applied sciences

MDPI

Review

Prediction and Analysis of Airport Surface Taxi Time: Classification, Features, and Methodology

Jianan Yin [1,2], Mingwei Zhang [2], Yuanyuan Ma [2,*], Wei Wu [1,2], He Li [2] and Ping Chen [2]

[1] College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China; j.yin@nuaa.edu.cn (J.Y.); ww0111ky@163.com (W.W.)
[2] State Key Laboratory of Air Traffic Management System, Nanjing 210007, China
* Correspondence: mayuanyuan2121@126.com

Abstract: Airport arrival and departure movements are characterized by high dynamism, stochasticity, and uncertainty. Therefore, it is of paramount importance to predict and analyze surface taxi time accurately and scientifically. This paper conducts a comprehensive review of existing studies on surface taxi time prediction and analysis. Firstly, the overall research framework of surface taxi time prediction and analysis is categorized from three perspectives: taxi time type, movement type, and modeling method. Then, focusing on the two means of taxi time analytical modeling and simulation modeling, the existing mainstream models and methods are categorized, and the main ideas and scope of application of the various methods are analyzed. Finally, the paper presents the future development direction of surface taxi time prediction prospects. The research results are aimed at providing basic support and methodological guidance for reducing the uncertainty in airport surface operation and enhancing the level of control and decision-making ability of airport surface operation.

Keywords: airport surface; taxi time; predictive modeling; machine learning; review

check for updates

Citation: Yin, J.; Zhang, M.; Ma, Y.; Wu, W.; Li, H.; Chen, P. Prediction and Analysis of Airport Surface Taxi Time: Classification, Features, and Methodology. *Appl. Sci.* **2024**, *14*, 1306. https://doi.org/10.3390/app14031306

Academic Editors: David Fernández-Llorca, Suchao Xie and Nadia Giuffrida

Received: 4 December 2023
Revised: 1 February 2024
Accepted: 2 February 2024
Published: 5 February 2024

1. Introduction

The complex layout of large airports, dense traffic flow, and random external environmental disturbances often lead to airport congestion and flight delays. Congestion is primarily a result of either an overly dense distribution of aircraft on the surface or the airport's current relatively low operating capacity, which is unable to meet the high traffic demand generated by actual operations. Currently, there are two solutions to address the airport congestion problem. Firstly, physical measures to expand the available resources of the airport can be taken. This can be achieved by increasing the number of stands, expanding the terminal building, and adding new runways and taxiways, among other strategies. However, these physical measures come with challenges, as they require significant investments and have long completion cycles, making their implementation difficult. Alternatively, planning measures can be employed; these focus on reasonable control or scheduling of factors during airport surface operations, i.e., the safe and efficient deployment of aircraft operations on the field. Unlike physical measures, planning measures offer a more practical approach to increase the relative capacity and available resources of airports. By carefully planning critical aspects of the aircraft arrival and departure process, these measures can effectively enhance airport operations [1]. The basis of the deployment decision lies in the prediction of the taxi time, and accurate prediction enables effective and efficient deployment. Surface taxi time refers to the total operating time between the airport runway and aircraft stands for arrivals and departures; this serves as a crucial metric to assess airport surface operation efficiency.

The airport movement area is a complex network comprising stands, taxiways, runways, and the personnel and vehicles involved in flight services [2]. Upon arrival, an aircraft follows a designated taxi route, guided by air traffic controllers, to reach its assigned stand.

Similarly, for departures, aircraft are pushed back from the stands by tractors, they then taxi to the runway end, join the runway queue, and finally take off. This interconnects and constrains the runway system, taxiway system, and aircraft stands assignment system, forming a cohesive spatial link in aircraft operations [3]. Therefore, accurate prediction of surface taxi time can significantly reduce uncertainty in airport surface operations, optimize aircraft scheduling, and enhance airport surface controllability and efficiency.

Moreover, precise taxi time prediction plays a pivotal role in aircraft pushback control [3–6], taxi route optimization [7–10], runway scheduling, stand assignment optimization [5,11], and other essential aspects of aircraft arrival and departure processes. As we pursue the advancement of intelligent civil aviation and smart airports, the scientific and accurate prediction of aircraft surface taxi time gains tremendous importance in reducing uncertainty in airport surface operations. This improvement can enhance the level of control and decision-making capabilities of airport surface operations while contributing to reduced fuel consumption and emissions from aircraft.

This paper focuses on addressing the challenge of predicting airport surface taxi time. It conducts a comprehensive review of the current state of domestic and international research from various angles, including movement type, taxi time type, and modeling method. By summarizing the existing mainstream prediction models and methods, it aims to shed light on future research directions in this domain. The ultimate goal is to offer valuable methodological guidance and references to researchers in this field.

The rest of the paper is organized as follows. Section 2 categorizes taxi time research perspectives in terms of both research objects and research methods. Section 3 focuses on the modeling methods of surface taxi time and reviews the mainstream models and methods. Section 4 provides an outlook for future research and summarizes the paper.

2. Classification of Research Perspectives

In this section, we present a comprehensive categorization of the surface taxi time prediction research problem, taking into account three key perspectives: taxi time type, movement type, and modeling method. This approach considers both the research object and research method. Figure 1 shows the surface taxi time prediction and analysis research framework.

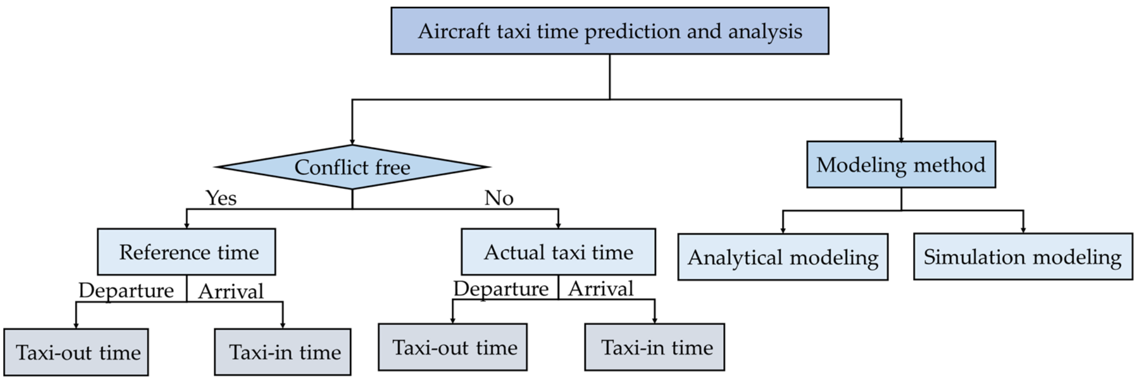

Figure 1. Research framework of surface taxi time prediction.

2.1. Type of Surface Taxi Time

As shown in Figure 2, a time mapping diagram for the taxiing phase is shown. Taxi time is defined as the time between the actual off-block time (AOBT)/actual landing time (ALDT) and the actual takeoff time (ATOT)/actual in-block time (AIBT).

From the perspective of taxi time type, surface taxi time prediction studies can be categorized into two main types: reference time analysis and actual taxi time prediction. Reference time is typically utilized as a reference for calculating additional time in taxi-phase, and the difference between the actual taxi time and the reference time is used to assess airport congestion and aircraft taxiing efficiency.

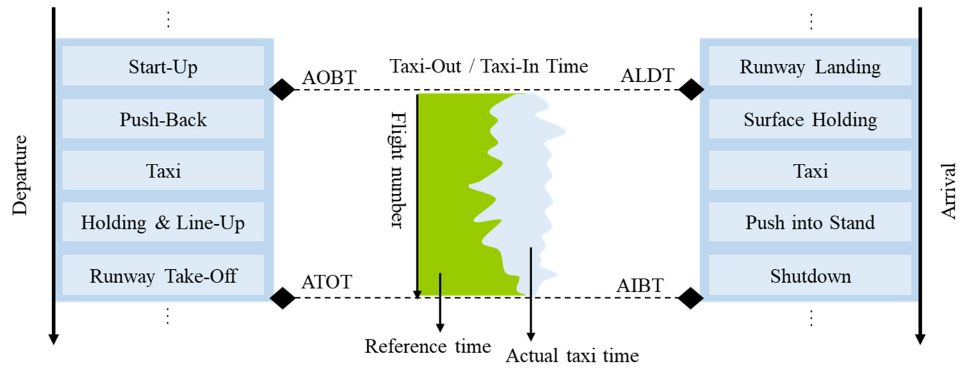

Figure 2. Time mapping of the taxiing phase.

There are three primary methods for estimating reference time: the FAA APO method, the regression modeling method [12–15], and the percentile method [16–18]. The difference between the actual taxi time and the reference time of an aircraft is then the additional time in taxi-phase.

Furthermore, some scholars have focused on predicting taxi times for arrival and departure aircraft, accounting for additional time in taxi-phase by calculating probability distributions of additional time in taxi-phase and takeoff time [19–23]. These predictions contribute to a more comprehensive understanding of taxi time variations and enable more effective management of additional time in taxi-phase at airports.

2.1.1. Reference Time

In this section, we introduce the methods for calculating the reference time of aircraft taxi movements, from the Aviation Policy and Planning Office (APO) within the FAA, and the Performance Review Unit (PRU) within EUROCONTROL.

(1) FAA APO method

The FAA defines reference time as the taxi duration of an aircraft under ideal operating conditions without any obstructions. That is, without encountering congestion on the surface, adverse weather conditions, or other factors that might affect the normal taxi time.

FAA APO has put forth a method for estimating reference time based on queueing theory [24]. The fundamental concept of this method involves categorizing flight data according to various parameters such as airline, arrival or departure aircraft type, operating season, airport, and actual gate. Subsequently, for each subgroup, a linear regression model is constructed to estimate the reference time, utilizing the departure and arrival queues as independent variables.

The constant term in the regression model represents the reference time; i.e., when an aircraft is pushed back from a stand without encountering any queues of aircraft either waiting to take off or taxi in. In other words, the regression model is established under the condition that the aircraft is not queued.

Figure 3 shows the steps of the FAA APO method for calculating unimpeded taxi-out time. The number of departure aircraft is usually set to one and the number of arrival aircraft is set to zero [13].

(2) EUROCONTROL PRU method

EUROCONTROL PRU monitors and reviews the performance of pan-European air navigation services, and utilizes saturation levels to calculate the reference taxi time from each stand to the runway [25]. The saturation level indicates the point at which the taxi time no longer decreases, even if the congestion level decreases.

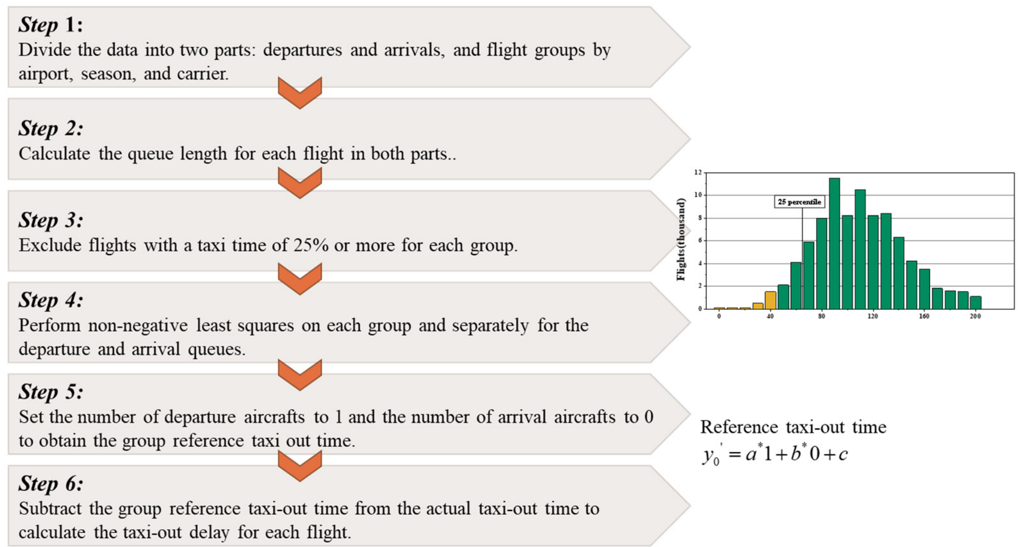

Figure 3. FAA APO method for determining unimpeded taxi-out time.

