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Airlines fleet assignment prediction model for new flights using deep neural network

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ABSTRACT

Airline fleet assignment is the process of allocating different types of aircraft to different scheduled flight legs in order to reduce operating costs and increase revenue. In this research, flights data records from Egypt Air airlines was employed to build an intelligent fleet assignment model to predict the optimal fleet type for new flights. Deep neural network (DNN) and support vector machines (SVM) was used for model formulations. We evaluated the performance of models on a fleet type prediction. The research results showed that various accuracy levels of fleet type multiclass classifications were attained by the models. In terms of accuracy, the deep neural network performed better than support vector machines. Besides, airline companies can use our proposed model for fleet type prediction for new flight with desired parameter values 5, 20 and 250 for hidden layers, number of neuron and number of epochs respectively if they use the same structure for data attributes.

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1. INTRODUCTION

Airlines have daily scheduled flights to many airports according to its network. The process of determine the fleet type for the flight leg is called the fleet assignment. The fleet assignment decision greatly affects on airlines profitability. Due to limited capacity, assigning a fleet smaller than necessary may result in customer losses; assigning a fleet bigger than necessary will result in unsold seats and possibly greater operational costs [1].

Therefore, airlines need to minimize the flight operating cost required for operating these flights. The main factor that influences the flight operating cost is the fleet type used to serve the flight [2]. So, Airlines must have an intelligent model to assign the optimal fleet type for each flight in the network by minimizing the total operating cost.

Airlines need to expand their business by open new flights with other countries. Airlines have challenge to offer the optimal flight price to meet customer financial availability. Choosing the best fleet type for new flight added to airline network is a significant challenge for airlines.

Numerous optimization techniques have been explored in attempts to solve the fleet assignment problem. Ant colony method is used to choose the best fleet for each flight in order to solve the problem of fleet assignment. It considered the dynamic demand and showed that it is produces major results including a minimizing of operating expenses with the maximizing in income [3]. Recent researches [4]-[7] proposed a solution for integrating two or more sub problems. They consolidate fleet assignment with other problems such as crew rostering, schedule design, routing, and maintenance. The multiple-criteria approach used to resolve the issue of fleet assignment by using either maximising profit or lowering emission costs as an objective function [8], [9]. Some researchers modeled the financial and operational data as an optimised fleet selection using data from 15 major US airlines representing 22 fleet types [10]. Other researchers [11] used a variable neighbourhood search to tackle the issue of airline fleet sizing and fleet assignment.

On the other side, Lui *et al.* [12] demonstrated how employing the intelligent fleet assignment solution can enhance airlines market share and boost customer satsifaction. A novel airline stochastic process with arbitrary passenger requirements was proposed by the research. Khanmirza *et al.* [13] use a parallel master-slave genetic method to address the integrated flight schedule planning and fleet assignment problem (PMS-GA). Support vector regression combined with a genetic algorithm is used by Su *et al.* [14] to build a strong model for fleet assignment with a double-objective that maximises flight operational profit while minimising the number of aircraft types in crowded airports. Moreover, Abouzeid *et al.* [15] have built an intelligent model to automate airlines fleet assignment process using particle swarm optimization (PSO). The model optimizes EgyptAir airlines profitability by minimizing the operating costs for available fleet types.

A subfield of artificial intelligence called machine learning (ML) focuses on creating algorithms that can be programmed to gain knowledge from the past [16], [17]. Overall, this technique has demonstrated greater problem-solving effectiveness when compared to other approaches [18]. A class of algorithms that aim to model high-level abstract notions via learning at multiple degrees and layers includes multilayer neural networks, often known as deep neural networks (DNN) which is a subset of machine learning subject [19], [20].

In this article, we suggest an intelligent fleet assignment model to predict the optimal fleet type for new flights using deep neural network model based on flights data. To justify the model accuracy, we will compare the results of DNN model with other machine learning method that is support vector machines (SVM). Besides, we will tune the DNN model parametrs to get the optimal fleet assignment model that can be used by any airline company.

