regional transportation plans, and autonomous vehicles. *Journal of Planning Education and Research*, *36*(2), 210–224. https://doi.org/10.1177/0739456X15613591

Gui, G., Liu, F., Sun, J., Yang, J., Zhou, Z., & Zhao, D. (2019). Flight delay prediction based on aviation big data and machine learning. *IEEE Transactions on Vehicular Technology*, *69*(1), 140–150.

Havens, T. C., Spain, C. J., Salmon, N. G., & Keller, J. M. (2008). Roach infestation optimization. *2008 IEEE Swarm Intelligence Symposium*, 1–7. https://doi.org/10.1109/SIS.2008.4668317

Hegazy, T., & Kamarah, E. (2022). Schedule optimization for scattered repetitive projects. *Automation in Construction*, *133*, 104042.

Hegazy, T., & Wassef, N. (2001). Cost optimization in projects with repetitive nonserial activities. *Journal of Construction Engineering and Management*, *127*(3), 183–191. https://doi.org/10.1061/(ASCE)0733-9364(2001)127:3(183)

Henderson, J., & Spencer, J. (2016). Autonomous vehicles and commercial real estate.

Herrero, J. G., Berlanga, A., Molina, J. M., & Casar, J. R. (2005). Methods for operations planning in airport decision support systems. *Applied Intelligence*, *22*(3), 183–206.

Hilt, D. E., & Seegrist, D. W. (1977). *Ridge, a computer program for calculating ridge regression estimates*. Department of Agriculture, Forest Service, Northeastern Forest Experiment . . .

Hinze, J. W. (2012). *Construction planning and scheduling*. Pearson. https://www.pearson.com/uk/educators/higher-education-educators/program/Hinze-Construction-Planning-and-Scheduling-International-Edition-4th-Edition/PGM1002109.html

Ho, T. K. (1998). The random subspace method for constructing decision forests. *IEEE transactions on pattern analysis and machine intelligence*, *20*(8), 832–844.

Hope, A. (2017). The complex process behind your flight's schedule. *Conde Nast Traveler*. https://www.cntraveler.com/story/the-complex-process-behind-your-flights-schedule

Horst, J. J., & Murray, P. S. (2014). Industry best practice for airport construction safety and phasing plans (cspps). *T&DI Congress 2014: Planes, Trains, and Automobiles*, 856–868.

Hubbard, S., Hubbard, B., & Sobieralski, J. (2021). Minimizing the negative impacts of airport construction. *51st International Symposium on Aviation Psychology*, 352–357. https://corescholar.libraries.wright.edu/isap_2021/59

Humbertson, R., & Sinha, A. (2012). Managing irregular airport operations. *Journal of Airport Management*, *6*(4), 318–328.

Hyari, K., & El-Rayes, K. (2006). Optimal planning and scheduling for repetitive construction projects. *Journal of Management in Engineering*, *22*(1), 11–19. https://doi.org/10.1061/(ASCE)0742-597X(2006)22:1(11)

Jordan, R., Ishutkina, M. A., & Reynolds, T. G. (2010). A statistical learning approach to the modeling of aircraft taxi time. *29th Digital Avionics Systems Conference*, 1–B.

Jun, D. H., & El-Rayes, K. (2010). Optimizing the utilization of multiple labor shifts in construction projects. *Automation in Construction*, *19*(2), 109–119. https://doi.org/10.1016/j.autcon.2009.12.015

Khalafallah, A., & El-Rayes, K. (2004). Safety and cost considerations in site layout planning. *Housing and Building Research Centre Journal*, *1*(1), 141–150.

Khalafallah, A., & El-Rayes, K. (2006a). Minimizing construction-related hazards in airport expansion projects. *Journal of Construction Engineering and Management*, *132*(6), 562–572. https://doi.org/10.1061/(ASCE)0733-9364(2006)132:6(562)

Khalafallah, A., & El-Rayes, K. (2006b). Optimizing airport construction site layouts to minimize wildlife hazards. *Journal of Management in Engineering*, *22*(4), 176–185. https://doi.org/10.1061/(ASCE)0742-597X(2006)22:4(176)

Khalafallah, A., & El-Rayes, K. (2008). Minimizing construction-related security risks during airport expansion projects. *Journal of Construction Engineering and Management*, *134*(1), 40–48. https://doi.org/10.1061/(ASCE)0733-9364(2008)134:1(40)

Khalafallah, A., & El-Rayes, K. (2011). Automated multi-objective optimization system for airport site layouts. *Automation in Construction*, *20*(4), 313–320.

