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MACHINE LEARNING APPROACH TO ANALYZE AIRPORT BOARDING STRATEGIES BASED ON PASSENGER' BEHAVIOR

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Abstract

Boarding is on the critical path for the turnaround time. It caused delays that reached almost $30billion in the pre-pandemic period according to FAA. The literature around airport boarding discusses which are the boarding strategies that minimizes boarding time, focused on pre-defined strategies that usually do not consider the context of passenger' behavior (agility, hand-on bags, if alone or in groups) for a specific flight. Because of that, there is no consensus in the literature about the best way to reduce boarding time and consequentially to increase perceived Level of Service (LoS) especially considering passenger' behavior. Aiming to contribute to this challenge, this study proposes using passenger behavior variables (queue interferences, bag distribution, priority rates and group travelling) to model boarding time for different boarding strategies. For that, this study combines two different techniques that can be replicated for other contexts: 1) A simulation of different boarding strategies based on a screening Design of experiments (DOE) to estimate boarding time for different passenger's behavior contexts in a A230 model 2) Five machine learning techniques applied on the simulation dataset. As results, a model that can be used to predict boarding time for a given context of passenger behavior is discussed which can assist airlines in the decision making process to set boarding strategies based on a data-driven approach, which helps to avoid delays and to increase passenger satisfaction. Regarding the literature contribution, this study takes steps to fulfill the gap around setting boarding strategies to minimize boarding time by providing a way to define them based on each context of passenger behavior. It was also found that between the simulated boarding strategies (random, back to front and Steffen's) the one that provides the lower boarding time is Steffen's with an average of 12+-0.02 minutes to board 180 passengers.

Keywords: Boarding Strategy, Boarding Simulation, Machine Learning.

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1. INTRODUCTION

Between all airport processes, boarding is the one which mostly depends on the way passengers behave and in their willingness to follow the established procedures. FAA (2022) estimates the pre-pandemic costs of airline delays in over $30billion and as Neuman (2019) illustrates "most of primary delays occurred at the gates". Several variables contribute to that: Priority fares, if the passenger is a frequent flyer and then used to the airport procedures, the number of hand-on luggage, if travelling in groups or alone, the passenger' agility, if delayed or not and simply the way the passenger behaves while in queue. Companies use different boarding strategies aiming to reduce boarding time and consequently the associated delays also looking for a way to improve perceived Level of Service (LoS) especially for the passengers that purchased priority fares or for frequent passengers which is naturally related to passenger' loyalty and their perception of LoS. The literature around boarding procedure is mainly focused on determining which are the variables that most impact boarding time and which is the best boarding strategy (the one that minimizes boarding time). There is still no consensus about it as it depends on each context (airplane and passenger's characteristics). Recent literature focus not only on boarding efficiency but also on how the passengers perceive LoS.

In this context, this study aims to contribute on answering the question: Which strategy to set and how to minimize boarding time considering the passenger behavior? Answering this question can help improving the perceived LoS which is related to loyalty and to avoid costs while reducing delays. To do that, two objectives are set: 1) Establishing an environment based on a screening Design of Experiments (DOE) in which different scenarios can be simulated to generate the database around boarding strategies, boarding time and passenger's behavior aiming to understand which strategy is the one that minimizes boarding time for a given passenger' behavior context. 2) Based on the dataset, using machine learning techniques to develop a model that can be used to predict boarding time for a given context and understanding the influence of the behavior variables. Achieving these objectives can help airlines managers to adapt boarding procedures dynamically (based on the passenger average profile for specific flights) and then reducing boarding time.

The structure of the study is presented in four sections after this introduction: The literature around airport boarding procedures focusing on boarding time modeling and boarding strategies is presented in light of machine learning techniques. The methodology shows the steps that are followed to achieve the objective of this study. The results of the simulation (database generation) and the model developed are presented and can be replicated in different contexts. Following the results, the conclusion discussion and next steps are presented.

2. LITERATURE REVIEW

Simulation and models

Milne and Kelly (2014) developed a discrete event simulation based on Steffen's boarding strategy to optimize boarding time by assigning seats to passengers based on the amount of luggage they were carrying. Steffen's method assigns passengers to specific numerical positions (seat location) in an optimized way, reducing boarding time. The authors added luggage storage to this method, increasing boarding efficiency, however, their method lacks consideration of personal factors such as seat preference, special needs, and cabin segmentation (e.g., first class). This highlights a gap in addressing individual passenger characteristics, which is critical for a predictive model of boarding time based on passenger behavior.