The method aims to calculate the reference taxi-out time for a set of similar flights. Initially, each flight is categorized according to the type of stand, the departure runway, and the congestion index, in which the congestion index represents the number of departures of other aircraft between the time a departure aircraft went off-block and its actual takeoff time. Subsequently, for each group of flights (e.g., the same stand–runway combination), the reference time is calculated by taking the truncated average of the flights within the group with lower congestion index values, taking into account the congestion index threshold. This involves setting a congestion index threshold for each group, then trimming flights within the group by applying the threshold on the congestion index. Subsequently, the truncated mean of the remaining flights in the group is calculated, averaging taxi-out times between the 10th and 90th percentiles. Then the surface movement delay, which is the difference between the average taxi-out time of all flights within the group and the previously determined reference time, is calculated. Finally, a more accurate result is obtained by performing a weighted average of all surface movement delay groups [13,26].

In estimating the reference taxi time, this method considers taxi distance; reference taxi time is estimated by applying the level of congestion associated with the surface travel time to the ground travel distance and surface operating conditions of an aircraft as it moves from a particular stand to the runway. In contrast to the FAA APO method, this approach incorporates taxi distance when estimating reference taxi-out time. Figure 4 shows the steps of the method used by the PRU to determine the reference time.

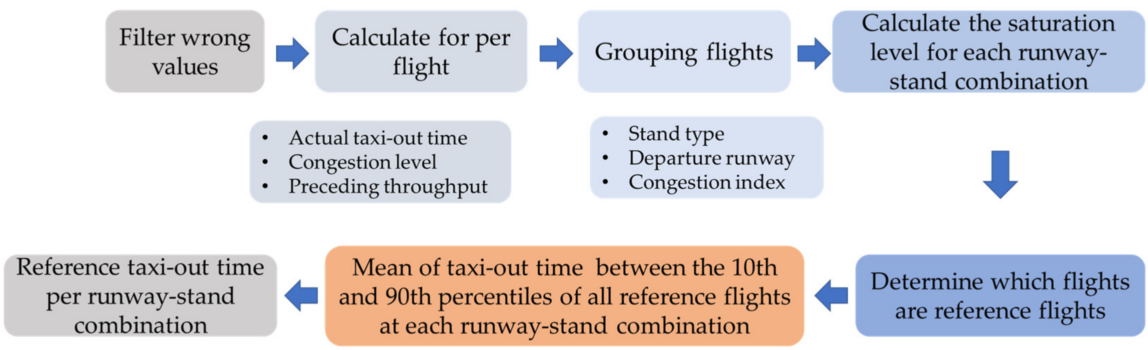

Figure 4. EUROCONTROL PRU method for determining unimpeded taxi-out time.

(3) Regression modeling method

Several scholars have proposed heuristic improvements to the FAA APO method, such as incorporating more independent variables to enhance the estimation of reference time.

Simaiakis et al. [12] developed a multivariate linear regression model based on historical data, providing estimates for the time it takes a departure aircraft to taxi from the stand to the runway head. Zhang [13] proposed an econometric regression model using a lognormal approach, resulting in more accurate predictions of reference time compared to the FAA APO method.

In a pioneering effort, Zhou et al. [14] considered runway resource utilization and selected the number of aircraft using the same runway for departure and arrival as an independent variable. They established a lognormal regression model to predict reference times for different aircraft types. Balakrishnan et al. [15] treated the aircraft departure process as a queuing system. They utilized variables such as pushback schedule, gate location, runway configuration, and weather conditions to construct a regression model predicting the estimated reference time. Their study revealed a significant correlation between the number of departure aircraft in the queue and additional time in taxi-phase.

(4) The percentile method

The percentile method is another commonly used approach for estimating reference time due to its simplicity in computation. Simaiakis et al. [16] estimated reference time as a normal random variable, assuming it to be equal to the mean of their estimation. Lee et al. [17] computed the reference time for an aircraft with the same combination of gates, locations, and runways by taking 10 percent of the actual taxi time as the reference time. Feng et al. [18], after analyzing factors influencing aircraft departure taxi time, proposed a measure of surface traffic state. Based on this indicator, they constructed a model for predicting reference time. The actual taxi time of aircraft within the same group with all measures lower than the congestion value is ranked from smallest to largest, and the aircraft ranked within 10–90% is selected. Subsequently, the average taxi time of the selected aircraft is calculated and taken as the reference time for that specific group.

(5) Other methods from the literature

Jeong et al. [27] devised a novel model for estimating reference time, utilizing the node-link structure of airports and Airport Surface Detection Equipment (ASDE) ground surveillance data. The data were organized based on taxiing sections, aircraft wake, and aircraft type. By calculating the reference time for each section and then summing them up, the total reference time for the aircraft was determined. Mirmohammadsadeghi et al. [28] conducted a comparative study of three methods for estimating reference time: a statistical regression, a percentile method, and an ASDE data monitoring method. The findings demonstrated that predictive models utilizing monitoring information were more effective and capable of swiftly identifying taxiway locations where delays were most likely to occur.

Furthermore, meta-heuristic algorithms have been employed to estimate reference time. Kim et al. [29] developed a meta-heuristic model using the tabu search method and genetic algorithms to calculate the shortest route from the gate to the takeoff point for an aircraft. They also incorporated the aircraft's average taxiing speed in that segment to estimate reference time. By optimizing gate assignments, they successfully minimized additional time in taxi-phase and reference time, contributing to improved efficiency in airport surface operations.

2.1.2. Actual Taxi Time

Using departing aircraft as an example, when an aircraft is unable to taxi unimpeded for takeoff, it typically encounters two situations that affect the taxi time. Firstly, due to the high number of aircraft operating on the surface, the aircraft must maintain a certain safety interval with other operating aircraft during taxiing. This safety measure impacts the taxiing speed, leading to prolonged taxi times. Additionally, the aircraft may encounter conflicts during taxiing, necessitating stops as per the controller's instructions, and waiting for the conflicts to be resolved. The combined effect of taxiing control restrictions and conflicts, and the time spent waiting in this queue at the end of the runway result in additional time ($T_{additional}$). Therefore, as shown in Figure 5, the total taxi time of an aircraft can be broken down into reference time and additional taxi time [30], as illustrated in Equation (1) below:

$$T_{actual} = T_{reference} + T_{additional} \tag{1}$$

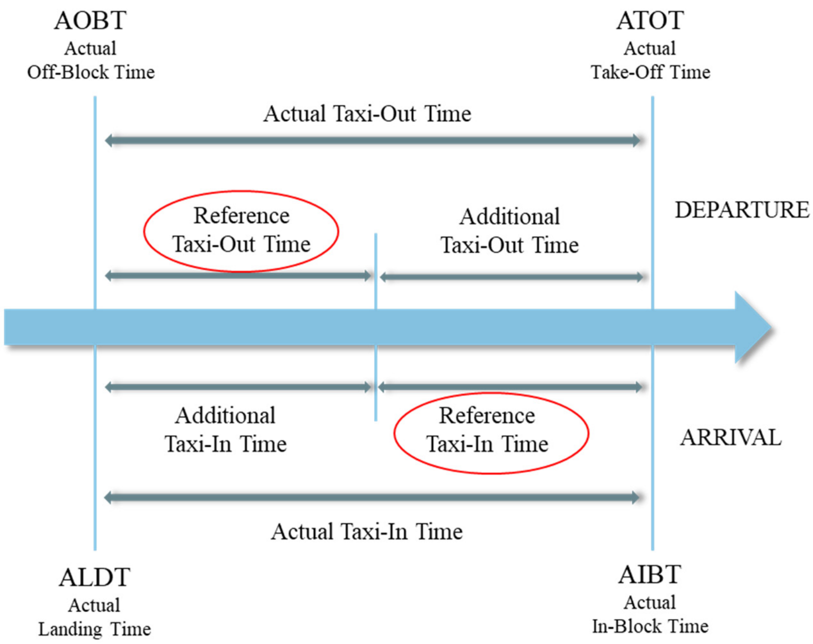

Figure 5. Definition of actual taxi time.

The variance between the actual taxi time and the reference time of an aircraft is referred to as the additional taxi time, which is also commonly known as additional time in taxi-phase. Researchers have used calculations based on probability distributions of takeoff delays and takeoff times to predict the taxi time. Welch et al. [19] employed accurate ground monitoring data to mitigate additional time in taxi-phase and offered optimization suggestions for runway allocation and departure sequencing to reduce taxi-out time. Futer et al. [20] developed a queuing model for aircraft departures and utilized a quantization matrix to compute taxi time by predicting takeoff time. Experimental results demonstrated that the application of this quantization matrix reduced the error in takeoff time estimation. Tu et al. [21,22] focused on estimating the degree of air traffic congestion and established a departure delay distribution model based on a genetic algorithm. They utilized a non-parametric estimation method to compute daily and quarterly trends of departure delays. Laskey et al. [23] developed a stochastic model to examine the relationship between flight delay components and the factors influencing delays. Using a Bayesian network approach, they predicted flight delay components, including departure delays.

2.2. Type of Movement

From the perspective of the movement category, surface taxi time prediction research is categorized into two main areas: arrival aircraft taxi time prediction and departure aircraft taxi time prediction. The arrival aircraft follows predetermined taxi routes set by the air traffic service unit (ATSU), resulting in relatively stable taxi times. Conversely, the departure process for aircraft is more complex and variable, making accurate prediction of departure taxi time vital in optimizing runway utilization and achieving flexible aircraft pushback control. There is a close correlation between aircraft pushback control, runway utilization optimization, and taxi time prediction. The goal of aircraft pushback control is to minimize taxi time, reduce fuel consumption, and improve takeoff efficiency. The goal of runway utilization optimization is to maximize runway usage efficiency, reduce wait time, ensure aircraft can take off and land smoothly as planned, and reduce congestion and delays. The goal of taxi time prediction is to accurately estimate how long an aircraft will be on the surface in order to better sequence the pushback and arrival of flights. Optimizing aircraft pushback control may involve adjustments to taxi speeds and routes, which can affect taxi time and runway utilization. Conversely, optimization of runway utilization may also reduce wait time and optimize taxi routes by adjusting the aircraft pushback sequence.

The specific arrival and departure process is shown in Figure 6. The arrival process encompasses the sequence of events in which an aircraft receives landing instructions from the tower controller, touches down on the designated runway, exits the runway via the fast departure route, and then taxis to the assigned parking stand under the guidance of the ground controller. At the parking stand, the aircraft undergoes maintenance and receives various ground services. On the other hand, the departure process involves receiving clearance instructions from the ground controller. The aircraft is then pushed back from its parking stand using a trolley or tractor and taxis to the runway gate along the designated taxiway, following the controller's instructions. Once the aircraft joins the queue of departing flights, it awaits its turn for takeoff. Finally, the aircraft follows the tower controller's instructions to approach the runway and complete the takeoff task [30].

