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Research Paper

Intelligent Air Traffic Management Methods, Case Study: a Proposed Deep Learning Method for Mashhad Airport Air Traffic Management

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Abstract

Air traffic management (ATM) is a set of management, analytical, and operational techniques and tools, which are used to optimize the traffic flow and exploit the existing flight system capacity. However, one of the challenges in ATM use is the prevention of flight delays. Several methods such as data mining, artificial neural network evolutionary algorithm, and fuzzy logic are available in the ATM field. But the complexity level as the number of the available categories for classification increases, making it impossible to use these algorithms in air traffic management. This study is aimed to comprehensively evaluate the techniques applied in ATM and assess the tools and criteria in this context. Also, show that the artificial neural network (ANN) and long short term memory (LSTM) algorithms are most frequently used in ATM. Then a hybrid deep learning model for Mashhad airport air traffic management systems was proposed. The analysis of the system was performed using the actual data of Mashhad Airport. Our results demonstrate that among various clustering algorithms, K-means and deep learning methods are more efficient and widely used. Evaluation criteria such as accuracy rate, delay, The Root mean square error (RMSE) and mean square error (MSE) are more commonly applied in air traffic system evaluation. The implementation of the air traffic management base on hyprid deep learning could be increase accuracy of flights control operation in airports.

Keywords: Data Mining, Deep Network, Air Traffic Management, MSE, RMSE

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1. Introduction

The air transport system is a complicated structure, which transfers millions of passengers around the globe each year. Modern air traffic management systems (ATMs) constitute a large portion of the airspace with various streams of air traffic, which interact with each other through complicated methods and are evolving dynamically [1]. ATMs are among the most challenging systems in the world. One of the challenges in the ATM field is the aircraft sequences problem (ASP) used to prevent flight delay [2].

In addition, the complexity of the modeling problem has become a major issue in this context. On the other hand, the complexity level is increased with the multiplying number of the available categories for classification due to the high scale of air traffic data (bulk data) in the classification learning process. Therefore, the extraction of important and effective features is using

Conventional data mining methods are almost impossible.

Various algorithms (e.g., data mining algorithms) are used for the management of the mentioned issues and airports have several flight runways [3]. The application of data mining algorithms such as the support vector machine and decision tree has been reported to increase the level of complexity due to the high-scale air traffic data (bulk data) in the classification learning process or the increased number of the available categories for classification. This phenomenon has complex algorithms in ATMs. Therefore, the simultaneous use of the mentioned algorithms along with deep learning methods and even feature selection methods can help minimize the estimated delay by determining the flight sequence, thus solving the issues associated with ATMs.

Therefore, this study aimed to evaluate the methods used in ATMs. The following section of the article is focused on the current

Methods in the ATM field, and the third section has been dedicated to the analysis of these methods. In the next section proposed a deep learning model for Mashhad airport as a case study .finally, the results of similar studies have been discussed, along with some recommendations for further investigations.

2. Review of ATM Methods

A major issue in air traffic management (ATM) is the inaccurate recognition of flight delay and lack of precise control over the flight interferences caused by human and systematic errors. Therefore, the implementation of the methods that could effectively discover and control the causes of delays could remarkably improve ATM. In this section, we have considered some methods that are used in traffic management. Figure 1 shows various ATM techniques.

As can be seen in Figure 1, the techniques applied in ATM are classified as fuzzy-based, machine learning-based, mathematical and probability statistics-based, and deep learning-based techniques, each of which is divided into several subcategories. These techniques have been presented in the following section, along with a review of the literature in this regard.

2.1. Machine Learning-based ATM

Machine learning has been successfully used in numerous tasks related to data analysis and image recognition. In addition, machine learning could define problem-solving processes [4]. Recognized as a branch of artificial intelligence, machine learning encompasses the algorithms that could predict the processing results of data [5]. Recent achievements have indicated that machine learning is commonly used in path prediction. In most cases, the performance of machine learning systems can be better predictable. Generally, path prediction is a pillar of the future air transportation system and its goal is improving operational capabilities and predicting air traffic.