Notomista et al. (2016) advanced Steffen's method by introducing a dynamic seat allocation system based on optical sensor data. These sensors measured each passenger's agility and estimated the size of their hand-luggage using computer vision techniques to obtain real-time data, which served as inputs for their algorithm. This study provides a significant contribution by incorporating real-time

passenger behavior data, which aligns well with the goal of creating a predictive model based on such data. Bidanda et al. (2017) reviewed various studies on operations research and physical models aimed at reducing boarding time, including Markov decision processes, queue theory, and simulation techniques such as discrete-event simulation, Monte Carlo, and agent-based modeling. They concluded that fixed boarding strategies lack flexibility; for example, Steffen's method is optimal for an A380 but not for a B777. They suggest developing a dynamic tool to tailor boarding strategies to specific contexts, considering variables such as the type of airplane and passenger characteristics. This underscores the necessity for adaptable models that can predict boarding time in various contexts, reinforcing the need for a flexible, passenger-behavior-based approach.

Kisiel (2020) used Monte Carlo simulation to analyze the impact of priority fares on boarding time across different boarding strategies. To validate the discrete event-based simulation model, 62 flights with 180 passengers each were observed through two cameras inside an A320 operated by a low-cost carrier. The study found that even the best boarding strategies can be disrupted by priority fares, as priority passengers board randomly, affecting the boarding sequence. Consequently, the number of priority passengers should be considered in any boarding strategy, and developing hybrid strategies that account for delayed passengers and sequence disruptions could enhance efficiency. This emphasizes the importance of accounting for variability in passenger behavior in predictive models.

In the context of COVID-19, Milne et al. (2020) conducted over 10,000 simulations using stochastic simulation and agent-based modeling (NetLogo software to model passenger mobility) to evaluate the risk transmission impact of different boarding strategies for a single-door Airbus A320. They used the Reverse Pyramid boarding strategy, which boards passengers in groups, as it minimizes risk transmission. Variations of the Reverse Pyramid strategy were tested based on the number of boarding groups, luggage volume, and aisle social distancing. This study illustrates the adaptability of boarding strategies to different scenarios, which is crucial for developing a robust predictive model.

Schultz and Soolaki (2021) employed a genetic algorithm to allocate seats to passengers during COVID-19. They modeled passenger behavior using a stochastic cellular automata model, incorporating a transmission risk model. Their findings suggested that group boarding reduces both boarding time and transmission risk. This aligns with the objective of using passenger behavior data to optimize boarding strategies. More recently, Kobbaey, Bilquise, and Naqi (2023) used autonomous agent-based simulation to compare the efficiency of different boarding strategies, considering luggage, walking speed, and passenger behavior (including non-compliance). They discussed which strategies minimize boarding delays and enhance passenger experience while improving sustainability at airports. Their work supports the need for comprehensive models that integrate various aspects of passenger behavior to predict boarding time accurately.

Pedestrian behavioral

According to Schultz and Fricke (2011), terminal handling progress depends on individual passenger behavior. They developed an agent-based model to analyze passenger movements and decision-making for route choice, validated with real and virtual terminal data. Schultz, Kunze, and Fricke (2013) further modeled passenger motions to understand the impact of behavior on boarding strategies, using three different airplanes (A320, B777, and A380) for validation with AirBerlin data. This study highlighted the influence of different aircraft types on boarding efficiency.

Schultz (2017) emphasized that aircraft boarding is driven mainly by passengers, not airport or airline employees. The author provided a dataset including passenger motion, luggage storage time, and interactions to calibrate boarding simulation models. This underscores the need to model individual behaviors accurately in predictive models. Schultz (2018) developed a sensor environment model using seats as sensors to evaluate boarding progress in real time, allowing airlines to adjust processes dynamically. Schultz and Reitmann (2019) improved this model with machine learning (Long Short-Term Memory) to predict boarding time, incorporating passenger interactions.