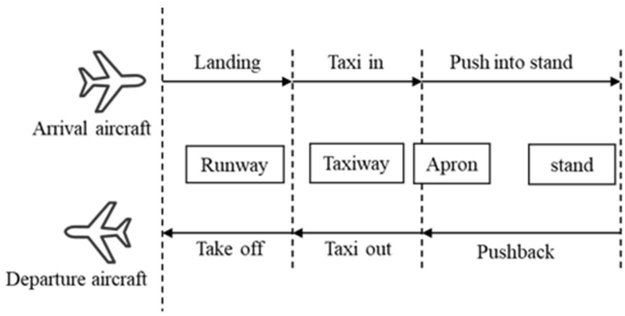

Figure 6. Aircraft arrival and departure process.

Furthermore, considering operational aspects, arrival aircraft have the advantage of directly taxiing into the stand without requiring a tractor, resulting in shorter taxiing durations. On the other hand, departure aircraft cannot directly face the apron during taxiing out and need tractors for pushback, leading to longer taxiing durations [31].

Due to the high dynamics and uncertainty of the surface departure process, current research efforts, both domestically and internationally, primarily focus on surface taxi time prediction for departure aircraft. This aspect can be further divided into two categories: surface taxi time prediction, which concentrates solely on the departure process; and surface taxi time prediction, which takes into account the influence of arrival aircraft.

2.3. Modeling Methodology

From the perspective of modeling methods, surface taxi time prediction research can be broadly categorized into two approaches: analytical modeling [2–7,30–72] and simulation modeling [8–10,12,16–18,20,27–29,73–77].

Analytical modeling relies on historical data analysis, in which different feature variables are selected to establish surface taxi time prediction models. Mainstream methods encompass regression algorithms, neural networks, support vector machines, integrated learning, fuzzy rule systems, and other machine learning techniques.

Simulation modeling involves modeling and analyzing the surface departure process. There are two primary aspects: (1) Fast-time simulation methods (e.g., SIMMOD, AIRTOP, LINOS, and other mainstream commercial software) accurately simulate the physical structure and topological modeling of the surface, enabling high-precision simulation of the surface running process. Statistical analysis is then performed on the simulation data to determine surface taxi times. (2) Queuing theory-based prediction models. The departure process of aircraft is divided into two stages: taxiing from the stand to the runway-end waiting point (considered as unimpeded time or fixed taxi time), and waiting in the departure queue for takeoff. For the first phase, the average taxi time for different aircraft positions can be derived from historical data or established surface posture measures. For the second phase, appropriate queuing models are used to calculate waiting time at the runway end to establish a prediction model for takeoff waiting time [5].

In addition, there is some literature [7–10] that combines taxi time prediction with taxi route optimization to build taxi route optimization models with the objective of finding the shortest taxi time, or solving the taxi time by the shortest route.

3. Mainstream Models and Methods

In this section, our focus is on exploring the various modeling methods used for surface taxi time prediction. We will review existing research in this area and categorize the representative literature based on the specific types of methods employed. By doing so, we aim to provide a comprehensive overview of the different approaches used to predict surface taxi time.

3.1. Model Feature Variables

In this section, we present an enumeration of various common features found in the literature, which are categorized based on their relevance as model inputs. These features are divided into two main groups: airport and aircraft operational features, as well as airport surface traffic flow features.

3.1.1. Airport and Aircraft Operational Features

Table 1 lists several common aircraft and airport operational features, including categorical features such as runway configuration mode, airline category, aircraft type, and operating hours; numerical features such as aircraft taxiing distance, turning angle/count of turns; and binary variables such as arrival or departure.

Table 1. Features of airport and aircraft operational information.

Features	Type	Literature
Runway configuration mode	Categorical	[3,32,40–42,48,55,56,60,61,63,70]
Airline category	Categorical	[3,31,32,34,41]
Aircraft taxiing distance	Numerical	[2,4–6,31,38,41,45,47,50,51,56,57,60,61,63,67,68]
Aircraft type	Categorical	[3,30,31,44,51,60,66]
Arrival or departure	Binary	[45–47]
Turning angle/count of turns	Numerical	[45,47,56,68]
Operating hours	Categorical	[6,31,32,38,53,59,60,66]

3.1.2. Airport Surface Traffic Flow Features

Table 2 lists the features related to traffic flow at the airport surface. Departure/arrival queue size refers to the number of aircraft at the head of the runway waiting to take off or waiting to land during the current aircraft taxi time period. Number of arrivals and departures refers to the number of aircraft taxiing in or out during the current aircraft taxi time period.

Table 2. Features of airport surface traffic flow information.

Features	Type	Literature
Departure queue size	Numerical	[4,32,33,36,39,40,42,49,57]
Arrival queue size	Numerical	[33,40,66]
Number of arrivals and departures	Numerical	[2,4,41,42,44,45,53,61,63]
Number of aircraft pushed back in the same time slot as the aircraft	Numerical	[67–69]
Number of departure and arrival aircraft taxiing on the same segment as the aircraft	Numerical	[67,69]

3.2. Analytical Modeling

3.2.1. Linear Regression Model

Linear regression models determine the parameters of the model by fitting the relationship between multiple independent and dependent variables, thus regressing back to the original equation to predict the trend of the dependent variable. As shown in Table 3, the domestic and international literature on the application of regression models to surface taxi time prediction over the last 20 years is summarized.

Table 3. Features of airport surface traffic flow information.

Literature	Authors	Approach	Features Considered in the Model
[36]	Idris et al. (2001)	Multiple linear regression	Surface traffic flow: departure queue size, scheduled/actual delay time, takeoff/landing time, gate arrival times Surface operation rules: departure/arrival runways, downstream restrictions, capacity
[38]	Kistler et al. (2009)	Simple linear and logarithmic regression	Airport layout: taxiing distance Surface traffic flow: combined surface traffic flow Surface operation rules: number of stands
[40]	Chauhan et al. (2010)	Multiple linear regression	Surface traffic flow: queue size, scheduled takeoff time Surface operation rules: runway configuration mode
[41]	Jordan et al. (2010)	Multiple linear regression	Airport layout: taxiing distance, runway orientation Surface traffic flow: congestion variables Surface operation rules: airline
[42]	Clewlow et al. (2010)	Multiple linear regression	Surface traffic flow: departure queue size, number of arrival aircraft Surface operation rules: departure terminal, runway configuration Others: weather
[44]	Deshpande et al. (2012)	Multiple linear regression	Surface traffic flow: congestion variables Surface operation rules: the route, destination, and departure airports Others: aircraft type
[45]	Ravizza et al. (2013)	Multiple linear regression	Airport layout: taxiing distance Surface traffic flow: amount of traffic on the surface of the airport while the aircraft is taxiing Surface operation rules: departure or arrival Others: angle of turn
[48]	Lordan et al. (2016)	Log-linear regression	Surface traffic flow: this takes into account the effect on the taxi time of surface operations carried out during the taxi time period of the aircraft, such as queuing before takeoff Surface operation rules: these take into account factors related to taxi time operations and define a set of binary variables representing the combination of the start and end points of each run, including the combination of the fast exit and the stand (for arrivals) and the combination of the stand and the runway (for departures).
[49]	Zhao et al. (2016)	Multiple linear regression	Surface traffic flow: number of aircraft in the departure queue, number of arrival and departure aircraft
[53]	Liu et al. (2018)	Multiple linear regression	Surface traffic flow: number of arrival aircraft, number of departure aircraft Surface operation rules: operating hours
[54]	Yin et al. (2018)	Linear models, support vector machines, integrated learning	Surface traffic flow: 21 characteristics such as surface instantaneous flow indices (SIFIs), surface cumulative flow indices (SCFIs), aircraft queue length indices (AQLIs), and slot resource demand indices (SRDIs).
[61]	Li et al. (2021)	Lasso regression	Airport layout: taxiing distance Surface traffic flow: number of arrival aircraft, number of departure aircraft Surface operation rules: runway operating pattern
[63]	Li et al. (2021)	Stepwise regression method	Airport layout: taxiing distance Surface traffic flow: number of arrival aircraft, number of departure aircraft, actual capacity sorties, flow control information Surface operation rules: runway operation mode

The impact of departure queue size on taxi time was initially considered a significant factor and incorporated into the characteristic variables of the model. Subsequently, researchers also introduced the number of arrival aircraft to study the combined effects of these two influencing factors on taxi-out time. In 2001, Idris et al. [36] pioneered the study of surface traffic flow characteristics' influence on taxi time and proposed the concept of the departure queue. They published the first paper on predicting taxi time based on a multiple linear regression model. Their analysis revealed that the departure queue size had the strongest correlation with the change in taxi-out time. However, the model's limitations in strategic ground traffic management arose from the lack of consideration of the relationship between additional time in taxi-phase and capacity constraints resulting from the runway service process. Building upon this foundation, Clewlow et al. [42] in 2010 employed the number of arrival aircraft as an important predictor variable and characterized departure traffic using the number of departing aircraft rather than the number located on the surface. They established a multiple linear regression model to assess the factors affecting aircraft taxi-out time. Experimental results indicated a correlation between the number of arrival aircraft and taxi-out time, which grew stronger with increased interactions between departure and arrival aircraft on the airport surface. However, the correlation between the number of arrival aircraft and taxi-out time was found to be weaker than that between the departure queue and taxi-out time. By replacing the number of departing aircraft on the surface with departure traffic characteristics, the prediction accuracy of the model significantly improved. In 2016, Zhao et al. [49] further enhanced the FAA APO method by simultaneously considering both the number of aircraft in the departure queue and the number of arrival aircraft. They developed a multivariate linear regression model, which aimed to capture a more comprehensive understanding of the factors influencing taxi-out time.

The selection of characteristic variables for studying taxi time encompasses a wide range of factors, from basic arrival and departure traffic characteristics such as departure queue size to more diverse elements such as runway configuration, turn angle, weather conditions, taxi route, and taxiing distance. In 2010, Chauhan et al. [40] expanded the scope of characteristic variables by incorporating runway configuration patterns and expected takeoff time, in addition to the departure queue size factor. They developed a multivariate regression equation to better predict taxi time. In 2012, Deshpande et al. [44] brought innovation to the field by introducing new characteristic variables such as route, carrier, destination and origin airports, congestion levels, and aircraft type. These variables offered a more comprehensive understanding of the factors influencing taxi time. In 2013, Ravizza et al. [45] analyzed variations in taxi time from the perspective of aircraft taxiing speed. They classified the aircraft departure taxiing distance into three sections: the pushback section, straight-line taxiing section, and turn section. Furthermore, they introduced the concept of the turn angle characteristic for the first time. The turning angle, distance, and surface traffic volume of aircraft passing through these three sections were identified as factors affecting taxiing speed. To predict taxi time accurately, they proposed a prediction model that combined taxiway structural characteristics with historical taxi time information using multiple linear regression analysis. Actual data from experiments demonstrated a strong correlation between the number of arrival aircraft and taxi-out time, with higher correlation levels observed in runway operation modes where the arrival and departure runways crossed more frequently.

To improve the accuracy of surface taxi time estimation, researchers have delved into comparing different surface taxi time prediction methods and have employed more complex functions to model the factors affecting taxi time. In 2009, a study by two scholars [38] explored the application of two functional forms: simple linear regression and logarithmic regression, to analyze the relationship between macro-traffic factors and taxi time. The test results revealed that the simple linear model performed better than the log-linear model, with differences staying within 1 min of the observed data. In 2021, Li et al. [61] conducted a comparative analysis of two prediction models; one based on traditional statistics and the other on Lasso regression, a machine learning approach. The results demonstrated the superiority of the machine learning approach, as it provided a higher model fit. Moreover, by employing the DBSCAN clustering algorithm to segment the time, the model's performance further improved.