2. RESARCH METHOD

2.1. Fleet assignment solution algorithm

This section will provide an overview of the algorithm of DNN in order to solve airlines fleet assignment for new flights. A DNN is a network with at least two hidden layers, an output layer, and at least one input layer. The output layer is used for either classification or prediction [21]-[23]. Flights data that have influence in determine the suitable fleet type for flight used for input layer. The fleet type used for output layer. Algorithm 1 displays the proposed solution of fleet assignment using DNN and SVM.

Algorithm 1. Fleet assignment for new flights model

```
Input: Dataset for flights records and each record associated with assigned fleet type (class
label)
Output: DNN classifiers that classify unknown class label for a given flight with data
features
Start
    1.  Load the dataset with class label of fleet type
    2.  Visualize the dataset based on class label
    3.  Encode the categorical data with values
    4.  Split the dataset into two independent datasets x and y one for training (x_train,
        y_train) and the second for testing (x_test, y_test)
    5.  Normalize the datasets
    5.1 Import DNN library
    5.2 Import SVM library
    6.  Create function for DDN model classification
    6.1 Set DNN model parameters
    6.2 Train the model with training data
    6.3 Test DNN model accuracy with testing data (x_test,y_test)
    7.  Create function for SVM model classification
    7.1 Set SVM model parameters
    7.2 Train the model with training data
    7.3 Test SVM model accuracy with testing data (x_test,y_test)
    8.  Repeat steps 6 and 7 with new parameter setting until reach to the best accuracy for
        each model
    9.  Predict fleet type based on new flight data tuple
     End
```

The algorithm starts with reading the dataset related to flights with associated class label of fleet type. Visualize the dataset to view interested insights in data. Prepare the dataset by encoding the categorical data, the data should be divided into training and testing groups and normalize data. We build the model by training data, evaluating the model by using testing data. After we reach the optimal accuracy for the DNN model we can predict the optimal fleet type for the new flight. During model training we must adopt the model parameter. These parameters are adjusted to optimize the model's accuracy and are particular to each model's architecture. Table 1, displays the parameter setting for SVM and DNN implemented in this article.

Table 1. SVM and DNN parameter setting

Method	Parameters	Values
SVM	Kernel function	RBF
	Regularization C	0.1,0.2,0.4,1,10
	Gamma γ	0.01,0.1,0.4
	Multiclass methodology	OVO
DNN	Activation function	RELU
	Solver	LBFGS
	Hidden layer size	2,3,4,5,6
	Number of neurons	2,3,5,10,20,50
	Learning rate	0.001
	Epochs	150,200,250,500
	Momentum	0.1,0.2,…,0.9

2.2. Data acquisition

Dataset obtained from EgyptAir Airlines over a two-year period. The information taken from EgyptAir's costing and accounting system. The data attributes are sector, route, cycle, variable operating cost, fixed operating cost, indirect operating cost, total revenues, block hours, flight hours, number of passengers, number of available seats, available seat kilo meter (ASK), revenue passenger kilo meter (RPK) and assigned aircraft type. Table 2, displays the dataset attributes and its description used in fleet assignment model formulation using SVM and DNN. We selected seven stations from the network of EgyptAir in order to simplify the fleet assignment model. Cairo International Airport (CAI) serves as the hub station, with Kuwait (KWI), New York (JFK), Frankfurt (FAR), London (LHR), Jeddah (JED), and Riyadh serving as the spokes (RUH). For the seven stations mentioned above, there are 20671 rows and 14 columns in the data set. Nine different categories of aircraft types are flown by EgyptAir airlines around the world. The fleet consists of the following aircraft types: A320-232, A321-231, A330-200, A330-300, B737-800, B737-800NEW, B777-200, B777-300, and B787-900. The following seven stations have approximately 30 flights every day: EgyptAir has 4, 2, 5, 4, 20, 9, 2, 6, and 6 of each type, respectively. Table 3 displays sample of data for 10 attributes with assigned aircraft for one-day flights schedule.