Gadaleta and Rossi (2018) introduced IDNet, a gait recognition model using smartphone motion signals (accelerometer and gyroscope) and convolutional neural networks for user authentication. This demonstrates the potential of using personal motion data to enhance boarding models. Similarly, Gjoreski et al. (2020) employed machine learning and hidden Markov models to classify human activities using smartphone sensor data, highlighting the feasibility of using such data to model passenger behavior. Kececi et al. (2020) also used machine learning for gait recognition with a large dataset, reinforcing the application of motion data in predictive models.

Rodríguez-Sanz et al. (2021) studied queue patterns in airports, using simulation and real data from a European airport to predict queue behaviors with Random Forest algorithms. This study illustrates the importance of understanding and predicting passenger flow in enhancing boarding efficiency. Fabrin et al. (2024) focused on individual passenger metrics in an agent-based model to reduce boarding time while considering passenger experience, aligning closely with the objective of integrating passenger behavior into predictive models.

3. METHODOLOGY

The methodology consists of three parts: The first is generating the database with simulations to estimate the boarding time for a given passenger behavior and for a given boarding strategy. The second part is the application of machine learning techniques to the dataset to predict which is the lower boarding time for a given passenger' behavior. The third part is defining a model that is able to suggest the definition of a boarding strategy for a given passenger behavior in order to reduce boarding time. Figure 1 shows a summary.

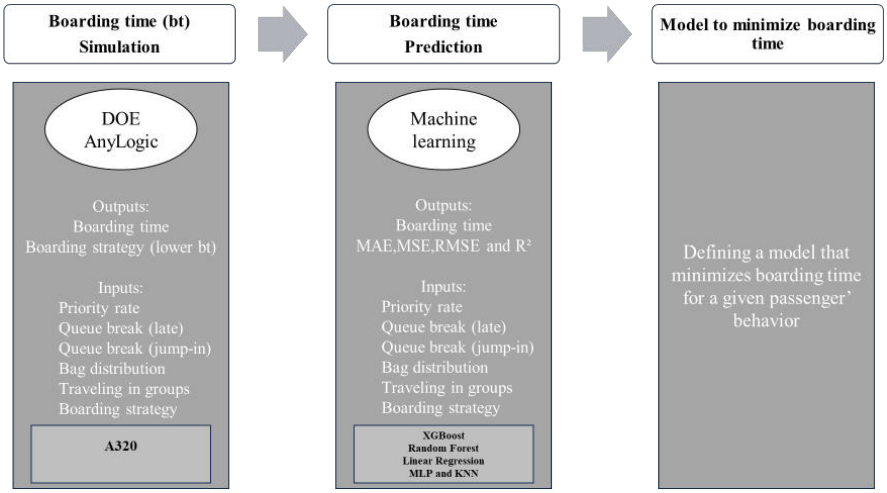


Figure 1: Methodology' steps

1) Simulation Anylogic: A screening Design of Experiments (DOE) is set for a pre-defined agent-based model from AnyLogic software that is used. The simulation data were generated using an agent-based model for an A320, based on AnyLogic's predefined passenger flow library. The model incorporates a trajectory model and a social force model, which considers interactions between people. DOE techniques were employed to develop and run the simulations within this environment.
2) Boarding time is the dependent variable and the independent variables are boarding strategy, priority rate, queue break, bag distribution, company and boarding strategy.
    a. Bag distribution: 1 for random distribution, -1 for even distribution.
    b. Priority rate: 1 meaning at least 25% of passengers have any type of priority and -1 no one has.
    c. Queue break (late passenger' rate): Variable related to interferences. 1 meaning 5% rate of passengers are late, -1 no interference (natural flow of the queue with no source of interruption).

d. Queue break (jump-in rate): Variable related to interferences. 1 meaning 5% rate of passengers interfere jumping-in the queues, -1 no interference (natural flow of the queue with no source of interruption).
e. Passenger company: 1 meaning the passengers are travelling in groups and -1 if alone.
f. Boarding strategy: Three of the most discussed boarding strategies in the literature are simulated; Random, Block and Steffen. Random: As the name says, passengers are boarded randomly with no pre-defined sequence. Blocks (Back to Front): The airplane rows are divided into sections and each section is boarded in order (back to front). Steffen's: As Kisiel (2020) describes, each passenger is boarded separately according to a sequence of seats that is set based on "back-to-front". Starting from the back, a passenger seats every second row and the sequence is repeated for the columns until everyone is seated.