In order to discuss the relevance of the characteristic variables and the degree of influence on the model, in 2010, Jordan et al. [41] proposed a statistical method to extract key variables from a large number of characteristic variables. The interactions between the factors affecting the taxi time were considered to form new variables with the factors themselves, and then the sequential forward floating subset selection method (SFFSS) was used to select the optimal set of variables from the combination of variables in order to construct the multivariate linear regression model. In 2016, Lordan et al. [48] used a log-linear regression analysis method to develop a predictive model for aircraft taxi time. The model considered two sets of independent variables: one set of route-specific (route-related) variables and one set of interaction-specific variables. The experimental results show that the route-related variables are effective characteristic variables and the inclusion of interaction variables can increase the predictive ability of the model; in addition, the route-related variables affect the model to a greater extent than the interaction variables affect the model. In 2018, Liu et al. [53] used a multiple regression model to discuss the magnitude of the correlation between each influencing factor and taxi time. Through the analysis of the regression coefficients in the regression equation, it was found that the number of arrival and departure aircraft, the operation time period, and the taxi-out time had a significant correlation, and the correlation increased with the increase of the number of arrival and departure aircraft. In 2021, Li et al. [63] used the stepwise regression method to establish the taxi time prediction model to study the effects of these parameters on taxi time at different airports.

3.2.2. Neural Network

Table 4 provides a summary of the representative literature from the last 10 years that utilizes the neural network method to predict and analyze taxi time, both domestically and internationally. In 2012, Chatterji et al. [43] developed a taxi time prediction model by employing state data indicators of the airport surface as inputs to the neural network. In 2019, Dalmau et al. [59] created a prediction model using a combination of gradient boosting trees and neural networks. They further conducted an analysis to determine the importance of feature variables. In 2020, Li et al. [60] proposed a novel prediction model called spatio-temporal environmental deep learning (STEDL). They considered three major feature variables, namely time, space, and environment, as inputs to the model. The STEDL model consists of three sub-models, namely the time flow sub-model, the spatial sub-model, and the environmental sub-model. Comparatively, this model outperformed other machine learning algorithms in terms of predictive performance. In 2022, He [33] extended the consideration of feature variables and classified 12 of them into numerical and categorical variables. Analyzing the magnitude of correlation between these variables and taxi time, they constructed a taxi-out time prediction model based on a deep multilayer feed-forward neural network. To accurately predict flight delays, Shao et al. [71] proposed a vision-based solution that leverages various vehicle trajectories and environmental sensor data in the airport apron area. By constructing a situational awareness map and employing the end-to-end deep learning architecture TrajCNN (Convolutional Neural Network), they captured spatial and temporal information, achieving high-precision forecasting of departure delays. This framework has demonstrated successful results, with a prediction error of approximately 18 min, at Los Angeles International Airport. This is crucial for airlines as traditional methods struggle to accurately predict departure delays.

In order to discuss the influence of the strength of the correlation of feature variables on the prediction accuracy of the model, in 2022, Huang et al. [67] proposed a taxi time prediction model based on the BP neural network to analyze the influence of weak, medium, and strong correlation factors on the prediction, and the results show that the 5-element combination model (medium and strong) has the best fit, and the addition of weak correlation factors reduces the accuracy of the prediction. However, the stability and accuracy of the model are not good, and the neural network is not sensitive to the initial thresholds and weights in prediction. Aiming at the above problems, on the basis of previous research, Huang et al. [69] proposed an improved BP neural network method prediction model based on SSA (Sparrow Search Algorithm), which improves the accuracy of model prediction by using the Sparrow Search Algorithm to obtain the optimal thresholds and weights for the neural network. Subsequently, Xia [68] constructed a taxi-out time prediction model based on correlation analysis, classified the influencing factors into significant correlation factors and moderate correlation factors, and also comparatively analyzed the model prediction results based on SVR and BP neural network. The experimental results show that for both models the prediction accuracy of the seven-element combination (significantly correlated factors and moderately correlated factors) model is the best, and the prediction accuracy of the SVR-based model is higher than the prediction accuracy of the BP neural network-based model.

Table 4. Summary of representative literature on neural networks.

Literature	Authors	Approach	Features Considered in the Model
[43]	Chatterji et al. (2012)	Neural network	Airport layout: gate to runway distance Surface traffic flow: average taxi-out delay in the previous 15 min, number of departure aircraft on the surface during departure taxiing, average taxi-out delay on the same runway in the previous 15 min, average taxi-out delay to the same fix in the previous 15 min Others: wind angle, airport arrival rate set by ATC
[5]	Yin (2018)	Support Vector Regression—BP neural networks	Airport layout: taxiing distance Surface traffic flow: number of arrival and departure aircraft during the average pre-departure taxi time at the same stand, surface congestion Others: minimum taxi time at the same stand
[59]	Dalmau et al. (2019)	Gradient-boosted trees and neural networks	Surface traffic flow: congestion, delay status Others: weather, time of day
[60]	Li et al. (2020)	Spatio-Temporal Environment Deep Learning (STEDL)	Surface traffic flow: airport capacity, number of taxiing aircraft, air traffic control Airport layout: taxiing distance Surface operation rules: runway configurations Others: different time periods, weather, aircraft type
[67]	Huang et al. (2022)	Neural network	Airport layout: the taxiing distance of departure aircraft Surface traffic flow: Number of departure aircraft taxiing at the same time, number of arrival aircraft taxiing at the same time, number of departure aircraft pushed back from a stand at the same time, average taxi time in half-hour time slices, average taxi time in 1 h time slices
[33]	He (2022)	Neural network	Surface traffic flow: departure instantaneous traffic index, arrival aircraft queue length, departure aircraft queue length, departure slot resource requirement index, departure cumulative traffic index Others: flight arrival-to-departure ratio, visibility, cloud base height, temperature, dew point, wind direction, wind speed
[68]	Xia (2022)	Support Vector Regression, neural network	Surface traffic flow: number of aircraft pushed back from a stand at the same time, number of aircraft taking off at the same time, number of arrivals at the same time, the average taxi time within 1 h, delays Airport layout: taxiing distance, number of turns, number of corners Others: time slots where departure aircraft are taking off
[69]	Huang et al. (2022)	Improved BP neural network based on SSA	Surface traffic flow: number of departure aircraft taxiing at the same time, number of arrival aircraft taxiing at the same time, number of departure aircraft pushed back from a stand at the same time, half-hourly average taxi-out time

Aircraft taxi time is influenced by a myriad of complex and diverse factors, encompassing both linear features such as taxiing distance and nonlinear features such as surface congestion patterns. Due to this complexity, the relationship between taxi time and characteristic variables cannot be entirely explained by a linear or nonlinear model alone. Consequently, using a single prediction method with one model may fail to capture the different behavioral characteristics present in the actual data. To overcome the limitations of a single model and harness the strengths of various models, a combined model approach can be employed to enhance prediction capabilities. In 2018, Yin [5] introduced a Support Vector Regression-BP neural network-based taxi time prediction model. This combined model utilized a feature vector set consisting of variables such as the number of arrival and departure aircraft during the average pre-takeoff taxi time of the same aircraft stand, taxiing distance, minimum taxi time of the same aircraft stand, and the degree of surface congestion. The model applied Support Vector Regression (SVR) to uncover linear relationships within the feature vector set, while using the BP neural network to explore nonlinear relationships. The results demonstrated that employing this combined model significantly improved prediction accuracy compared to using a single SVR model or a single BP neural network model in isolation. By integrating the complementary aspects of SVR and the BP neural network, the combined model effectively addressed the challenges posed by the diverse factors affecting taxi time and offered more accurate predictions.

3.2.3. Support Vector Machine

Table 5 shows a compilation of recent research on the application of Support Vector Machine (SVM) in taxi time prediction. Scholars commonly approach taxi time prediction in two stages, or they utilize the improved Support Vector Regression (SVR) method for modeling. SVR, being the regression version of SVM, finds application in both nonlinear and linear regression, making it a widely used technique in taxi time prediction.

Table 5. Summary of representative literature on support vector machines.

Literature	Authors	Approach	Features Considered in the Model
[2]	Meng et al. (2015)	KNN (K Nearest)-SVR	Airport layout: taxiing distance Surface traffic flow: number of aircraft taxiing out from the same runway at the off-block time, number of aircraft using the same runway for takeoff and landing during the taxi-out time, average taxi-out time from the same runway in the 15 min before the off-block time, number of aircraft expected to take off and number of aircraft expected to arrive during the taxi-out time
[50]	Feng et al. (2017)	KNN (K Nearest)-SVR	Airport layout: taxiing distance Surface traffic flow: number of arrival and departure aircraft on the same runway, average taxi time on the same runway for 15 min before the off-block time
[54]	Yin et al. (2018)	Linear models, support vector machines, integrated learning	Surface traffic flow: 21 characteristics such as surface instantaneous flow indices (SIFIs), surface cumulative flow indices (scfi), aircraft queue length indices (AQLIs), and slot resource demand indices (SRDIs)
[4]	Lian et al. (2018)	Support Vector Regression	Airport layout: taxiing distance Surface traffic flow: Length of departure queue on the taxiway, number of arrival aircraft during the taxi-out time Others: scheduled takeoff time
[5]	Yin (2018)	Support Vector Regression—BP neural network	Airport layout: taxiing distance Surface traffic flow: number of arrival and departure aircraft during the average pre-departure taxi time at the same stand, surface congestion Others: minimum taxi time at the same stand
[57]	Lian et al. (2018)	Two Improved Support Vector Regression Methods	Surface traffic flow: departure queue length, number of aircraft that may arrive during taxi time, departure delay Airport layout: taxiing distance Others: planned takeoff time, actual pushback time
[65]	Liu et al. (2021)	ARIMA (differential autoregressive moving average)—SVR	Surface traffic flow: number of aircraft taxiing on the same runway during taxiing out, the sum of departure and arrival aircraft using the same runway during taxiing out, the sum of the number of aircraft that were taxiing and the number of departure aircraft when the aircraft was pushed back form a stand, sum of aircraft taxiing out when the aircraft was pushed back from a stand, the sum of aircraft pushed back from a stand during taxiing out and aircraft arriving on the same runway
[68]	Xia et al. (2022)	Support Vector Regression, neural network	Surface traffic flow: number of aircraft pushed back from a stand at the same time, number of aircraft departing at the same time, number of aircraft arriving at the same time, delays Airport layout: taxiing distance, number of turns, number of corners Others: average taxi time in 1 h, time slots in which departure aircraft are at the takeoff time

In previous studies, the characteristic variable of the number of arrival and departure aircraft during the taxi time period is usually estimated using the expected takeoff or landing time of the aircraft. This method is reasonable when the airport surface traffic is more stable, but in the case of more flight delays, the number of aircraft calculated by this method may differ significantly from the actual number of arrival and departure aircraft. Therefore, in order to predict the taxi time more accurately, the set of feature variables in the model needs to be optimized, and the number of arrival and departure aircraft during the taxi time period can be predicted by using statistical or machine learning methods with actual data. In 2015, Meng et al. [2] conducted real-time and static prediction of taxi time, respectively, and used K-nearest-neighbors and Support Vector Regression methods to forecast the taxi time in real-time. That is, firstly, the K-nearest neighbor (KNN) method is used to predict the number of aircraft taking off from the same runway during the taxi-out time period, which is combined with other influencing factors to form a set of feature variables as model inputs, and the Support Vector Regression method is used to predict the taxi-out time. On this basis, in 2017, Feng et al. [50] similarly divided the taxi time prediction into two stages but optimized the previous study. In contrast to the method of directly constructing the SVR model in the literature [2], this literature grouped the data according to the aircraft's off-block time. The experimental structure shows that the prediction model using the KNN-SVR method is superior to the direct construction of the SVR nonlinear regression prediction model, and KNN is more suitable for predicting the number of aircraft departing from the same runway during the taxi-out time period than the SVR method, while SVR is more suitable for predicting the taxi-out time than KNN, and it has a higher prediction accuracy after grouping the data.