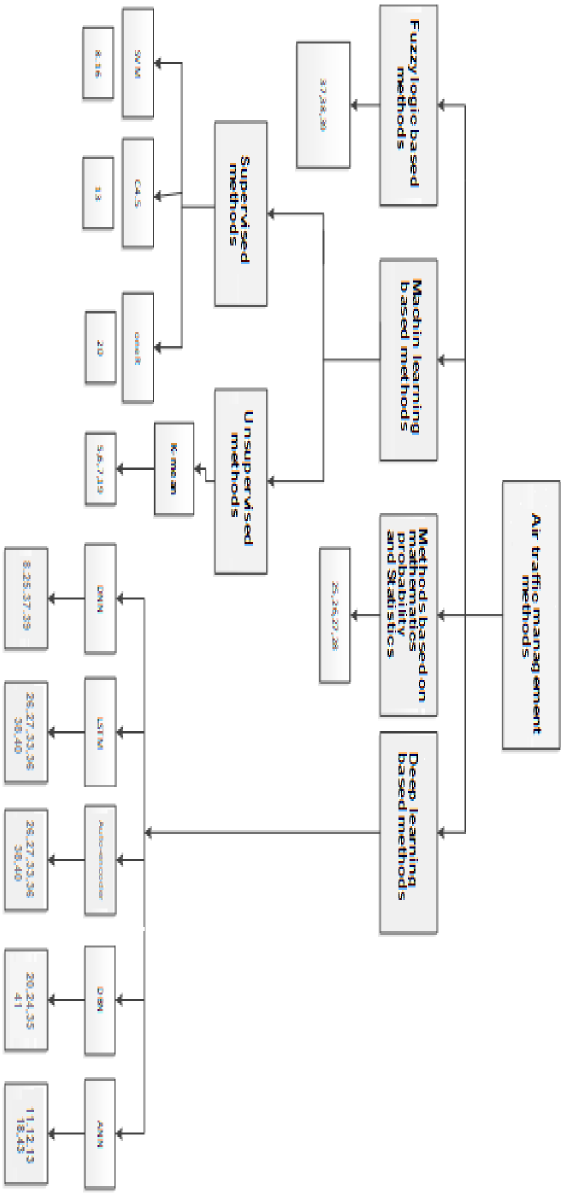

Figure 1. Various ATM Sections

2.2. Clustering-based ATM

Clustering-based ATM is an unsupervised learning algorithm [6, 22], some benefits which include applicability in solving clustering problems and relative flexibility and efficiency for large datasets [55]. The K-means algorithm is most commonly used in the clustering practice as a simple, comprehensible, and logically scalable algorithm, which could be corrected easily. However, noise in the data affects the final results of this algorithm and causes errors [7].

In [8], the researchers are using a combination of clustering and neural network algorithms to teach the TMA airport system and minimize the estimation of the means, along with flight sequencing in solving ATM issues. In addition, the outputs of the k-means clustering method were compared with each other to get the prediction model of hybrid machine learning and ML-CNN that could provide accurate and efficient forecasting in TMA through the density-based spatial clustering of applications with noise preprocessing (DBSCAN). In general, the preprocessing stage encompasses resampling, reducing the size of data by the principal component analysis (PCA) algorithm, and DBSCAN. In this stage, the model first normalizes the data and changes the data sizes. Afterward, it identifies the 4D-based paths to different clusters and removes the possible noise simply. Each cluster is a symbol of the similar patterns of the related routes. The noise encompasses the routes with maintenance patterns, routes with magnification, routes in special cases, and the maximum flight routes. In the end, the quality of the route data increases significantly. The MCNN model is used in the forecasting stage to predict the 4D density path. There was one predictor in each partition of the path, which was included in NN-based learning cells. Each exclusive learning cell was trained with a set of related paths. As a result, each route had its forecasting model. The new input paths were also classified into correspondingly different clusters using decision trees based on the entry point. At the next stage, the forecasting of the input data path was generated using the multiple-trained forecasting model. The comparison of the results showed that the proposed method in the present study yielded a more efficient and stronger output and was more efficient in short-term forecasts. Nevertheless, some issues of the method included the small data scale and lack of learning methods with higher accuracy (e.g., deep machine learning methods). In the proposed method in the dissertation, the two challenges were removed that using the bulk data and deep learning technique.

In another research, a clustering method was proposed using the time warp edit distance (TWED) measurement and K-means algorithms to improve the accuracy of nominal flight specifications [9]. Initially, the researchers used a series of data with favorable duration in terms of routing with the same flight origin and destination before processing to eliminate the effect of the exit point. The second stage involved presenting a new mathematical, compatible clustering algorithm, in which the distance between different paths was considered based on the TWED algorithm rather than the usual measurement method of elastic similarity in the proposed clustering algorithm. Ultimately, the predicted route encompassing various control purposes was presented to predict the aircraft route. Some benefits of the method included the increased accuracy of the clustering technique and higher productivity of the controlled airspace. On the other hand, the disadvantages of the technique were the lack of a larger scale of data and using bulk data, which increased the clustering accuracy. According to researcher's consequences, the K-means algorithm is simpler and more cost-effective compared to other clustering algorithms, while it is not considered suitable for large datasets.

2.2.1. Support Vector Machine Algorithm-based ATM

The support vector machine (SVM) is a supervised learning method is used for classification, which is also applied for analysis and regression classification. The SVM is primarily exploited for the linear classification of data, where attempts are made to select a line with the highest safety margin. In [10], the SVM was used for ATM in the recognition of critical routes. The proposed method was designed by using the actual data obtained from a Chinese aircraft. According to the obtained results, the proposed method and SVM application were increased productivity and accuracy in the recognition of critical routes. Overall, this education-stage algorithm aimed to select a decision-making border, so that its distance to each of the desired classes would be maximized. In practice, such decisions have been made and could tolerate noisy conditions and have a proper response.