3) Boarding time dataset: Using a screening DOE to define scenarios and simulate boarding time looking for the boarding strategy that minimizes it. Independent variables are the ones regarding passenger's behavior.
4) Model (machine learning): Developing a model that can predict boarding time based on the previous simulations and analyze the impact of the passenger' behavior variables on it.

To determine which and how many simulations to run, a Design of Experiments (DOE) is set. Vanaja and Rany (2008) describe the Plackett-Burman technique that is used to screen variables that can influence a determined output (in this case boarding time). According to the authors *"Statistical experimental design, also known as DOE, is the methodology of how to conduct and plan experiments in order to extract the maximum amount of information with the lowest number of analyses"*. It helps to measure interactions and it allows extrapolation of data. The experiments to simulate boarding time are based on five variables of passenger's behavior: Priority rate, queue break, bag distribution, company and three different boarding strategies (Random, Block and Stefen). The boarding strategies represent different approaches to board and the time to board everyone between the gate check until the last passenger is seated. The output of the simulation is the boarding time for each strategy.

It results in 8 runs for each of the three boarding strategies that are simulated resulting in 24 samples for each boarding strategy as shown in Table 1.

Table 1: Design of Experiments results for the 5 variables **(first 5 samples)**

Run Order	Bag distribution	Priority rate	Passenger company (if in groups)	Queue Break Late passenger rate	Queue Break Jump-in rate
1	1	-1	1	-1	-1
2	1	1	-1	-1	1
3	1	1	-1	1	-1
4	-1	1	1	1	-1
5	1	-1	1	1	1

The simulation based on a AnlyLogic application was developed by Nadtochiy and its interface used for the simulation is presented on Figure 2 where it is possible to visualize inputs and outputs in a user-friendly interface.

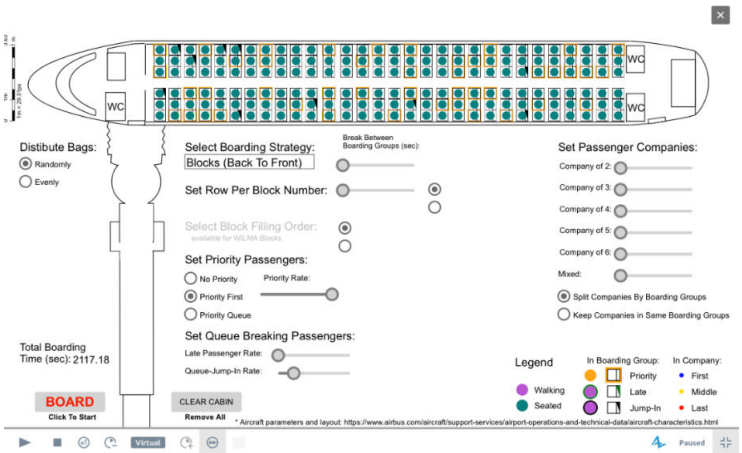


Figure 2: AnyLogic simulation tool interface. Available at: https://www.anylogic.com

As results, the simulation presents the boarding time in minutes for different passenger's behavior. It is composed of autonomous agents of human behavior that interact to each other and it simulates a single-aisle aircraft boarding using various boarding policies. The aircraft' type is an Airbus A320 (one of the most used and referred in the literature review) with 180 passengers split in 20 rows. There is no cabin segmentation in this simulation, meaning that all passengers are assigned to the same kind of seats (there is only economy class). Only economy class is considered and the airport gate infrastructure are kept unchanged for the simulations.

Five machine learning techniques are selected to predict which is the boarding time for a specific boarding strategy considering the passenger's behavior for a specific flight based on the dataset from the simulation. Those regressors are chosen as they are between the most used techniques: Linear regression, Key-Nearest-Neighbor (KNN), Multi-Layer-Perceptron (MLP), Random Forest and XGBoost.