Khoury, H. M., Kamat, V. R., & Ioannou, P. G. (2006). Simulation and visualization of air-side operations at detroit metropolitan airport. *Proceedings of the 2006 Winter Simulation Conference*, 2029–2038.

Kim, J.-G., & Kim, Y.-D. (2000). Layout planning for facilities with fixed shapes and input and output points. *International Journal of Production Research*, *38*(18), 4635–4653.

Kitchens, M. (1996). Estimating and project management for building contractors. *American Society of Civil Engineers*. https://doi.org/10.1061/9780784401484

Kumar, A., & Khan, A. (2017). Hyperloop high speed of transportation. *International Journal of Innovative Research in Science and Engineering*, *3*(4), 832–841.

Kwakkel, J. H., Walker, W. E., & Marchau, V. (2010). Adaptive airport strategic planning. *European Journal of Transport and Infrastructure Research*, *10*(3).

Lary, J. A., & Rothnie, J. (1994). Nighttime cement concrete pavement replacement seattle-tacoma international airport. *Aviation Crossroads: Challenges in a Changing World*, 92–101.

Lee, H., Malik, W., & Jung, Y. C. (2016). Taxi-out time prediction for departures at charlotte airport using machine learning techniques. *16th AIAA Aviation Technology, Integration, and Operations Conference*, 3910.

Lee, H., Malik, W., Zhang, B., Nagarajan, B., & Jung, Y. C. (2015). Taxi time prediction at charlotte airport using fast-time simulation and machine learning techniques. *15th AIAA Aviation Technology, Integration, and Operations Conference*, 2272.

Legge, J., & Levy, B. (2008). Departure taxi time predictions using asde-x surveillance data. *The 26th Congress of ICAS and 8th AIAA ATIO*, 8958.

Li, X., & Chen, X. (2018). Airport simulation technology in airport planning, design and operating management. *Applied and Computational Mathematics*, *7*(3), 130–138.

Li, Z., Shen, W., Xu, J., & Lev, B. (2015). Bilevel and multi-objective dynamic construction site layout and security planning. *Automation in Construction*, *57*, 1–16.

Lian, G., Zhang, Y., Desai, J., Xing, Z., & Luo, X. (2018). Predicting taxi-out time at congested airports with optimization-based support vector regression methods. *Mathematical Problems in Engineering*, *2018*.

Litman, T. (2017). *Autonomous vehicle implementation predictions*. Victoria Transport Policy Institute Victoria, BC, Canada.

Long, L. D., & Ohsato, A. (2009). A genetic algorithm-based method for scheduling repetitive construction projects. *Automation in Construction*, *18*(4), 499–511. https://doi.org/10.1016/j.autcon.2008.11.005

Lopez, R., Mascione, D., & Liu, H. J. (2017). Management of issues in the delivery of airport infrastructure within western australia. *Proceedings of the Institution of Civil Engineers-Management, Procurement and Law*, *170*(5), 207–217.

Malakooti, B. (1987). Computer-aided facility layout selection (caflas) with applications to multiple criteria manufacturing planning problems. *Large scale systems*, *12*(2), 109–123.

Marzouk, M., Abdelhamid, M., & Elsheikh, M. (2012). Selecting building materials using system dynamics and ant colony optimization. In *Icsdc 2011: Integrating sustainability practices in the construction industry* (pp. 577–584).

Mawdesley, M. J., Al-Jibouri, S. H., & Yang, H. (2002). Genetic algorithms for construction site layout in project planning. *Journal of construction engineering and management*, *128*(5), 418–426.

Monismith, D. R., & Mayfield, B. E. (2008). Slime mold as a model for numerical optimization. *2008 IEEE swarm intelligence symposium*, 1–8.

Moore, J. (1999). Application of particle swarm to multiobjective optimization. *Technical report*.

Morries, H., & Smith, O. (2018). Airlines extending flight times to avoid payouts for delays, report claims. *The Telegraph*. https://www.telegraph.co.uk/travel/travel-truths/Are-airlines-exaggerating-flight-times-so-theyre-never-late/

Ning, X., Lam, K.-C., & Lam, M. C.-K. (2011). A decision-making system for construction site layout planning. *Automation in Construction*, *20*(4), 459–473.