2.3. Neural Network-based ATM

Artificial neural networks (ANNs), also referred to as neural networks, are new computational systems for machine learning, knowledge display, and the application of the acquired knowledge to predict the output responses from complex systems. In [11], delays in air routes were assessed using ANNs, and the random search technique was also exploited for the better adjustment of the ANN algorithm parameters. The data used in the mentioned study were obtained from Brazilian air traffic, and the results indicated the correct prediction capacity of more than 90%. Compared to the other studies in the scope, the proposed model is demonstrated that the day of the week, as well as block and airline clocks, had more significant effects on flight delay compared to meteorology.

In [12], air traffic was forecasted using ANN. The data used in the mentioned study were collected from the airport of Spain. The assessed criteria in the study were MAD and RMSE, and the comparison of the results in the proposed method with other studies indicated the higher flexibility and performance of the proposed method.

In [13], the researchers used a hybrid ANN. with an NLS-based regression curve based on the data obtained from the United States. In the mentioned research, experimental tests were performed to demonstrate the effectiveness of the proposed model in an actual passenger dataset. According to the results, the basic model was able to make accurate predictions compared to other algorithms despite its simplicity. In general, neural networks are considered to be viable options for the management of air traffic in terms of accurate delay calculations.

2.4. Deep Learning-based ATM

Deep learning is a recent, unsupervised learning algorithm, which is used for problem-solving with high breadth and complexity and massive volume. Deep learning works the same as multilayered neural networks or deep neural networks [9]. Figure 1 depicts several algorithms of deep learning, which are used to extract text attributes. Deep learning is different from conventional methods because their performance is based on largely automated learning features rather than intentional features, and depends more on developers' predictive knowledge while using massive data is impossible. Deep learning could automatically learn feature representation from large data, including millions of parameters.

In [24], the deep belief network (DBN) [R] was combined with the PCA algorithm to evaluate and predict transportation safety. The DBN could predict severe flight accident rates based on PCA results. In this regard, the main component and PCA weight were considered to be the primary parameters and DBN input. In the mentioned study, the proposed method was implemented using MATLAB, and the evaluated factors were the takeoff and landing of the aircraft, aircraft, airport and aviation operations, ground, and meteorological factors. According to the obtained results, the predicted PAC DBN data were consistent with the actual data on actual flight accidents. In addition, the proposed method proved superior to the gray neural network, backup vector regression, and DBN in terms of the forecasting of the flight accident rate.

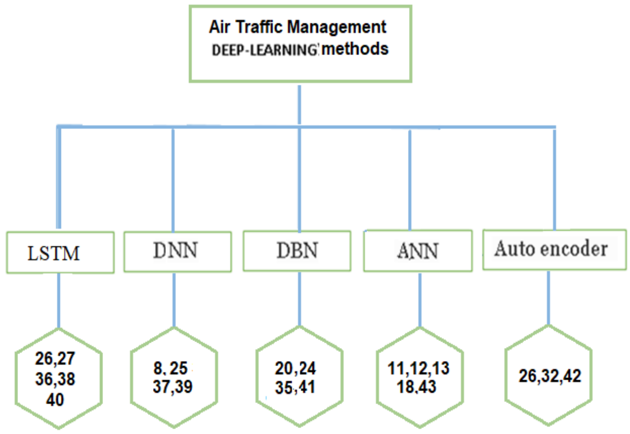

Figure 2. Deep learning methods

In [25], a new model known as the Levenberg-Marquardt algorithm was introduced, the goal of which was to generate a deep neural network architecture aimed at improving the accuracy of traffic flow predictions. The Taguchi method was employed in the design of the proposed model to develop an optimized structure and recognize the features of traffic flow through the layer by granulating the properties of the layers using an unsupervised greedy learning algorithm. Data were collected from the M6 freeway in the United States and compared to three traffic predictors. According to the obtained results, the proposed model with an optimized structure had superior performance in the prediction of the traffic flow.

In [26], deep learning architectures such as stacked auto-encoder, convulsive neural networks, and recurrent neural networks (RNN) were used to predict daily delay status owing to their ability to record the temporal and sequential correlations of the data. The mentioned study primarily aimed to evaluate the daily delay of each airport and estimate the delay for a specific flight based on the results of the previous stage. To predict the daily delay, delay of the inbound and outbound flights meant determined and added to the RNN, along with the weather data as a sequence. Furthermore, the results were transferred to the output after determining the weight and bias of each data. Weighing and bias estimation are repetitive processes, and at each iteration step, the cost function value is determined using the stacked long-short term memory network (LSTM) and Sigmoid and Tanh functions, followed by the replacement of the RNN and data storage of each hidden layer, which in turn increased the efficiency of the model. One of the limitations of the proposed model was the elimination of details from the courses related to the ground delay management of aircraft preparation for flights. Another issue was the lack of considering a deeper LSTM structure in the structure of the time-based forecasts, which increases accuracy.