Given those results, a training database is available resulting in a boarding time based on passenger behavior. This database is used to train different machine learning regressors. Inputs are passenger' behavior variables and the output is boarding time. Those regressor's performance are compared using four different metrics: Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and R-squared. MAE measures the difference between the predicted boarding time and the real boarding time (residual). It does it for all boarding time values and divide it by the number of simulations. The MSE squares the difference of the MAE before summing it allowing to identify outliers. RMSE is the square root of MSE and it helps understanding how the residuals are spread out. R squared varies from 0 to 1 and it measures how accurate a regression line is to predict each output (in this case boarding time).

The lower the boarding time, probably the better is the Level of Service (LoS) perception by passengers. Defining which boarding strategy to use based on boarding time considering passenger's behavior can not only reduce delays but it can also increase the passenger's perceived LoS. Airports and airlines willing to increase better LoS can use this model to choose which boarding strategy to set for a specific flight depending on the average passenger profile characteristics for that flight. Although airports and airlines could always use paid tools to simulate boarding process strategies, it can be expensive and usually it requires training and cost of licenses. One of the objectives of developing a model is that it can be a plug and play tool for decision making. As it is replicable it can be adapted when changing parameters, adding or removing variables.

4. RESULTS

The strategy that shows the lower boarding time is Stefen's which presents an average of 12,25 minutes to board 180 passengers with a low standard deviation of 0.02 for the 24 runs. Following Stefen's, the random strategy presents an average of 19.12 minutes to board while Back to Front resulted in an average of 35.38 minutes with a standard deviation of 2 minutes as Table 2 and Figure 3 show. Those are results from the Anylogic simulation.

	Steffen	Random	Block (Back to Front)
average (min)	12.24	19.12	35.38
median (min)	12.24	18.82	35.62
standard deviation (min)	0.02	0.73	2.55

Table 2: Boarding strategies scenarios results

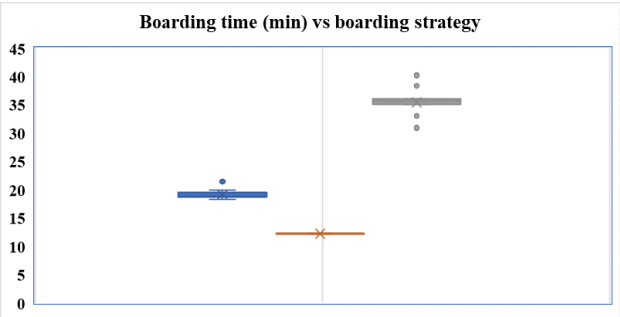


Figure 3: Boarding time vs boarding strategy: Random in blue, Steffen in orange and Grey Back to Front

These findings validate the effectiveness of Steffen's method, aligning with previous studies that highlight its efficiency. The Random strategy (19.12 minutes) and Back to Front (35.38 minutes) are consistent with the literature that shows fixed strategies often fall short of dynamic solutions.

Regarding the prediction results of this study, Figure 4 shows how accurate each of the machine learning regressors are when comparing MAE, MSE, RMSE and R_squared.