Ohmori, S., Yoshimoto, K., & Ogawa, K. (2010). Solving facility layout problem via particle swarm optimization. *2010 Third International Joint Conference on Computational Science and Optimization*, *1*, 409–413.

Olugboyega, O., & Wemimo, O. T. (2018). Construction site layout optimization and 3d visualization through bim tools= visualización 3d y optimización a través de herramientas bim aplicado a los planos de proyecto. *Building & Management*, *2*(2), 35–52.

Park, Y., & Ha, H.-K. (2006). Analysis of the impact of high-speed railroad service on air transport demand. *Transportation Research Part E: Logistics and Transportation Review*, *42*(2), 95–104.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Pendyala, R. (2013). Next generation infrastructure implications of autonomous vehicles and transport automation.

Philadelphia International Airport. (2019). Projects that make a difference: Freshening up: Restroom renovations at phl. *PHL*. https://www.phl.org/about/cdp/project-updates

Philanthropies, B. (2017). Taming the autonomous vehicle, a primer for cities. *Aspen Institute Center for Urban Innovation: New York, USA*, *117*.

Pour, H. D., & Nosraty, M. (2006). Solving the facility and layout and location problem by ant-colony optimization-meta heuristic. *International Journal of Production Research*, *44*(23), 5187–5196.

Ravizza, S., Atkin, J. A., Maathuis, M. H., & Burke, E. K. (2013). A combined statistical approach and ground movement model for improving taxi time estimations at airports. *Journal of the Operational Research Society*, *64*(9), 1347–1360.

Rezazadeh, H., GHAZANFARI, M., SAIDI-MEHRABAD, M., & SADJADI, S. J. (2009). An extended discrete particle swarm optimization algorithm for the dynamic facility layout problem. *Journal of Zhejiang University Science A*, *10*(4), 520–529. https://doi.org/10.1631/jzus.A0820284

Rosenblatt, F. (1961). *Principles of neurodynamics. perceptrons and the theory of brain mechanisms* (tech. rep.). Cornell Aeronautical Lab Inc Buffalo NY.

RSMeans data. (2020). *Heavy construction cost with rsmeans data*. Gordian RSMeans Data. Rockland, MA.

Said, H., & El-Rayes, K. (2010). Optimizing the planning of construction site security for critical infrastructure projects. *Automation in Construction*, *19*(2), 221–234.

Said, H., & El-Rayes, K. (2012). Optimal material logistics planning in congested construction sites. In *Construction research congress 2012* (pp. 1580–1589). https://doi.org/10.1061/9780784412329.159

Said, H., & El-Rayes, K. (2013a). Optimal utilization of interior building spaces for material procurement and storage in congested construction sites. *Automation in construction*, *31*, 292–306.

Said, H., & El-Rayes, K. (2013b). Performance of global optimization models for dynamic site layout planning of construction projects. *Automation in Construction*, *36*, 71–78.

San Diego county regional airport authority. (2021). Th11a – 6 – 2021 – report – exhibit 1. *California Coastal Commission*. https://documents.coastal.ca.gov/reports/2021/6/th11a/th11a-6-2021-exhibits.pdf

Sander, D. E., Chapman, R. B., Ward, S. A., Marr, S., & Arnold, S. (2014). *Guidebook on general aviation facility planning*.

Sarker, I. H. (2021). Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, *2*(6), 420.

Sciacca, A. (2017). SFO flight delays, cancellations could continue as airport revamps runway. *East Bay Times*. https://www.eastbaytimes.com/2017/04/24/sfo-flight-delays-cancellations-could-continue-as-airport-revamps-runway/

Shami, M., & Kanafani, A. (1997). Coping with construction in operational airports: Sfia case study. *Journal of Transportation Engineering*, *123*(6), 417–428. https://doi.org/10.1061/(ASCE)0733-947X(1997)123:6(417)

Shi, B., & Liu, J. (2018). Nonlinear metric learning for knn and svms through geometric transformations. *Neurocomputing*, *318*, 18–29.