In [27], a new deep architecture was presented to predict hard landings based on a quick access recorder (QAR). In terms of the industrial internet of things (IoT), IoT devices collect IoT data and send them to the IoT open cloud platform to be analyzed. The forecasting of hard landings is a common use of the IoT in the field of aviation. Initially, the researchers selected 15 aircraft landing sensor data of 260 parameters based on meteorological and engineering characteristics. Following that, a forecasting model based on the LSTM was developed to predict hard landing accidents using the selected sensor data. The experimental results showed higher performance through increased forecast accuracy in the QAR data, indicating the effectiveness and accuracy of the model in the prediction of hard landings, which ensures the safety of passengers and reduces the incidence of landing accidents.

2.5. Methods Based on Mathematics and Statistics

Linear programming, also known as linear optimization, is a method in mathematics, which determined the minimum or maximum value of a linear function on a convex polygon that is a graph representation of some constraints of the unequal type on the function variables. In simple terms, linear programming could lead to obtaining an optimal outcome (highest profit/lowest cost) in specific situations with specific constraints.

In [28], researchers presented a dynamic programming-based optimization approach to the planning of the arrival and departure of aircraft off the band with non-3D separation time and cross-heterogeneous runways. Attention was paid to band scheduling and allotted time in departing and landing, while meeting the separation needs depending on the sequence and minimization of the costs of delay. Some runways could only be used for takeoff, landing, or a specific type of aircraft, while the program was considered for the interdependent runways. A key benefit of the mentioned study was the use of diagonal separation constraints as a dynamic planning approach to optimization within a short calculation period. On the other hand, one of the limitations was the lack of planning for large samples to achieve near-optimal results.

In [29], the study was focused on delay prediction using the specific data patterns of the previous flight data. The applied data were extracted from the data obtained at major airports' in-flight information systems. In the mentioned research, the mixed integer programming (MIP) technique was employed to evaluate the influential factors in flight delay, as well as the intensity of delay. The final results were indicative of certain patterns in flight delays, which distinguish these flights from temporary flights. Therefore, it was concluded that flight delays could be predicted rather accurately based on key features such as the departure time, arrival time, origin, and destination.

In [30], the researchers proposed a model based on the Bayesian inference and Gaussian mixture model expectation-maximization (GMM-EM) algorithm to predict and analyze the influential factors in the flight delays in Brazil at specific points along the route. Initially, the impact factor of each component was calculated using old data and the Bayesian rules at specific points along the route, followed by determining whether the delays occurred within a wider range. Furthermore, the probability of the delays was calculated using the GMM-AM and EM algorithms based on similarity. According to the obtained results, the probability of the delays could be predicted at high levels by identifying the low-level factors. Moreover, the GMM-EM demonstrated more values similar to the EM algorithm for the function at each step, which in turn resulted in earlier convergence, followed by the higher accuracy of the model and more reliable prediction.

In [31], the researchers studied real-time aircraft routing and scheduling. The investigated problem was related to the crowding terminal control area (TCA) in case of traffic. The issue of TCA operational management is particularly challenging due to the continuous growth of traffic demand, which has caused TCAs to become the bottleneck of the entire air traffic control system. In the mentioned study, the mixed linear programming formulations that contain safety rules were the modeling of practical interest based on the minimization of the total travel time and greatest delays due to the aircraft collision potential computational tests on the real data obtained from Roma Fiumicino Airport, which is the largest Italian airport in terms of passenger demand with high accuracy. The provided solutions offered the ideal compromise between various goals.

2.6. Fuzzy Algorithms

Air traffic control systems may be considered to be unstable systems. To design an optimal fuzzy system, the membership functions and appropriate fuzzy rules must be defined to recognize the accurate identification of the physics of the evaluated system, as well as the previous observations and experiences. The structure of fuzzy systems based on type-one fuzzy systems has indicated their high applicability. Nevertheless, researchers have demonstrated the inappropriateness of type-one fuzzy systems in the modeling and minimization of the effect of uncertainty. While there is a unit membership degree for each input in type-one fuzzy systems, the membership degree in type-two fuzzy systems is in the form of fuzzy sets.

In accord with research, a combination controller with a fuzzy PD controller and controller could be used to control air traffic and prevent accidents. One of the most optimal and recently integrated studies on fuzzy traffic controllers has been performed in [32], which has been focused on the detection of traffic accidents to increase road safety. Considering the complexity and non-linear features of traffic accidents, the mentioned research is proposed a diagnostic technique, in which deep networks are used with a stacked auto-encoder model. In addition, the researchers applied the back-propagation algorithm to fine-tune the parameters in the deep grid. Ultimately, a fuzzy controller was exploited to increase the output accuracy of the deep network and match the neural network learning parameters based on the MSE error. This fuzzy logic control system encompassed four components, and the simple fuzzy converted the data into fuzzy data or membership functions (MFs). Furthermore, the basic fuzzy rules contained the correlations between the inputs and outputs, and the fuzzy inference process was a combination of the MFs with the control rules to generate the fuzzy output.