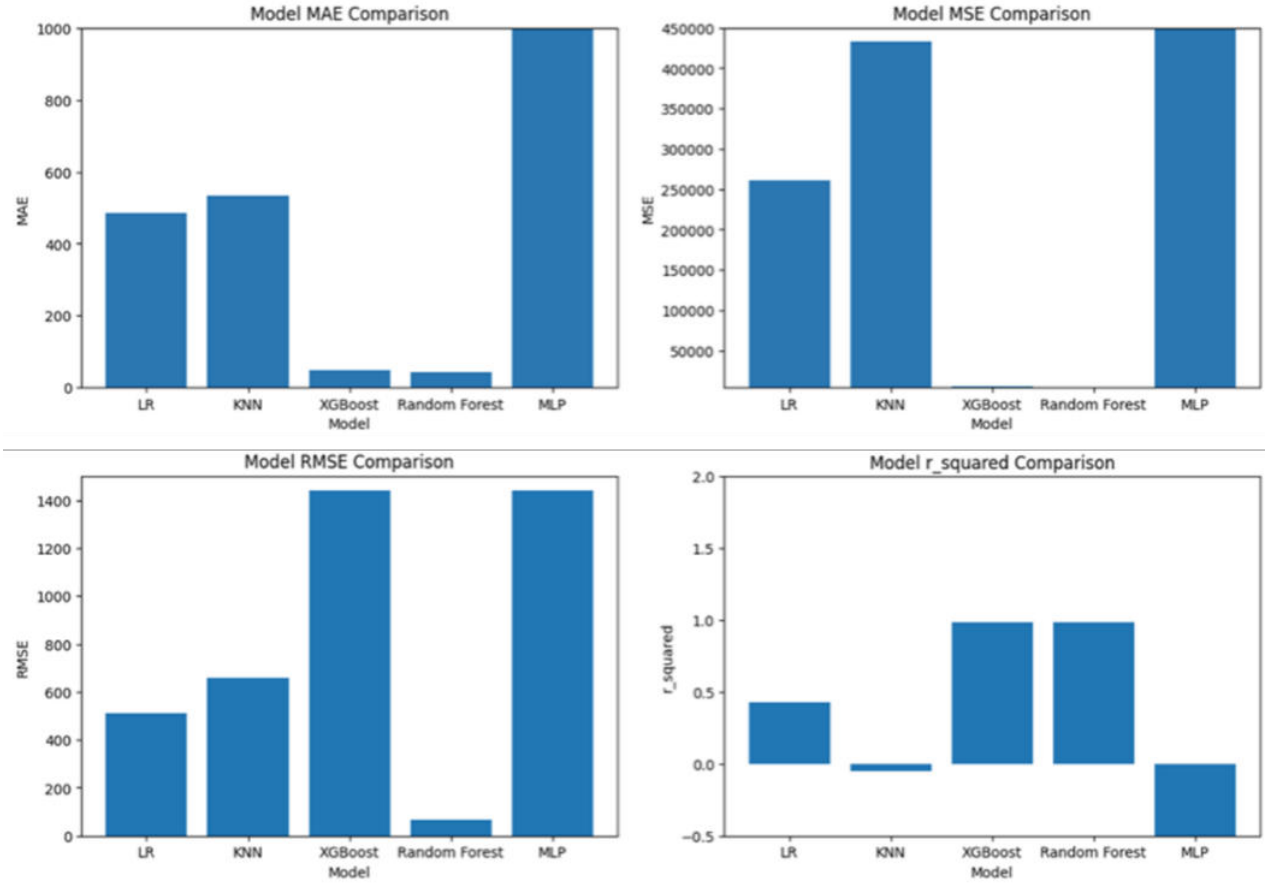


Figure 4: Comparison of different regressor's performance (MAE, MSE, RMSE, R_squared)

XGBoost and Random Forest showed R_squared of 0.9877 and 0.9887, meaning that the variables used in the simulation would explain 98% of the boarding time variance, or in other words that the variables would be great predictors of boarding time. Also, those showed respectively the lowest values of residuals with a MAE of 49.5 and 42.1 seconds respectively. The variables related to interferences (queue break) and if passengers are travelling in groups are the ones with the highest importance for boarding time prediction when using XGBoost as Figure 5 shows, while the boarding strategy and bag distribution are the lowest.

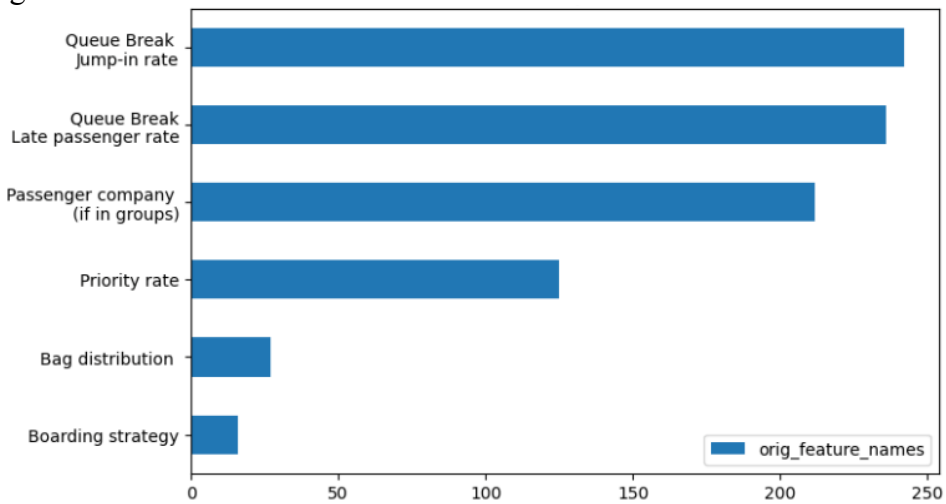


Figure 5: Coefficients of boarding time XGBoost model

Considering Random Forest, as Figure 6 shows, the great majority of boarding time is explained by the Boarding strategy, or in other words, defining the boarding strategy itself is the main predictor for boarding time.