The above-mentioned studies have demonstrated the effectiveness of combined models and improved SVR methods in optimizing taxi time prediction. However, some scholars have achieved even greater advancements in prediction accuracy by focusing on enhancing the SVR method itself. In 2019, Lian et al. [4] utilized the least squares Support Vector Regression method to predict taxi-out time and further optimized its parameters using the improved firefly algorithm. Building upon this research, in the same year, Lian et al. [57] established a taxi-out time prediction model employing two improved Support Vector Regression (SVR) methods based on swarm intelligence algorithms: the particle swarm algorithm (PSO) and the firefly algorithm. Historical data validation revealed that departure delay significantly influenced taxi-out time. The improved SVR methods, particularly the optimized SVR method based on the improved firefly algorithm (IFA), exhibited enhanced prediction accuracy. Additionally, these methods demonstrated strong performance in handling abnormal taxi-out time states. Through the application of advanced optimization techniques, such as the improved firefly algorithm and swarm intelligence algorithms, researchers have effectively improved the accuracy of taxi time prediction and enhanced the ability to handle complex and challenging prediction scenarios.

From the existing studies on aircraft taxi time, it becomes evident that taxi time exhibits continuity, linearity, and autocorrelation within its time series. However, the intricate nature of airport surface operations often leads to nonlinear fluctuations in taxi time. To address these challenges, Liu et al. [65] conducted an analysis of the time series and modeled its linear components using the ARIMA (Autoregressive Integrated Moving Average) method to obtain predicted values and residuals. They further applied Support Vector Regression (SVR) to model the nonlinear behavior of the residuals. The experimental results revealed that this method significantly improved the prediction accuracy, which reached up to 90%. By adopting a hybrid approach that combines ARIMA for linear modeling and SVR for nonlinear modeling, the researchers effectively captured both the continuous and linear aspects of taxi time series while also addressing the nonlinear fluctuations.

3.2.4. Ensemble Learning

Ensemble learning accomplishes the task by constructing multiple learners; the two most common types of ensemble learning are Bagging and Boosting. Table 6 summarizes research on the application of ensemble learning algorithms in taxi time prediction over the last five years. In 2018, Yin et al. [54] established a macro network topology from the perspective of aggregation, and compared the accuracy of the linear regression, support vector machine, and random forest three machine learning methods; and the results show that the prediction accuracy of the random forest model is significantly better than the other two models under one month training samples. In 2021, Zhao et al. [6] combined the takeoff rate saturation curve to establish a departure aircraft taxi-out time prediction model based on random forest to optimize the control of pushback rate. Wang et al. [64] for the first time considered the runway operation mode, cheap/non-cheap airlines and aircraft speed characteristics, compared five prediction models, Multi-Layer Perceptron (MLP), Linear Regression (LR), Polynomial Regression (PR), Gradient Boosting Regression Trees (GBRT), and Random Forest (RF), and the results showed that the random forest-based prediction model was superior to other prediction models. In addition, the important features are extracted from the random forest model using backward exclusion, which is a quantitative analysis of the importance of features that is rarely seen in previous studies. Pham et al. [72] considered the controller's decision preferences and achieved high-precision taxi-out time prediction using both random forest regression and linear regression. In 2022, Zhang et al. [66] established a prediction model based on random forest regression and kernel density estimation, and used the kernel density estimation method to fit the set of results predicted by the decision tree with probability distributions, to obtain the probability density function of the taxi time; this method can analyze the probability distribution of the taxi time of a single aircraft while predicting the uncertainty of the taxi time. Zhao et al. [32] selected the XGBoost algorithm to construct the arrival and departure aircraft taxi time prediction model, this algorithm is better than the random forest and support vector machine algorithms and at the same time, the impact of the sample data volume on the accuracy of the prediction time is analyzed for the first time.

Table 6. Summary of representative literature on integrated learning.

Literature	Authors	Approach	Features Considered in the Model
[54]	Yin et al. (2018)	Linear models, support vector machines, random forest	Surface traffic flow: 21 characteristics such as surface instantaneous flow indices (SIFIs), surface cumulative flow indices (scfi), aircraft queue length indices (AQLIs), and slot resource demand indices (SRDIs)
[55]	Diana (2018)	Ensemble Machine Learning, Least Squares, Penalty Algorithms	Surface traffic flow: number of aircraft ready to take off, takeoff requirements, available airport capacity Surface operation rules: runway configurations Others: approach conditions
[6]	Zhao et al. (2021)	Random forest	Surface traffic flow: number of surface operation periods, number of arrival and departure aircraft Airport layout: taxiing distance Others: minimum taxi times for the same stand
[64]	Wang et al. (2021)	Random forest	Surface operation rules: characterization of aircraft and airport operations Surface traffic flow: characterization of airport congestion Others: characterization of average aircraft speed, characterization of weather information
[72]	Pham et al. (2021)	Random forest	Airport layout: taxiing distance Surface traffic flow: traffic density mapSurface operation rules: runway configurationsOthers: weather features, aircraft type, estimated taxi time
[66]	Zhang et al. (2022)	Random forest	Surface traffic flow: traffic flow related variables (surface departure instantaneous flow/surface departure cumulative flow/takeoff time gap demand index/departure queuing index/entry queuing index) Others: pushback time related variables (pushback month/pushback period), surface flight related variables (flight number/aircraft type/stand)
[32]	Zhao et al. (2022)	XGBoost algorithm	Surface traffic flow: number of aircraft taxiing at the same time on the surface, length of departure queue Surface operation rules: runway number, stand Others: the airline, type of aircraft, time period, inclement weather, whether or not crossing the runway, whether or not cross-taxiing, number of passes through the HS, whether or not cross-taxiing, number of passes through the HS

3.2.5. Fuzzy Rule System

Currently, the majority of taxi time predictions focus on representing the dynamics and complexity of taxi time. Among machine learning methods, the fuzzy rule system has shown higher accuracy in taxi time prediction compared to statistical methods and other machine learning approaches. Table 7 summarize some of the studies applying fuzzy rule system in taxi time prediction. In 2014, Ravizza et al. [47] compared and analyzed the results of multivariate linear regression, least median squared linear regression, Support Vector Regression, M5 model tree, and TSK fuzzy model, and the results showed that the TSK fuzzy rule system model outperforms the other models in terms of prediction accuracy. In 2017, Obajemu et al. [51] utilized a type-2 fuzzy logic system to establish a taxi time prediction model with the innovative introduction of speech information and, compared to the traditional one-layer fuzzy system, the method improves the taxi time prediction accuracy and generalization ability, with stronger robustness and accuracy. Subsequently, Chen [56] improved the previous work; after mathematically processing the influencing factors of taxi time delays, a multi-objective fuzzy rule-based system was added to the uncertainty factors in the aircraft taxiing process in the historical data in order to reduce the delays and conflicts in the taxiing process, which in turn made the taxi time prediction more accurate and resilient. For the uncertainty of taxi time, in 2018, Brownlee et al. [7] proposed the Fuzzy-QPPTW flight taxi route assignment method, which is based on the fuzzy system method and time window algorithm to estimate the taxi time and its uncertainty, so as to combine the taxi route assignment with the taxi time prediction.

Table 7. Summary of representative literature on fuzzy rule systems.

Literature	Authors	Approach	Features Considered in the Model
[47]	Ravizza et al. (2014)	TSK fuzzy rules	Airport layout: taxiing distance, taxiing turn angle Others: departure or arrival, flight number characteristics, and some less important factors
[51]	Obajemu et al. (2017)	Type-2 fuzzy logic system	Surface traffic flow: number of aircraft stopped during taxiing, total number of taxiing aircraft, Airport layout: taxiing distance Others: arrivals/departures, large aircraft/small aircraft Surface operation rules: mode of operation at the airport when the aircraft starts taxiing
[56]	Chen (2017)	The multi-objective fuzzy rule system	Surface operation rules: mode of airport operation (one/two runways used) Airport layout: total taxiing distance and its logarithmic transformation, distance on a straight-line segment, total angle of turn along the route and its logarithmic transformation Surface traffic flow: the number of aircraft taxiing on the surface at the time of commencement of taxiing by an aircraft, and the number of aircraft stopping to taxi while an aircraft is taxiing on the surface Others: type of movement (arrival/departure), whether or not a pushback maneuver has been performed

3.2.6. Other Methods

Some other advanced machine learning methods have also shown excellent performance in taxi time prediction. As can be seen from Table 8, the research methods have gradually evolved from linear models in the early years to machine learning methods such as reinforcement learning and decision trees.

In 1995, Shumsky et al. [34] first proposed the correlation between different influencing factors and taxi-out time, taking the categories of airlines, surface traffic flow, runway selection, and arrival and departure capacity demand as the characteristic variables, of which surface traffic flow and the number of departure aircraft are the most critical influencing factors, based on which dynamic and static linear models were established to predict the taxi time, respectively. The results show that the dynamic linear model has better prediction performance. In order to better realize the dynamic estimation of taxi time, in 2018, Xing et al. [58] established a dynamic estimation model of the taxi time of departure aircraft based on Bayesian nets by real-time processing of new data. The experimental results show that compared with the static Bayesian net model, the dynamic estimation model has higher accuracy, and the change rule of the taxi-out time can be derived from the analysis of the changes in the indicators.

Table 8. Summary of representative literature on other methods.

Literature	Authors	Approach	Features considered in the Model
[34]	Shumsky et al. (1995)	Linear model	Surface operation rules: runway selection Surface traffic flow: surface traffic flow, arrival and departure capacity requirements Others: airline category
[39]	Balakrishna et al. (2010)	Intensive learning	Surface traffic flow: the number of aircraft, departure traffic flow, and departure queue size Others: average taxi time, time of day
[46]	Diana et al. (2013)	Survival and vulnerability analysis	Surface traffic flow: blockage delays, departure/arrival delays, capacity utilization Others: good or bad weather
[55]	Diana et al. (2018)	Ordinary least square (OLS)	Surface traffic flow: number of aircraft ready to take off, takeoff requirements, available airport capacity Surface operation rules: runway configuration Others: approach conditions
[58]	Xing et al. (2018)	Bayesian net	Surface traffic flow: flight density, flight delays, surface traffic conditions, traffic distribution Surface operation rules: aircraft stand groups Others: variable taxi times for departure flights
[70]	Herrema et al. (2018)	Decision tree	Surface traffic flow: congestion level, saturation level, number of departures in the last 20 min Surface operation rules: de-icing station, departure station, runway heading Others: reference time, month, actual takeoff time, actual gear removal time
[3]	Qian (2019)	Gradient boosted tree	Surface traffic flow: number of aircraft taxiing in the same time period, number of aircraft arrive and departure during the taxiing period Airport layout: taxiing distance Surface operation rules: runway number, terminal, aircraft stand number Others: scheduled takeoff time, airline, destination, registration number, aircraft type, average taxi time for the first 15 min
[30]	Lin (2020)	Gradient boosting regression algorithm	Airport layout: taxiway length Surface traffic flow: dynamic departure demand, simultaneous arrival and departure flights Others: average taxi time of departure aircraft 15 min before pushback, aircraft type
[62]	Chen et al. (2021)	Decision tree	Airport layout: taxiing distance Surface traffic flow: congestion variables (number of aircraft departing from the same runway and the instantaneous flow of arrivals and departures) Others: average taxi time of departure aircraft 15 min before pushback, aircraft type category, airline category, aircraft stand impact index
[31]	Tang et al. (2022)	Gradient boosting regression algorithm	Airport layout: taxiing distance Surface traffic flow: surface traffic, arrival runways, Surface operation rules: inter-area operations Others: operating hours, aircraft type, carrier attributes

In 2010, Balakrishna et al. [39] proposed a method that is suitable for the stochastic nature of departure operations, using a nonparametric reinforcement learning algorithm to predict the trend of the average taxi-out time 30–60 min before takeoff. Compared to the traditional parametric regression-based approach, this method has better robustness against stochastic factors during aircraft departure operations. Since the factors affecting taxi time may not be expressed in parametric and semiparametric models, in 2013, Diana et al. [46] developed a survival and vulnerability analysis model to analyze the relevant factors related to excessive taxi time. The results showed that two factors: obstruction delays and high airport capacity utilization were more likely to contribute to excessive taxi times than other influencing factors.