In general, fuzzy logic systems are preferable for two reasons; first, fuzzy systems are considered appropriate for uncertain or approximate reasoning and allow decision-making with the estimated values in incomplete or uncertain information. In [33] as the third basic article in this scope, two fuzzy models were used based on the rules determined by the International Civil Aviation Organization (ICAO) by tools such as MATLAB to prevent the collision of airplanes in air traffic routes based on the horizontal aircraft speed and their permitted separation. In the mentioned study, both the fuzzy models functioned collaboratively with a dynamic approach; the first model provided a metric to measure the level of the longitudinal collisions between two aircraft in a common direction (located on the same air route), and the second model provided the longitudinal acceleration of the aircraft based on the detection of the impact surface. One of the disadvantages of the proposed model was the lack of considering the speed factor and vertical separation of flights.

In (34), the Leven berg method inspired by the fuzzy control matching rules based on slip mode controller was applied to train an intelligent fuzzy neural network controller on a quad-copter. One of the advantages of this model was that it allowed the use of uncertainty modes and eliminated the defects of the model in low computational costs, while the main limitation of the model was the lack of type-two fuzzy, which reduced the noise according to the obtained data.

3. Analysis of the Methods

In this section, we have compared and analyzed the discussed assessment methods, as well as the datasets used in ATM.

3.1. Comparison and Analysis of the Algorithms

Table 1 and Table 2 show the algorithms, datasets, and metrics used in ATM.

Table 1. Algorithms Used in ATM

Row	Research	The best algorithm	Data set	Criterion	Suggested method
[1]	[8],2019	NN	ADS-B records of Beijing Capital International	Accuracy MAE RMSE	k-mean, NN
[2]	[9],2017	k-mean	Rainfall, Temperature, Wind, Humidity Peak hour	Correlation cost	k-mean
[3]	[35],2017	k-mean	ten radar trajectories from the flight from Xiamen	Cumulative Distance	k-mean
[4]	[10],2018	SVM	collected from Chinese airspace	Accuracy, Precision, Recall, Error Cost, Time	SVM
[5]	[11],2018	ANN	delays in the air route between São Paulo (Congonhas) - Rio de Janeiro (Santos Dumont) data	Precision, Dely	ANN
[6]	[12],2018	ANN	data airport traffic from the Australian Government	RMSE,MAD,R^2	ANN
[7]	[13],2019	ANN	data are monthly data of air traffic activity in the United States,	MAD MAPE	ANN
[8]	[14],2020	C4.5	Taiwan air-traffic dataset on 168-month	Error	K-Means, C4.5
[9]	[15],2020	CRT	Simulator sessions of terminal radar approach control in a variety of scenarios.	Accuracy	CHAD, CRT
[10]	[16],2009	appropriate CD	air traffic management	Accuracy	Genetic

		algorithm and using genetic algorithms (GA)	(ATM) free flights dataset		
[11]	[17],2019	SVM	Atlanta International Airport	AUC	SVM,LR
[12]	[18],2017	ANN	Bureau of Transportation Statistics	Accuracy	ANN
[13]	[19],2017	linear regression	www.umetrip.com	Delay, Accuracy, Precision-Recall F-score	C4.5, NB, linear regression
[14]	[20],2015	K-mean	Secondary Surveillance Radar (SSR) can obtain real-time trajectory data from Gaoqi Airport to Wuxi Shuofang	accuracy and stability	K-mean
[15]	[23],2018	KDD	Hartsfield–Jackson Atlanta International Airport WEATHER AND FLIGHTS DATASET	Delay, Accuracy	KDD-D-TREE
[16]	[24],2019	DBN	CCAR-396-R2) safety data from 2010 to 2015 are used as the training samples, and the safety data from January 2016 to May 2016 are used as the testing samples	MSE	PCA-DBN SVR
[17]	[25],2016	The greedy layer-wise unsupervised learning algorithm	data collected from the M6 freeway in the U.K	Accuracy	NN, SAE-LM
[18]	LSTM, NN	Accuracy, Delay	New York JFK airport	LSTM	[26],2017
[19]	LSTM, RF	Accuracy, RSME	collected from commercial aircrafts Airbus 300 of a local airline	LSTM	[27],2018
[20]	DBN, ANN	MSE	TMS data sets	DBN	[35],2016
[21]	LSTM	MSE	data is flight trajectories with 20 seconds updating period in China	LSTM	[36],2019
[22]	DNN	Predicting	Flight and airspace data, including actual trajectories observed from radar tracks, was taken from the period 15 December 2015 – 12 December 2017. The dataset includes more than 328,600 flights	DNN	[37],2017
[23]	LSTM,NN ,RNN	RMSE	data of Heathrow Airport	LSTM	[38],2017

[24]	SAE-LM, RBFNN	Accuracy	real-world data collected from the M6 freeway in the U.K.	SAE-LM	[39],2016
[25]	RNN, LSTM	Delay	data of airports in the U.S.	LSTM	[40],2016
[26]	DBN, ANN	Delay, Accuracy	Datasets required for training and testing have been acquired from Kaggle.com. This dataset consists of 30 features/attribute	ANN	[41],2017
[27]	Deep by stacked auto-encoders BP SVM RBF	MAE, RSME,	System (PMS) database as a numerical example. The traffic data are collected every 30 s from over 15 000 individual detectors,	Deep by stacked auto-encoders	[42],2014
[28]	ANN	Accuracy	A large dataset of 119432 regular commercial passenger flights was performed from November 3, 2015, to March 5, 2016. T	ANN	[43],2019