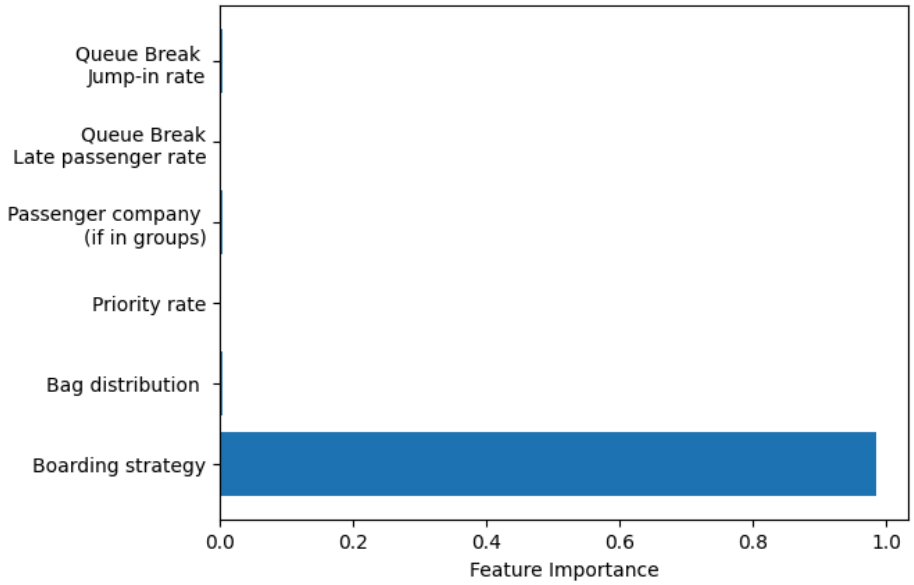


Figure 6: Feature importance of boarding time variables using RandomForest model

Specifically, XGBoost identified queue breaks and group travel as significant predictors, aligning with studies that emphasize passenger behavior's impact on boarding efficiency. Conversely, Random Forest highlighted the boarding strategy itself as the primary determinant, underscoring the literature's call for adaptable and context-specific strategies.

The variables that impact boarding time for different contexts have been discussed in many studies as the literature review presented. Although some studies achieve high levels of prediction, it is known that modelling the passenger behavior and the airport operations for different scenarios and contexts is not an easy task. The disagreement and the lack of consensus around which are the variables that most influence the process is a common sense around the literature about the boarding procedure subject which is coherent with the divergence between the importance of the variables achieved in this study. Nevertheless, considering that both Random Forest and XGBoost achieved 98% R-Squared and knowing the limitations of this study (only 72 samples, 3 boarding strategies and 5 variables) it would be superficial to affirm that both models are close to 100% as predictors. It could be caused by overfitting and it requires further investigation (next steps of this study). Another factor is the challenge to interpret machine learning models such as XGBoost and RandomForest. Although it can be done, it is not an easy task to provide a simple visual way to interpret how each variable relates to each other and how it influences the output (boarding time in this case).