Through comparative experiments, Diana et al. [55] and Herrema et al. [70] found that with different models, the same feature variable inputs may also lead to different perspectives of predicted time result outputs. Diana et al. [55] analyzed the ordinary least squares and ridge models and concluded that the ordinary least squares and ridge models performed better than the other integrated learning models in predicting the taxi-out time. Herrema et al. [70] compared four machine learning methods—neural networks, decision trees, reinforcement learning, and multilayer perceptual machines—for taxi time prediction, and the results of the model evaluation showed that the decision tree-based prediction model had the best accuracy and the smallest mean error.

Previous studies have shown that the combined model has a greater propelling effect on the accuracy of taxi time prediction. In 2019, Qian [3] first built models based on searching for improved K-nearest neighbors and based on a non-parsimonious Bayesian classifier to predict the taxi route of aircraft surface and the number of flights with short takeoff times, respectively. After the results obtained from the prediction and other influencing factors constituting the set of feature variables, the aircraft taxi time is then predicted based on the gradient boosting tree method.

From the perspective of feature selection, some scholars have improved the taxi time prediction model. In 2020, Lin [30] divided the aircraft departure process into the process from the ramp to the taxiway to the runway to the final takeoff, and then analyzed the factors affecting the taxi time in terms of the reference time, taxiway congestion waiting time, and departure queuing and waiting time involved in these processes, so as to select the feature variables. By comparing the four regression algorithms, it can be seen that the prediction model based on the gradient boosting regression algorithm has the best fitting effect. Existing studies rarely consider the effect of the interaction between features on taxi time. However, in 2021, Chen et al. [62] innovatively introduced interaction features; that is, the use of the product of two features with one-time feature to constitute a candidate feature set. They then compared the K nearest neighbor, Support Vector Regression, and decision tree methods. They found that the decision tree algorithm was the best method to construct a taxi time prediction model, compared with using only one-time feature. In 2022, Tang et al. [31] introduced "cross-region features" to construct a feature set. They compared six commonly used machine learning methods, and selected the gradient boosting regression tree with the highest degree of model fit to construct a taxi time prediction model. They then analyzed the importance level of each feature. After analyzing the degree of importance of each feature, it was concluded that the surface flow feature is the most important, with the highest correlation with the taxi time, and the newly introduced "cross-area feature" ranks third in importance among all the features. This indicates that this feature is meaningful for the prediction of taxi time.

3.3. Simulation Modeling

Compared with machine learning methods based on historical data analysis and other methods, simulation modeling methods are relatively weak in terms of both efficiency and convenience. Table 9 counts the research of this method in the last 20 years in terms of taxi time prediction, and the main methods include constructing a prediction model based on queuing theory or using a fast time simulation method to simulate the actual operating state of the surface.

Table 9. Summary of representative literature on simulation modeling.

Literature	Authors	Methodology
[74]	Pujet et al. (1998)	Queuing theory
[73]	Gotteland et al. (2001)	Genetic algorithm
[75]	Carr et al. (2002)	Stochastic parametric simulation
[20]	Futer (2006)	Queuing theory
[76]	Gao et al. (2007)	Queuing theory
[8]	Gupta et al. (2010)	Mixed-integer linear programming
[16]	Simaiakis et al. (2010)	Queuing theory
[9]	Dong et al. (2011)	Subdivision and delimitation (math.)
[17]	Lee et al. (2015)	Fast time simulation methods
[18]	Feng et al. (2016)	Queuing theory
[12]	Simaiakis et al. (2016)	Queuing theory
[2]	Meng et al. (2016)	Queuing theory
[10]	Dong (2018)	Taxi route optimization model
[77]	Postorino et al. (2019)	Mixed-integer linear programming model
[27]	Jeong et al. (2020)	Node-link model

To research the model based on queuing theory, in 1998, Pujet et al. [74] used a stochastic queuing model to predict the taxi time, defined the departure taxi time as the fixed time of taxiing on the taxiway and the time of waiting in the departure queue of the runway, estimated the fixed taxi time and focused on the prediction of the time of the aircraft waiting in line in the departure queue by using a stochastic queuing model. In 2007, Gao et al. [76] developed a simulation-based aircraft departure queuing model to test different emission scenarios related to taxi-out time, and the results of the study showed that congestion is an important factor contributing to the long taxi-out time. In 2010, Simaiakis et al. [16] divided the aircraft departure taxi-out time into three parts—the reference time, the time spent queuing up in the departure queue time, and delay time due to congestion caused by ramp and taxiway interactions—modeling the aircraft departure process as a queuing system. In 2016, Feng et al. [18] divided the departure aircraft taxiing out process into two phases: from the stand to the runway end waiting point and waiting for takeoff at the runway end waiting point. On the basis of analyzing the factors affecting the departure aircraft taxi-out time, a measure of surface traffic state is proposed, based on which a reference time prediction model is constructed, and the process of aircraft waiting at the runway end and runway providing service is simulated as a $M/G/1/\infty$ stochastic service system in order to predict the waiting time for takeoff of the aircraft. Meng et al. [2] performed real-time prediction and static prediction of taxi-out time, respectively. For the static prediction, a queueing theory-based taxi-out time prediction model was developed. Simaiakis et al. [12] modeled the aircraft departure process, and the model consists of two main parts: one is the estimation of the distribution of the reference time, which is the estimation of the time for the departure aircraft to pushback to the head of the runway from the stand based on historical data. One is a runway system queuing model based on the

D/E/1 queuing system, where the aircraft taxi-out time is considered as a function of the size of the departure queue in order to predict the takeoff time of the aircraft and estimate the taxi time. The above prediction of taxi time based on the queuing model theoretically investigates the estimation method and principle of taxi time, but the model does not have good robustness in terms of the treatment of random factors, the prediction accuracy needs to be improved, and the experimental results differ greatly from the actual ones.

In 2002, Carr et al. [75] established a parameter matrix by considering airport throughput, departure congestion, average taxiing delay time, etc., and simulated aircraft departure queuing process through stochastic parameters as a way to predict taxi time under the flow restriction. In 2015, Lee et al. [17] applied the linear optimization sequencing method to develop a discrete-event fast simulation tool, LINOS, to simulate the current airport state and during each run of the simulation, the simulated taxi time of each aircraft is calculated by LINOS. In order to assess the performance level of the method, the prediction results were compared with the results of using a machine learning approach based on historical data and with the results of a reference time-based trajectory projection method, which showed that the model prediction accuracy was comparable to that of the support vector machine method, and outperformed the linear regression algorithm and the reference time based trajectory projection method. This method, which relies on simulation software to predict the taxi time, requires simulation software with very high simulation capability to realize, and the parameters of the software need to be constantly adjusted according to the actual operation status of the surface to realize the simulation requirements. Therefore, although the prediction accuracy of this method is high, it has the disadvantages of high cost and time-consuming adjustment of parameters.

In order to dynamically predict the taxi time so as to better control the taxiing process to reduce carbon emissions, in 2019, Postorino et al. [77] established a mixed-integer linear programming model containing an uncertain set of taxi times from the perspective of flight sequencing and runway scheduling. The taxi-out time is predicted by simulating the taxiway queue during aircraft departure. In 2020, Jeong et al. [27] established an reference time model based on the airport node-link model. The data were categorized according to taxiing section, aircraft wake, and flight type; and the total taxi time of the aircraft was obtained by calculating the reference time of each section on the node-link model.

In addition, some scholars combined taxi time prediction with taxi route optimization. In 2010, Gupta et al. [8] used Dijkstra's algorithm to solve for the shortest paths on the runway and taxiway operation network, and used mixed-integer linear programming methods to generate flight routes that satisfy a given time window with minimum total delays and no conflicts, and solved for the taxi time by shortest paths. In 2011, Dong et al. [9] considered the airport surface as a network structure of nodes and arcs and comprehensively considered factors such as conflict avoidance, safety intervals, and taxiway operation rules to find the optimal taxi route with the objective of minimizing the sum of taxi time and waiting time by using the branch-and-bound method. In 2018, Dong et al. [10] established a taxi route optimization model based on the conflict-point selection and avoidance mechanism and used an heuristic algorithm to solve the optimal taxi route with the objective of minimizing the taxi time by using the heuristic algorithm for dynamic and static planning of taxi routes. The experimental results show that the algorithm can reduce the conflicts of aircraft on the optimal taxi route in order to reduce the taxi time.

3.4. Performance Metrics

Regarding the evaluation metrics of prediction, Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) are commonly used error metrics to assess the deviation between predicted and actual values. Among them, RMSE is the root mean square value of the difference between the predicted value and the actual value, MSE is the mean value of the square of the difference between the predicted value and the actual value, and MAE is the mean value of the absolute value of the difference between the predicted value and the actual value, and the smaller the value of the three indicates that the prediction accuracy is higher. Furthermore, a smaller error is usually acceptable in actual taxi time prediction. The prediction accuracy in three ranges of 1, 3, and 5 min is also used to measure the accuracy of the prediction results as well. Table 10 lists the model predictors from the literature [4,17,61,64,65]. Models in the selected literature include Multilayer Perceptron (MP), Linear Regression (LR), Polynomial Regression (PR), Gradient Boosting Regression Trees (GBRT), Random Forest (RF), Generalized Linear Model (GLR), Support Vector Regression (SVR), Adaptive Least Squares Support Vector Regression based on improved Firefly algorithm (IFA-LSSVR), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), Linear and Linear Optimized Sequencing (LINOS), Multi Regression (MR), Spatial—Temporal—Environment Deep Learning Model (STEDL), Autoregressive Integrated Moving Average (ARIMA).

Table 10. Evaluation of model prediction accuracy.

Performance Metrics	Range of Values
MAE	[0.26, 2.81]
RMSE	[0.901, 3.98]
<1 min (%)	[26.04, 33.80]
<3 min (%)	[53.98, 84.71]
<5 min (%)	[76.77, 95.66]

In the literature [64], compared to the other four models, the RF model has the best predictive performance, its handling of outliers is better, and it shows better generalization ability on various datasets. Additionally, the RF model is less prone to overfitting compared to some other models due to the voting of multiple trees. Meanwhile, the literature [64] uses feature importance selection in RF to provide a quantitative measure of the contribution of model features, and also provides guidance for optimizing the model and improving explanatory and predictive performance. For the application of the discrete-event fast-time simulation tool to predict the taxi time, it can be seen that the LINOS prediction accuracy is comparable to that of the SVM [17]. In the literature [4,61,65], the combined model showed higher prediction accuracy. For the treatment of abnormal glide time states, the SVR algorithm based on IFA optimization shows good prediction performance. The use of IFA allows the model to learn the data features more efficiently, which improves the accuracy and robustness in predicting the abnormal glide time states [4]. The three main sub-models of the STEDL model consist of a spatial-temporal model and an environmental model (based on a convolutional neural network), and a fully connected spatial model. This structure allows the STEDL model to predict aircraft taxi times more comprehensively and accurately. The spatial-temporal model takes into account the spatial-temporal variations of the aircraft, the environmental model takes into account external factors such as weather and airport traffic, and the convolutional neural network and fully-connected layer help to efficiently learn and integrate the various features, thus improving the prediction performance [61]. Compared with a single prediction model, the slip time prediction model based on the combination of ARIMA and SVR methods can better cope with the linear and nonlinear features of the data. The characterization role of SVR function for nonlinear data is used, and the machine learning approach is applied to the combined model, which effectively reduces the error of single ARIMA model in predicting the time series and improves the prediction accuracy [65].