Several techniques and methods have been employed for the assessment of air traffic management and the issues of minimizing the estimated time of arrival and sequencing flights, some of which were discussed earlier in the article. One of the most effective approaches to solving the mentioned issues is using the structure of ANNs. Following the evolution of neural networks, deep learning networks are among the newest and most complete solutions offered in this regard, which can solve the issues associated with high accuracy due to accepting a large number of problem data (bulk data) and integrating neural networks, learning techniques, and the structural dynamics in the formation of the number of the hidden layers. Aviation and air traffic flow management issues are no exception, and the most recent findings regarding flight delay forecasting and air traffic layout have benefited from this technique. Therefore, it could be claimed that the subject and solution of today in the field of air traffic solutions are deep learning techniques and the associated hybrid models, along with the use of large-scale data (bulk data) (Table 1).

Among the algorithms presented in Table 1, ANN and LSTM had a higher efficiency in ATM. LSTM networks are a specific form of RNNs, which can learn long-term dependencies. Furthermore, LSTM networks have a similar sequence or chain structure, while the iterative module has a different structure [44-49] and encompasses four neural network layers instead of one, which interacts with each other through a specific structure. The LSTM also can add or remove new information to a state cell through accurate structures known as 'gates'. Gateways enable the voluntary entry of information and consist of a layer of the sigmoid neural network with a point-by-point multiplication operator. Figure 3 shows the use of these algorithms over the years.

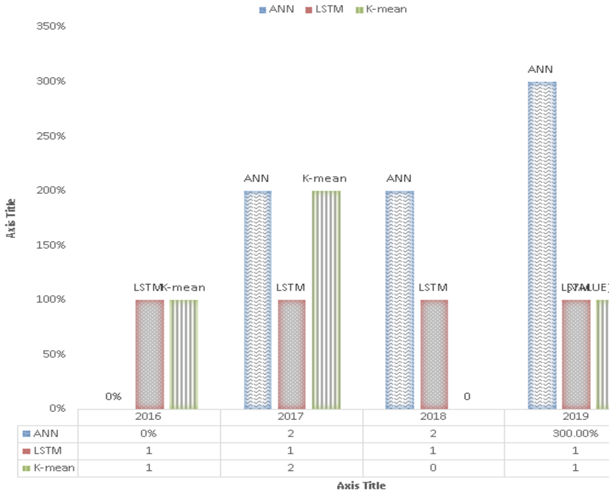

Figure 3. Comparison of Commonly Used Algorithms in ATM

The purpose of designing LSTM networks has been to solve the problem of long-term dependency. Memorizing information for a lengthy period is the default behavior of LSTM networks, and their structure enables the proper learning of very distant information. One of the advantages of this algorithm is its ability to learn its long-term dependencies. As is shown in Table 1 and Figure 3, among the algorithms based on clustering, the K-means algorithm has been observed to be most applicable in ATM owing to its simplicity, comprehensibility, and scalability. Another important feature of this algorithm is its easy modification to manage data flow.

3.2. Analysis of the Evaluation Criteria

Figure 4 depicts the most commonly used evaluation criteria in ATM.

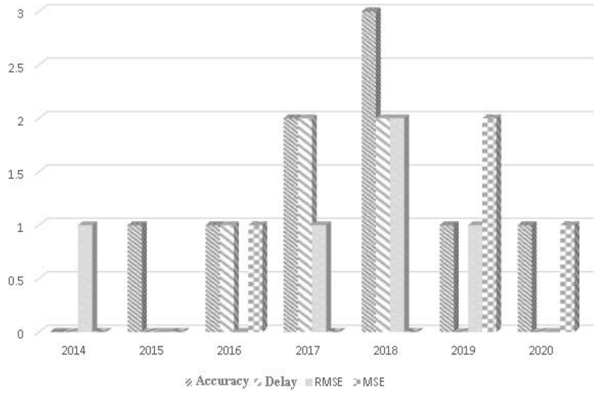

Figure 4. Most Commonly Used Evaluation Criteria in ATM

As is observed in Figure 4, the criteria of accuracy, delay, RMSE, and MSE have been used more frequently in ATM. The accuracy criterion is used to determine the proximity of the answer to the actual size and the delay criterion. RMSE is the third criterion, which is used to measure the accuracy of the predicted rates relative to the correct rates. In this regard, low RMSE shows higher predictive accuracy. As RMSE doubles the error before adding up its value, it tends to penalize large errors more significantly, which is mainly because these metrics treat all of them equally regardless of the position of the rates in the bid list. Owing to their simplicity, RMSEs are still widely used in the evaluation of bidding systems, and the MSE standard has also been cited as one of the most widely used criteria in ATM.

3.3. Dataset Analysis

Figure 5 shows the types of important databases used in various studies in this regard. In some cases, more than one database was used, while in others, the name of the applied database has not been stated for security measures. In the case studies, only the database of the same country or specific airport has been used.