Siewart, D., & Le Bris, G. (2015). Safety of runway operations during construction works. https://onlinepubs.trb.org/Onlinepubs/webinars/151130.pdf

Siow, B. T., Kivanc, O., Bender, G., Evlioglu, R., & Tunasar, C. (2002). Managing airport traffic disruptions during construction. In *Designing, constructing, maintaining, and financing today's airport projects* (pp. 1–15). https://doi.org/10.1061/40646(2003)21

Skarbek-Zabkin, A., & Szczepanek, M. (2018). Autonomous vehicles and their impact on road infrastructure and user safety. in 2018 xi international science-technical conference automotive safety (pp. 1–4). *IEEE. https://doi. org/10.1109/AUTOSAFE*.

Srivastava, A. (2011). Improving departure taxi time predictions using asde-x surveillance data. *2011 IEEE/AIAA 30th Digital Avionics Systems Conference*, 2B5–1.

Stewart, C. (2001). Airfield safety: Developing operational procedures and schedules for airside construction projects. In *Advancing airfield pavements* (pp. 309–321). https://doi.org/10.1061/40579(271)26

Stockton, K. (2015). Tsa construction project: Eugene airport case study. *Journal of Airport Management*, *9*(1), 51–59.

Tam, C., Tong, T. K., Leung, A. W., & Chiu, G. W. (2002). Site layout planning using nonstructural fuzzy decision support system. *Journal of construction engineering and management*, *128*(3), 220–231.

Tettamanti, T., Varga, I., & Szalay, Z. (2016). Impacts of autonomous cars from a traffic engineering perspective. *Periodica Polytechnica Transportation Engineering*, *44*(4), 244–250.

vanRossum, G. (2017). *The python language reference*. Python Software Foundation. https://scicomp.ethz.ch/public/manual/Python/3.6.0/reference.pdf

Jaroch, W. (2020). Paving the airfield. *Aviation Pros*. https://www.aviationpros.com/aoa/runway-management/taxiway-ramp-maintenance-training/article/21148524/paving-the-airfield

Weise, T., Skubch, H., Zapf, M., & Geihs, K. (2008). Global optimization algorithms and their application to distributed systems.

Wong, K. Y., et al. (2010). Applying ant system for solving unequal area facility layout problems. *European Journal of Operational Research*, *202*(3), 730–746.

Xu, J., & Li, Z. (2012). Multi-objective dynamic construction site layout planning in fuzzy random environment. *Automation in construction*, *27*, 155–169.

Yang, X.-S. (2009). Firefly algorithms for multimodal optimization. *International symposium on stochastic algorithms*, 169–178.

Yang, X.-S. (2010). A new metaheuristic bat-inspired algorithm. In *Nature inspired cooperative strategies for optimization (nicso 2010)* (pp. 65–74). Springer.

Ye, B., Liu, B., Tian, Y., & Wan, L. (2020). A methodology for predicting aggregate flight departure delays in airports based on supervised learning. *Sustainability*, *12*(7), 2749.

Yee, P., Fischer, M., & Haymaker, J. (2013). Automated identification of occupant interactions in renovations of occupied buildings. *Journal of Information Technology in Construction (ITcon)*, *18*(10), 182–213.

Yin, J., Hu, Y., Ma, Y., Xu, Y., Han, K., & Chen, D. (2018). Machine learning techniques for taxi-out time prediction with a macroscopic network topology. *2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC)*, 1–8.

Yousefikhoshbakht, M., Didehvar, F., & Rahmati, F. (2013). Modification of the ant colony optimization for solving the multiple traveling salesman problem. *Romanian Journal of Information Science and Technology*, *16*(1), 65–80.

Yuan, Y., Yuan, J., Du, H., & Li, L. (2012). An improved multi–objective ant colony algorithm for building life cycle energy consumption optimisation. *International Journal of Computer Applications in Technology*, *43*(1), 60–66.

Zhang, H., & Wang, J. Y. (2008). Particle swarm optimization for construction site unequal-area layout. *Journal of construction engineering and management*, *134*(9), 739–748.

Zhang, J., Peng, Z., Yang, C., & Wang, B. (2022). Data-driven flight time prediction for arrival aircraft within the terminal area. *IET Intelligent Transport Systems*, *16*(2), 263–275.

Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P. N., & Zhang, Q. (2011). Multiobjective evolutionary algorithms: A survey of the state of the art. *Swarm and evolutionary computation*, *1*(1), 32–49.

Zouein, P., & Tommelein, I. (1999). Dynamic layout planning using a hybrid incremental solution method. *Journal of construction engineering and management*, *125*(6), 400–408.