Table 2. Data attributes used in SVM and DNN for fleet assignment model formulation

Attribute Name	Description	Type of attribute
Sector	A flight segment between two airports	Categorical
Route	It is out-and-back trip and land at the same airport from which they took off.	Categorical
Cycle	The activity of an Engine from the time an aircraft leaves the ground until it contacts the ground toward the finish of a flight.	Numeric
Variable operating cost	Variable costs change in relation to airplane use, and incorporate fuel and oil, support and crew costs	Numeric
Fixed operating cost	Costs that broadly stay the same even if flying increases or decreases	Numeric
Indirect operating cost	Expenditure which are not directly related to the operation of a particular aircraft	Numeric
Total revenues	The total income the airline generates from this flight segment	Numeric
Block hours	Time from the second the airplane entryway closes at takeoff until the second the airplane entryway opens at the arrival gate	Numeric
Flight hours	The time duration the aircraft takes when it leaves the ground until it touches the ground at the end of a flight.	Numeric
Number of passengers	The actual number of passengers travelled by this flight	Numeric
Number of available seats	The seat capacity for aircraft assigned to this flight	Numeric
Available seat kilo meter (ASK)	The total flight passenger capacity of an airline in kilo meters	Numeric
Revenue passenger kilo meter (RPK)	The number of kilo meters travelled by paying passengers	Numeric
Assigned aircraft type	The assigned aircraft for this flight	Categorical

Table 3. Sample of data for ten attributes with assigned aircraft for one-day flights

Sector	Route	Variable cost	Fixed cost	Indirect cost	Total revenues	Number of KM Flown	Seat Capacity	Number of passengers	Assigned aircraft type
CAIKWI	CAIKWICAI	8515	1722	2578	16857	1601	144	85	B737-800
KWICAI	CAIKWICAI	13529	2560	2839	22086	1601	144	107	B737-800
CAIKWI	CAIKWICAI	8800	1552	2951	28350	1601	144	119	B737-800
KWICAI	CAIKWICAI	13067	2968	2845	20986	1601	144	108	B737-800
CAIJED	CAIJEDCAI	8500	1968	2646	20228	1216	144	127	B737-800
JEDCAI	CAIJEDCAI	12148	2039	2778	20007	1216	144	139	B737-800
CAIJED	CAIJEDCAI	7652	1373	2154	10979	1216	144	82	B737-800
JEDCAI	CAIJEDCAI	12007	1581	2704	22192	1216	144	132	B737-800
CAIJED	CAIJEDCAI	15696	2569	4253	28321	1216	268	180	A330-200
JEDCAI	CAIJEDCAI	18588	2373	5155	42058	1216	268	262	A330-200
CAIJED	CAIJEDCAI	8877	2014	2540	18930	1216	144	117	B737-800
JEDCAI	CAIJEDCAI	18498	2698	5099	48019	1216	268	257	A330-200
CAIJED	CAIJEDCAI	8356	2135	2133	10735	1216	144	80	B737-800
JEDCAI	CAIJEDCAI	11814	2047	2628	23070	1216	144	125	B737-800
CAIJED	CAIJEDCAI	16625	3324	4589	27845	1216	301	185	A330-300
JEDCAI	CAIJEDCAI	19768	3099	5710	43324	1216	301	287	A330-300
CAILHR	CAILHRCAI	43226	17824	0	113962	3531	346	329	B777-300
LHRCAI	CAILHRCAI	45010	14747	11390	82549	3531	346	263	B777-300
CAILHR	CAILHRCAI	23366	6277	5417	45198	3531	154	139	B737-800 NEW
LHRCAI	CAILHRCAI	19763	5470	5249	32103	3531	154	125	B737-800 NEW
CAIFRA	CAIFRACAI	14714	6092	4338	28181	2921	154	128	B737-800 NEW
FRACAI	CAIFRACAI	19104	5112	3993	19459	2921	154	98	B737-800 NEW
CAIJFK	CAIJFKCAI	94765	38751	25393	211486	9010	346	319	B777-300
JFKCAI	CAIJFKCAI	131937	34535	25229	175609	9010	346	311	B777-300
CAIKWI	CAIKWICAI	23138	7534	6364	51472	1601	346	227	B777-300
KWICAI	CAIKWICAI	27389	10320	6888	50981	1601	346	272	B777-300
CAIJED	CAIJEDCAI	6724	1542	1258	101	1216	144	0	B737-800
JEDCAI	CAIJEDCAI	9871	1777	2630	19356	1216	144	125	B737-800
JEDCAI	CAIJEDCAI	9394	1844	2575	23231	1216	144	120	B737-800
CAIJED	CAIJEDCAI	6850	1674	1272	101	1216	144	0	B737-800