4. Discussion and Conclusions

This paper documents the problem of taxi time prediction in airport operations. Firstly, from the perspectives of taxi time type, movement type, and modeling method, the research framework for taxi time prediction is systematically organized. This includes a review of the relevant literature on reference time and actual taxi time. From the analysis and simulation modeling aspects, the main focus is on categorizing and summarizing the current mainstream taxi time prediction models and methods, both domestically and internationally.

Currently, the predominant analysis and modeling approaches for taxi time prediction are based on machine learning methods including linear regression, neural networks, support vector machines, ensemble learning, and fuzzy rule systems. Linear regression is a simple yet effective model that assumes a linear relationship between input features and output. In the context of taxi time prediction, it can be used to capture the linear correlation between input features and taxi times. It is suitable for situations where a linear relationship exists between input features and output, yielding favorable results for simple datasets and problems. Neural networks, being a powerful model capable of learning complex nonlinear relationships, are particularly advantageous in taxi time prediction. In this context, neural networks can automatically learn the intricate relationships among input features, making them suitable for various data patterns. They excel in addressing complex taxi time prediction problems characterized by strong nonlinear relationships. However, it is important to note that neural networks require substantial amounts of data and parameter tuning for optimal performance. Support vector machines, on the other hand, leverage the identification of an optimal hyperplane in feature space for classification or regression. In taxi time prediction, support vector machines demonstrate efficiency in handling high-dimensional feature spaces. They are applicable to scenarios involving high-dimensional feature spaces and complex boundaries, performing well even with small sample sizes. Ensemble learning, which is a methodology involving the combination of predictions from multiple models such as random forests or gradient boosting trees, enhances overall performance in taxi time prediction. This approach is versatile, suitable for various data patterns and problems, and it mitigates overfitting risks while improving generalization capabilities. Fuzzy rule systems employ fuzzy logic to model systems with inherent fuzziness. In the context of taxi time prediction, these systems consider uncertainty and fuzziness, providing a more flexible approach to address complex traffic situations. Fuzzy rule systems are particularly suitable for problems requiring the handling of fuzzy and uncertain information, offering adaptable modeling techniques.

Similarly, the selection of data is crucial for the performance and generalization ability of machine learning models. Regardless of how powerful a model is, if the quality of input data is poor, the model's performance will be adversely affected. In the feature selection process, highly correlated features can be excluded by correlation analysis to reduce redundant information. Then, feature selection techniques, such as statistical methods (ANOVA and correlation tests) and model-based methods [64] (LASSO regression and feature importance of decision trees), are applied to identify the features that have the greatest impact on the target variable. This allows for more accurate selection of features that are relatively independent and provide independent information without reducing predictive effectiveness, while controlling the number of features and reducing model training costs.

To improve the reference for further research on taxi time prediction and analysis, the future research outlook is as follows:

(1) Research on scientific feature extraction methods for taxi time prediction: Existing studies mainly consider input features such as surface arrival/departure flow rates, taxiing distance, pushback time, and departure queue length for predicting taxi time based on historical data. However, other factors such as surface congestion, human factors [72,78], and traffic management strategies that influence taxi time have received limited attention. Future studies should conduct in-depth analyses of factors affecting taxi time to determine the characteristic variables for the prediction model. Additionally, when grouping the data, researchers can explore different classification bases, such as grouping historical data into scenarios for different weather conditions, to establish prediction models for surface taxi time under specific weather conditions. This can enhance feature refinement and improve the predictability of arrival and departure taxiing processes. At the same time, consideration should be given to how

to select features more accurately without reducing the effectiveness of forecasting. When selecting features, there is a trade-off between the number of features and the cost of model training. Too many features may lead to dimensionality catastrophe, increasing the training complexity and computational cost of the model. Moreover, choosing appropriate and highly relevant features is crucial for improving prediction.

(2) Improvement of prediction performance under incomplete data conditions: The quality of the data is critical to the performance of the model, but the current surface data suffer from low quality and missing data, and consideration should be given to how to improve the accuracy of predictions under incomplete data conditions. In addition to improving data quality through handling outliers and imputing missing values, another viable approach is to focus on constructing more informative features to enhance the model's interpretability. Furthermore, when it comes to model selection, considering the incompleteness of the data, it is advisable to opt for robust models such as tree-based models and deep learning models.

(3) Research on distributional uncertain taxi time prediction methods: Current research on surface taxi time prediction mainly revolves around deterministic prediction, providing a single fixed value as the prediction result. However, considering the high dynamics and uncertainty of the surface taxiing process, future research can explore probabilistic prediction methods to address uncertain taxi time distribution [66]. This approach can enhance the robustness and flexibility of surface operation control by considering the probabilistic nature of taxi time predictions.

Author Contributions: Conceptualization and determination of research direction, design of research framework, J.Y. and M.Z.; Design and implementation of the entire classification system for the literature related to taxi time prediction, J.Y.; Feature extraction and analysis of the literature related to taxi time, Y.M. and W.W.; Original draft preparation, J.Y. and W.W.; Classification of research methods, categorization and review of methods in the literature related to taxi time prediction, J.Y. and Y.M.; Investigation, H.L. and P.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (No. 52002178), States Key Laboratory of Air Traffic Management System (No. SKLATM202206) and Natural Science Foundation of Jiangsu Province (No. BK20190416).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lian, G. *Research on Aircraft Departure Dynamic Pushback Control Method Based on Predicted Taxi-Out Time*; Harbin Institute of Technology: Harbin, China, 2019.
2. Meng, J. *Research on Aircraft Taxi-Out Time Prediction for A-CDM*; Civil Aviation University of China: Tianjin, China, 2016.
3. Qian, J. *Research on the Aircraft Pushback Time Decision Based on Machine Learning*; Nanjing University of Aeronautics and Astronautics: Nanjing, China, 2019.
4. Lian, G.; Zhang, Y.; Xing, Z.; Luo, Q.; Cheng, S. A new dynamic pushback control method for reducing fuel-burn costs: Using predicted taxi-out time. *Chin. J. Aeronaut.* **2019**, *32*, 660–673. [CrossRef]
5. Yin, M. *Research on Optimization Strategy of Arport Surface Operation Based on Taxi Time Prediction*; Nanjing University of Aeronautics and Astronautics: Nanjing, China, 2018.
6. Zhao, W.; Wan, L.; Tian, Y.; Peng, Q. Research on pushback rate control method based on taxi time forecast. *Aeronaut. Comput. Techni.* **2021**, *51*, 22–26.
7. Brownlee, A.E.I.; Weiszer, M.; Chen, J.; Ravizza, S.; Woodward, J.R.; Burke, E.K. A fuzzy approach to addressing uncertainty in airport ground movement optimisation. *Transp. Res. Part C Emerg. Technol.* **2018**, *92*, 150–175. [CrossRef]

8. Gupta, P.; Subramanian, H.; Pant, R. Generation of optimized routes and schedules for surface movement of aircraft on taxiways. In Proceedings of the 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, Fort Worth, TX, USA, 13–15 September 2010; p. 9211.
9. Dong, Y.; An, R. Optimization of aircraft taxiing time. *J. Transp. Syst. Eng. Inf. Technol.* **2011**, *11*, 141–146.
10. Dong, B. Optimization of aircrafts taxiing path based on the choice of conflict point avoidance mechanism. *Sci. Technol. Eng.* **2018**, *18*, 334–338.
11. Bagamanova, M.; Miguel, M.M. A multi-objective optimization with a delay-aware component for airport stand allocation. *J. Air Transp. Manag.* **2020**, *83*, 101757. [CrossRef]
12. Simaiakis, I.; Balakrishnan, H. A queuing model of the airport departure process. *Transp. Sci.* **2016**, *50*, 94–109. [CrossRef]
13. Zhang, Y.; Wang, Q. Methods for determining unimpeded aircraft taxi time and evaluating airport taxiing performance. *Chin. J. Aeronaut.* **2017**, *30*, 523–537. [CrossRef]
14. Zhou, J.; Zhao, Y.; Liu, H.; Zhou, Q. Research on Aircraft Unimpeded Taxi Out Time. *Comput. Simul.* **2021**, *38*, 53–57+77.
15. Simaiakis, I.; Balakrishnan, H. Queuing models of airport departure processes for emissions reduction. In Proceedings of the AIAA Guidance, Navigation, and Control Conference, Chicago, IL, USA, 10–13 August 2009; p. 5650.
16. Simaiakis, I.; Pyrgiotis, N. An analytical queuing model of airport departure processes for taxi out time prediction. In Proceedings of the 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, Fort Worth, TX, USA, 13–15 September 2010; p. 9148.
17. Lee, H.; Malik, W.; Zhang, B.; Nagarajan, B. Taxi time prediction at Charlotte Airport using fast-time simulation and machine learning techniques. In Proceedings of the 15th AIAA Aviation Technology, Integration, and Operations Conference, Dallas, TX, USA, 22–26 June 2015; p. 2272.
18. Feng, X.; Meng, J. Aircaft taxi-out time prediction based on queuing theory. *J. Nanjing Univ. Aeronaut. Astronaut.* **2016**, *48*, 772–780.
19. Cooper, W.W., Jr.; Cherniavsky, E.A.; DeArmon, J.S.; Foster, G.; Mills, M.J.; Mohleji, S.C.; Zhu, F.Z. Determination of Minimum Push-Back Time Predictability Needed for Near-Term Departure Scheduling Using DEPARTS. In Proceedings of the 4th USA/Europe Air Traffic Management Seminar ATM, Santa Fe, NM, USA, 4–7 December 2001; EUROCONTROL: Bruxelles, Belgium; US Federal Aviation Administration: Washington, DC, USA, 2001.
20. Futer, A. Improving Etms' Ground Time Predictions. In Proceedings of the IEEE/AIAA 25TH Digital Avionics Systems Conference, Portland, OR, USA, 15–19 October 2006; pp. 1–12.
21. Tu, Y.; Ball, M.O.; Jank, W.S. Estimating flight departure delay distributions—A statistical approach with long-term trend and short-term pattern. *J. Am. Stat. Assoc.* **2008**, *103*, 112–125. [CrossRef]
22. Tu, Y. *Air Transportation System Performance: Estimation and Comparative Analysis of Departure Delays*; University of Maryland: College Park, MD, USA, 2006.
23. Laskey, K.B.; Xu, N.; Chen, C.H. Propagation of delays in the national airspace system. *arXiv* **2012**, arXiv:1206.6859.
24. Federal Aviation Administration Office of Aviation Policy and Plans. *Documentation for the Aviation System Performance Metrics: Actual Versus Scheduled Metrics*; Federal Aviation Administration Office of Aviation Policy and Plans: Washington, DC, USA, 2002.
25. EUROCONTROL Performance Reviews Unit. Unimpeded Taxi-Out Time–Technical Note. Available online: http://ansperformance.eu/references/methodology/unimpeded_taxi-out_time.html (accessed on 18 June 2020).
26. Capelleras, L. *Additional Taxi-Out Time Performance Indicator Document*; EUROCONTROL: Bruxelles, Belgium, 2015.
27. Jeong, M.; Eun, Y.; Jeon, D.; Bang, H. Unimpeded taxi-time prediction based on the node–Link model. *J. Aerosp. Ina. Syst.* **2020**, *17*, 591–602. [CrossRef]
28. Mirmohammadsadeghi, N.; Hotle, S.; Trani, A.; Gulding, J. Taxi Event Extraction from Surveillance for Surface Performance Evaluation. *J. Air Transp.* **2020**, *28*, 28–35. [CrossRef]
29. Kim, S.H.; Feron, E.; Clarke, J.P. Gate assignment to minimize passenger transit time and aircraft taxi time. *J. Guid. Control. Dyn.* **2013**, *36*, 467–475. [CrossRef]
30. Lin, Y. *Research on Aircraft Pushback Control Based on Taxi-Out Time Prediction in Busy Airports*; Nanjing University of Aeronautics and Astronautics: Nanjing, China, 2020.
31. Tang, X.; Ding, Y.; Zhang, S.; Ren, S.; Wu, J. Taxi-in time prediction of arrival flight. *J. Beijing Univ. Aeronaut. Astronaut.* **2022**, 1–10. [CrossRef]
32. Zhao, Z.; Feng, S.; Song, M.; Hu, L.; Lu, S. Prediction Method of Aircraft Dynamic Taxi Time Based on XGBoost. *Adv. Aeronaut. Sci. Eng.* **2022**, *13*, 76–85.
33. He, Y. *Research on Optimization Method of Airport Surface Operation Based on Flight Taxi-out Time Prediction*; Nanjing University of Aeronautics and Astronautics: Nanjing, China, 2022.
34. Shumsky, R.A. *Dynamic Statistical Models for The Prediction of Aircraft Take-Off Times*; Massachusetts Institute of Technology: Cambridge, MA, USA, 1995.
35. Hebert, J.E.; Dietz, D.C. Modeling and analysis of an airport departure process. *J. Aircr.* **1997**, *34*, 43–47. [CrossRef]
36. Idris, H.; Clarke, J.P.; Bhuva, R.; Kang, L. Queuing model for taxi-out time estimation. *Air Traffic Control. Q.* **2001**, *10*, 1–22. [CrossRef]
37. Signor, D.B.; Levy, B.S. Accurate OOOI data: Implications for efficient resource utilization. In Proceedings of the IEEE/AIAA 25th Digital Avionics Systems Conference, Portland, OR, USA, 15–19 October 2006; pp. 1–12.