There are several reasons that could explain the high values of the residuals and the low R_squared for the other algorithms (MLP, KNN, Linear Regression): First is the small sample as it was based on a screening DOE, aiming to illustrate and take first steps to investigate the problem of this research (24 runs for each of the three strategies that were simulated). For machine learning techniques, their capability to be good predictors is also associated with higher samples which can be achieved as this study evolves. The second reason is the low number of variables that were used in the models (only 5 with two states each). Based on those factors, the linear regression model is further analyzed. It showed a MAE of 486.4 seconds or 8 minutes and a Rsquared close to 0.5. The regression model is shown in Equation 1 and Figure 7 shows the model coefficients for the boarding time regression model.

$$boarding\ time\ (s) = 457.14 * boarding\ strategy + 73.9 * bag\ distribution + 26.5 * priority\ rate + 6.3 * queue\ break\ (late\ pax) - 21.5 * queue\ break\ (jump - in\ rate) - 22.2\ pax\ company$$

Equation 1: Boarding time regression model

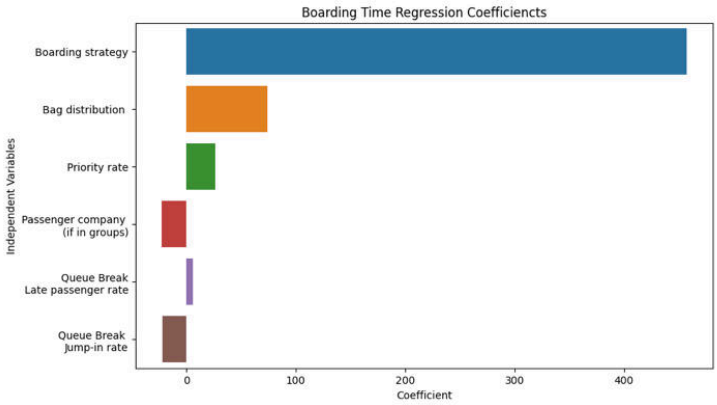


Figure 7: Coefficients of boarding time regression model

Although the R_squared is only close to 50% and then the coefficients only explain 50% of the boarding time variance, it can be seen that boarding strategy has the higher influence on the variance of boarding time: Steffen's was the strategy with the lowest values of boarding time followed by random. In consensus with the literature that often points "bags" as an important factor influencing boarding time, bag distribution is the second higher coefficient meaning that there is an influence on how the bags are distributed in the overhead bins (randomly or evenly) that affect boarding time. The other variables such as "priority rate and Queue-breaks due to late passengers" have low impact on the boarding time variance. One hypothesis is that as priority rate in the simulations were only varied from 0 to 25% of passengers and that interferences only varied from 0 to 5%. Higher variations could provide another effect, meaning that higher level of interferences could lead those variables to be more impactful in the explanation of boarding time variance. Queue jump-in rate and if passengers are travelling in groups or not impact negatively the variance of boarding time. This effect is probably related to low rates of interferences caused by jump-in and passengers travelling alone (tend to be faster) which tend to reduce boarding time.

Airlines can use these findings to refine boarding strategies, particularly by adopting dynamic methods. Machine learning models offer a data-driven approach to predict boarding times based on various factors, enabling airlines to make informed decisions about boarding procedures. By integrating real-time data and advanced predictive models, airlines can enhance operational efficiency and perceived LoS.

5. CONCLUSION

This study achieved the objective of taking steps to help answering which boarding strategy to set in order to minimize boarding time based on passenger behavior contributing by integrating advanced machine learning techniques to model and predict boarding times.

To do that a screening DOE was developed and applied to a model in Anylogic to simulate different scenarios based on three boarding strategies and machine learning techniques were applied in order to predict boarding time for a given boarding strategy. Results from Anylogic simulation show that Seteffen's strategy is the better choice for the context, taking 12minutes on average and a standard deviation of 0.02min to board 180 passengers in a A320. Between the machine learning techniques, although Random Forest and XGBoost presented the highest R_square it requires further investigations (overfitting analysis). Then a linear regression model was proposed with a R_squared close to 0.5 revealing that the boarding strategy and the way bags are distributed are the variables that most influence boarding time in consensus with the literature. The study is limited to scenarios based on one airplane (A320) and in three different boarding strategies. As next steps, using real data to improve the model would be a significant contribution and exploring the use of IoT sensors to monitor real time boarding dynamics can provide insights to improve the process' efficiency. Finally, modelling the passenger' behavior while boarding has several challenges and it can be improved as it was limited to five variables in this study (bag distribution, priority rate, interferences queue breaks & queue jump-in rate and if travelling alone or in groups). Some other variables to be considered could be interferences caused by passenger's themselves while looking for seats, gait/biometric

recognition or simply behavior issues when not following the required procedures established by airlines.

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