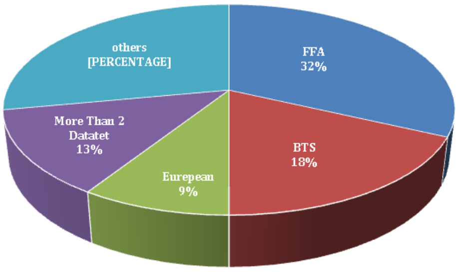

Figure 5. Comparison of Data Mining Criteria

As is shown in Figure 5, the FAA and BTS datasets are more widely, respectively compared to other databases.

4. Case Study: a Proposed Deep Learning Method for Mashhad Airport Air Traffic Management

In the previous section, an overview of methods and research has been done to increase the accuracy of management. Discussed air traffic based on deep learning, machine learning based on the snow phase. The structure of deep neural networks is such that they can slow down in various areas such as speech recognition, machine vision, suggestion systems, urban traffic forecasting, and air traffic using more variables for forecasting, modeling, and simulation. Therefore, we used deep neural networks to increase the accuracy of air traffic management and flight delay prediction for Mashhad airport. Mashhad international airport is the Iran's second-busiest airport, behind Tehran-Mehrabad. In 2016, Mashhad Airport handled a record 10 million-plus passengers, up 17% from 2015, along with 86,681 tons of cargo. It has flights to 57 destinations, including frequent flights to 30 Iranian cities, and 27 destinations in Central Asia, the Middle East, East Asia and Europe. Mashhad International Airport has three terminals: a domestic flight terminal (Terminal 1), an international flight terminal (Terminal 2), and a Hajj flight terminal (Terminal 3) (figure 6).

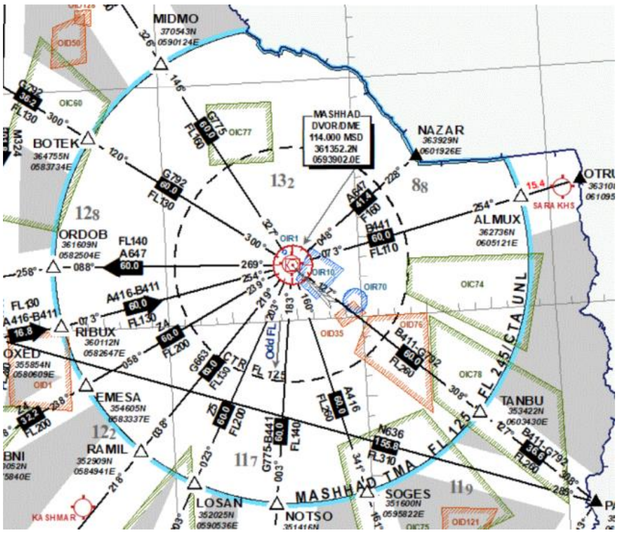

Figure 6. Mashhad International Airport terminal maneuvering area (TMA)

Some of accident and incident occurs in Mashhad Int airport as follow: On 1 September 2006, Iran Air Tours Flight 945, a Tupolev Tu-154 flying from Bandar Abbas skidded off the Mashhad runway after a tire blew during landing. The aircraft caught fire, and 29 of the 147 people on board died in the accident. On 24 July 2009, Aria Air Flight 1525, an Ilyushin Il-62, route THR-MHD (Teheran Mehrabad, Iran to Mashad, Iran) crashed with 173 people on board and caught fire; 5 passengers and 11 crew members died. On 24 January 2010, Taban Air Flight 6437, a Tupolev Tu-154M, crashed while making an emergency landing at Mashhad International Airport due to a medical emergency; all 157 passengers and 13 crew survived the accident; 42 received minor injuries. It was reported that the aircraft was on an ILS landing in fog when the tail struck the ground, causing the plane to veer off the runway. This was followed by a nose gear collapse, then the right wing struck the ground, causing the aircraft to burst into flames. On 28 January 2016, Zagros Airlines Flight 4010 was landing at Mashhad International Airport Runway 31R when the McDonnell Douglas MD-83, registration EP-ZAB, skidded off the runway. The aircraft was damaged beyond repair and 7 people. To consider machine learning and human factor simultaneously as well as the large scale of data, the deep learning model based on Bidirectional long-short term memory neural (B-LSTM) was used to provide a deep learning model so that we can deepen the depth. Learning (two-dimensional) in short daily and long-term annual windows increases the accuracy of prediction (Figure 6).

The deep model output is also fed to the extreme learning machine (ELM) deep learning neural machine, which can estimate the amount of time-based on other input data such as NAS system data, Mashhad air traffic standard system data for US airports on the Kaggle site. Calculate landing flights for each flight. After predicting the estimated time of arrival (ETA) for the arrival flights and the estimated departure (ETD) for the outgoing flight, and considering the delays and the new flight schedule, we will solve the gate allocation problem with three objectives. First, using the whale algorithm and considering the distribution of passengers on each flight, the distance of passengers to the nearest gate is calculated, and the number of repetitions of this algorithm is important to achieve the minimum objective function. Then, using the output of the whale algorithm as well as the parameters related to the aircraft and passengers and defining the rules fuzzy type 2, the gate is allocated to prevent the collision of two aircraft and reduce airport costs. In the following, we first provide an overview of the proposed algorithm. Then we briefly explain the steps of our proposed algorithm.