38. Kistler, M.; Gupta, G. Relationship between airport efficiency and surface traffic. In Proceedings of the 9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO) and Aircraft Noise and Emissions Reduction Symposium (ANERS), Hilton Head, SC, USA, 21–23 September 2009; p. 7078.
39. Balakrishna, P.; Ganesan, R.; Sherry, L. Accuracy of reinforcement learning algorithms for predicting aircraft taxi-out times: A case-study of Tampa Bay departures. *Transp. Res. Part C Emerg. Technol.* **2010**, *18*, 950–962. [CrossRef]
40. Chauhan, A. Modeling and Predicting Taxi Times at Airports. Master's Thesis, University of South Florida, Tampa, FL, USA, 29 October 2010.
41. Jordan, R.; Ishutkina, M.A.; Reynolds, T.G. A statistical learning approach to the modeling of aircraft taxi time. In Proceedings of the 29th Digital Avionics Systems Conference, Salt Lake City, UT, USA, 3–7 October 2010; pp. 1.B.1-1–1.B.1-10.
42. Clewlow, R.; Simaiakis, I.; Balakrishnan, H. Impact of arrivals on departure taxi operations at airports. In Proceedings of the AIAA Guidance, Navigation, and Control Conference, Toronto, ON, Canada, 2–5 August 2010; p. 7698.
43. Chatterji, G.; Zheng, Y. Wheels-off time prediction using surface traffic metrics. In Proceedings of the 12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Indianopolis, IN, USA, 17–19 September 2012; p. 5699.
44. Deshpande, V.; Arıkan, M. The impact of airline flight schedules on flight delays. *Manuf. Serv. Oper. Manag.* **2012**, *14*, 423–440. [CrossRef]
45. Ravizza, S.; Atkin, J.A.D.; Maathuis, M.H.; Burke, E.K. A combined statistical approach and ground movement model for improving taxi time estimations at airports. *J. Oper. Res. Soc.* **2013**, *64*, 1347–1360. [CrossRef]
46. Diana, T. An application of survival and frailty analysis to the study of taxi-out time: A case of New York Kennedy Airport. *J. Air Transp. Manag.* **2013**, *26*, 40–43. [CrossRef]
47. Ravizza, S.; Chen, J.; Atkin, J.A.D.; Stewart, P.; Burke, E.K. Aircraft taxi time prediction: Comparisons and insights. *Appl. Soft Comput.* **2014**, *14*, 397–406. [CrossRef]
48. Lordan, O.; Sallan, J.M.; Valenzuela-Arroyo, M. Forecasting of taxi times: The case of Barcelona-El Prat airport. *J. Air Transp. Manag.* **2016**, *56*, 118–122. [CrossRef]
49. Zhao, Y.; Tang, H. Aircraft unimpeded taxi time in Beijing Capital International Airport. *J. Civ. Aviat. Univ. China* **2016**, *34*, 1–5.
50. Feng, X.; Meng, J. Flight Taxi-out Time Prediction Based on KNN and SVR. *J. Southwest Jiaotong Univ.* **2017**, *52*, 1008–1014.
51. Obajemu, O.; Mahfouf, M.; Allerton, D.; Weiszer, M.; Chen, J. A type-2 fuzzy modelling framework for aircraft taxi-time prediction. In Proceedings of the IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 16–19 October 2017; pp. 1–6.
52. Li, X. *Research of the Taxi Time Prediction Method for Arrived Flights*; Civil Aviation University of China: Tianjin, China, 2017.
53. Liu, J.; Yin, M.; Zhu, X.; Zeng, Y. Capacity of Uncontrolled Intersection Based on Monte Carlo Simulation. *J. Wuhan Univ. Technol.* **2018**, *42*, 195–200.
54. Yin, J.; Hu, Y.; Ma, Y.; Xu, Y. Machine learning techniques for taxi-out time prediction with a macroscopic network topology. In Proceedings of the IEEE/AIAA 37th Digital Avionics Systems Conference (DASC), London, UK, 23–27 September 2018; pp. 1–8.
55. Diana, T. Can machines learn how to forecast taxi-out time? A comparison of predictive models applied to the case of Seattle/Tacoma International Airport. *Transp. Res. Part E Logist. Transp. Rev.* **2018**, *119*, 149–164. [CrossRef]
56. Chen, J.; Weiszer, M.; Zareian, E.; Mahfouf, M.; Obajemu, O. Multi-objective fuzzy rule-based prediction and uncertainty quantification of aircraft taxi time. In Proceedings of the IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 16–19 October 2017; pp. 1–5.
57. Lian, G.; Zhang, Y.; Desai, J.; Xing, Z.; Luo, X. Predicting taxi-out time at congested airports with optimization-based support vector regression methods. *Math. Probl. Eng.* **2018**, *2018*, 7509508. [CrossRef]
58. Xing, C.W.; Jiang, J.; Luo, X.; Luo, Q. Dynamic estimation about estimated taxi-out time based on Bayesian network. *Comput. Eng. Appl.* **2018**, *54*, 66–71+203.
59. Dalmau, C.R.; Belkoura, S.; Naessens, H.; Belkoura, S.; Wangnick, S. Improving the predictability of take-off times with Machine Learning: A case study for the Maastricht upper area control centre area of responsibility. In Proceedings of the 9th SESAR Innovation Days, Athens, Greece, 2–6 December 2019; pp. 1–8.
60. Li, N.; Jiao, Q.Y.; Zhu, X.H.; Wang, S.C. Prediction of Departure Aircraft Taxi Time Based on Deep Learning. *Trans. Nanjing Univ. Aeronaut. Astronaut.* **2020**, *37*, 232–241.
61. Li, N.; Jiao, Q.; Zhang, L.; Fan, R. Taxi Time Prediction of Departure Aircraft. *J. Chongqing Jiaotong* **2021**, *40*, 1–6.
62. Chen, Z.; Tang, X.; Lin, Y.; Ren, S. Prediction Method and Model of Aircraft Taxi-Out Time Based on Decision Tree. *J. Wuhan Univ. Technol.* **2021**, *45*, 448–453.
63. Li, N.; Jiao, Q.Y.; Fan, R.; Sun, B.X. Research on Influencing Factors of Aircraft Taxiing Time Based on Stepwise Regression Method. *Comput. Simul.* **2021**, *38*, 57–63.
64. Wang, X.; Brownlee, A.E.I.; Woodward, J.R.; Weiszer, M. Aircraft taxi time prediction: Feature importance and their implications. *Transp. Res. Part C Emerg. Technol.* **2021**, *124*, 102892. [CrossRef]
65. Liu, J.; Bai, M.; Hao, L. Predition of flight taxi-out time based on ARIMA-SVR combination method. *China Sci.* **2021**, *16*, 661–667.
66. Zhang, Y.; Li, X.; Yin, J.; Zhou, X. Flexible control of aircraft departure pushback time based on probabilistic taxiing time. *Acta Aeronaut. Astronaut. Sin.* **2023**, *44*, 327452.
67. Huang, L.; Xia, Z. Taxi-out time prediction of departure flight based on BP neural network. *Comput. Eng. Des.* **2022**, *43*, 1039–1044.

68. Xia, Z.; Jia, X. Support vector machine prediction model of departure flight taxi-out time. *Sci. Technol. Eng.* **2022**, *22*, 11262–11267.
69. Huang, L.; Xia, Z.; Jia, X. Departure flights'taxi-out time prediction based on SSA-BP algorithm. *Sci. Technol. Eng.* **2022**, *22*, 6607–6612.
70. Herrema, F.; Curran, R.; Visser, H.; Huet, D. Taxi-out time prediction model at Charles de Gaulle Airport. *J. Aerosp. Inf. Syst.* **2018**, *15*, 120–130. [CrossRef]
71. Shao, W.; Prabowo, A.; Zhao, S.; Koniusz, P. Predicting flight delay with spatio-temporal trajectory convolutional network and airport situational awareness map. *Neurocomputing* **2022**, *472*, 280–293. [CrossRef]
72. Pham, D.T.; Ngo, M.; Tran, N.; Alam, S. A data-driven approach for taxi-time prediction: A case study of Singapore Changi airport. In *Air Traffic Management and Systems IV: Selected Papers of the 6th ENRI International Workshop on ATM/CNS (EIWAC2019)*; Springer: Singapore, 2021.
73. Gotteland, J.B.; Durand, N.; Alliot, J.M.; Page, E. Aircraft ground traffic optimization. In Proceedings of the 4th USA/Europe Air Traffic Management Seminar, Santa Fe, NM, USA, 4–7 December 2001; pp. 4–7.
74. Pujet, N.; Feron, E.; Rakhit, A. Modeling of an airline operations control center as a queueing network. In Proceedings of the American Control Conference. ACC (IEEE Cat. No. 98CH36207), Philadelphia, PA, USA, 26 June 1998.
75. Carr, F.; Evans, A.; Clarke, J.P.; Feron, E. Modeling and control of airport queueing dynamics under severe flow restrictions. In Proceedings of the 2002 American Control Conference (IEEE Cat. No. CH37301), Anchorage, AK, USA, 8–10 May 2002; pp. 1314–1319.
76. Gao, H.O. Aircraft Taxi-Out Emissions at Congested Hub Airports and the Implications for Aviation Emissions Reduction in the United States. In Proceedings of the Transportation Research Board 86th Annual Meeting, Washington, DC, USA, 21–25 July 2007.
77. Postorino, M.N.; Mantecchini, L.; Paganelli, F. Improving taxi-out operations at city airports to reduce CO_2 emissions. *Transp. Policy* **2019**, *80*, 167–176. [CrossRef]
78. Rahaman, M.S.; Ren, Y.; Hamilton, M.; Salim, F.D. Wait time prediction for airport taxis using weighted nearest neighbor regression. *IEEE Access* **2018**, *6*, 74660–74672. [CrossRef]