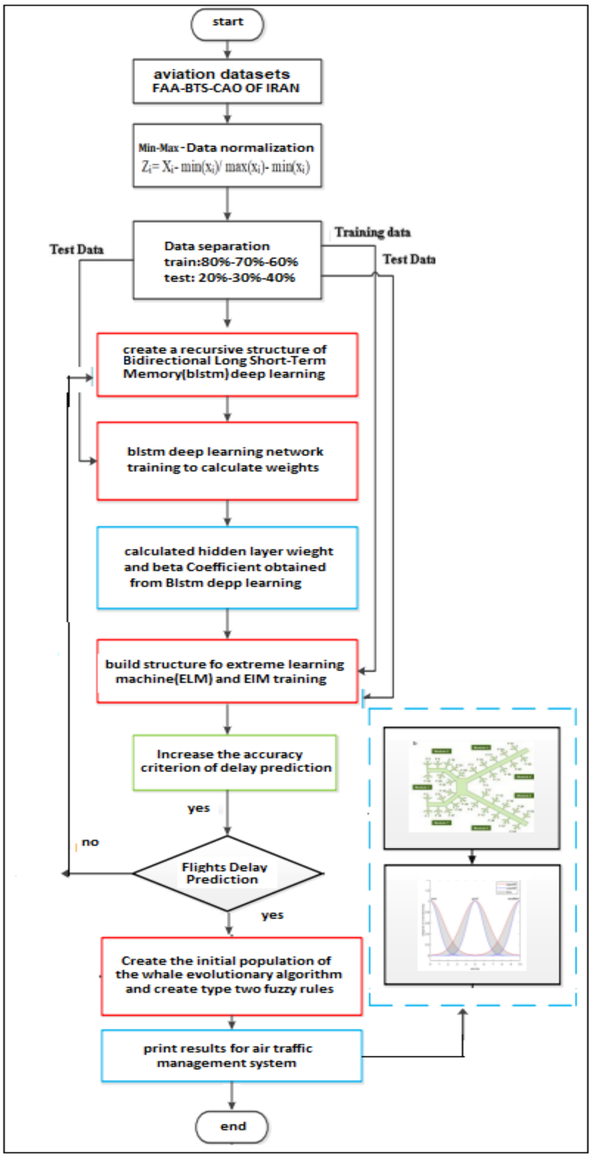

Figure 7. A deep learning model for Mashhad airport ATM system

The proposed algorithm for air traffic management and flight gate allocation is presented in 5 phases: In the first phase, data were collected and pre-processed. Then, in the second phase, to consist of learning and human factor simultaneously as well as the large data scale, the deep learning model based on the Bidirectional long-short term memory neural (B-LSTM) model was used and by changing the structure. LSTM cells we were able to increase the accuracy of prediction by deepening the depth of learning in the short days and long-term annual windows. In the third phase, the output of the deep model is given to the deep neural machine of rapid ELM, which can calculate the estimated landing time of flights for each flight according to the input data of the standard system for Mashhad airport. In the fourth phase, to redistribute the flight gate, first using the Mashhad airport data as an airport sample from the database of the previous part in the national flight network and using the whale algorithm to reduce the walking distance of passengers, the nearest gate is found based on passenger distribution. Then, in the fifth phase, due to the uncertainty in the parameters affecting the gate allocation, the calculated distance, along with other variables, enters the type two fuzzy system, gate allocation using delayed delay data and flight arrangement obtained from the previous phase. All three factors are considered: reducing the walking distance of passengers, preventing the collision of planes, and reducing the costs of the airline [55].

5. Conclusion

The present study was focused on ATM and the applied methods in this regard. According to the results, the applied techniques are mainly based on data mining, deep learning, fuzzy, and statistics, and probability algorithms. In addition, the neural network algorithm among the data mining algorithms, the LSTM algorithm among the deep learning algorithms, and the K-means algorithm among the clustering algorithms have been reported to have the optimal performance in increasing the criteria in the discussion of ATM. The obtained results also indicated that the criteria of accuracy, delay, RMSE, and MSE are among the most widely used evaluation criteria in the field of air traffic. A hybrid deep learning model for Mashhad airport air traffic management systems was proposed. The analysis of the system was performed using the actual data of Mashhad Airport. Our results demonstrate that among various clustering algorithms, K-means and deep learning methods are more efficient and widely used. Evaluation criteria such as accuracy rate, delay, The Root mean square error (RMSE) and mean square error (MSE) are more commonly applied in air traffic system evaluation. The implementation of the air traffic management base on hyprid deep learning could be increase accuraccy of flights control opration in airports

In conclusion, it is recommended that a combination of the existing algorithms be used in further investigations to select a valuable subset of features among the datasets obtained from valid websites. Valid research could also be conducted to improve these algorithms.

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