3. RESULTS AND DISCUSSION

In this article, we formulated the fleet assignment prediction model to predict the fleet type for new flight added to EgyptAir airlines. We evaluated the accuracy of prediction for DNN and SVM. The performance of these methods was experimentally measured in predicting the fleet type for new flights to identify which of the approaches perform best in our case study. We implemented a multiclass classification model using DNN and SVM to find out the optimal fleet from available fleets to new flight. The proposed model implemented by authors using python programming on EgyptAir dataset specified in section (3).

To measure the accuracy of models we used the confusion matrix. Table 4 describes the structure of confusion matrix for calculation of fleet prediction accuracy [24]. The confusion matrix is arranged according to total true positive (TTP), total false negative (TFN), total true negative (TTN), and total false positive (TFP). TFN, TTN and TFP for each class i calculated based on (1) where $n = 9$ which represent the number of classes used in SVM and prediction model. TTP calculated for all classes in (2) [25]. The precision (P) and recall (R) for each class i computed in (3) and (4) respectively. The overall model accuracy computed using (5) [26]. Where c_{ij} represents the number of predicted samples. When $i = j$ the classifier gets the predicted class as actual class, otherwise the classifier gets mislabeling the sample. Since we have nine fleet types described as class label. Therefore, we have nine class for predicted number of classes and nine for actual number of classes. Class labels are presented as 1, 2 ,…, 9 for fleet types A320-232, A321-231, A330-200, A330-300, B737-800, B737-800NEW, B777-200, B777-300, and B787-900 respectively. The performance comparison results for SVM and DNN are displayed in Table 5.

$$
\begin{aligned}
TFN_i &= \sum_{\substack{j=1 \\ j\neq i}}^{n} c_{ij} \\
TFP_i &= \sum_{\substack{j=1 \\ j\neq i}}^{n} c_{ji} \\
TTN_i &= \sum_{\substack{j=1 \\ j\neq i}}^{n} \sum_{\substack{k=1 \\ k\neq i}}^{n} c_{jk}
\end{aligned}
\tag{1}
$$

$$TTP_{all} = \sum_{j=1}^{n} c_{jj} \tag{2}$$

$$P_i = \frac{TTP_{all}}{TTP_{all} + TFP_i} \tag{3}$$

$$R_i = \frac{TTP_{all}}{TTP_{all} + TFN_i} \tag{4}$$

$$Accuracy = \frac{TTP_{all}}{\text{Total Number of Testing Entries}} \tag{5}$$

Table 4. Confusion matrix accuracy computation for multiclass fleet classification of flights

		Predicted Classes								
		1	2	3	4	5	6	7	8	9
Actual Classes	1	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}	c_{16}	c_{17}	c_{18}	c_{19}
	2	c_{21}	c_{22}	c_{23}	c_{24}	c_{25}	c_{26}	c_{27}	c_{28}	c_{29}
	3	c_{31}	c_{32}	c_{33}	c_{34}	c_{35}	c_{36}	c_{37}	c_{38}	c_{39}
	4	c_{41}	c_{42}	c_{43}	c_{44}	c_{45}	c_{46}	c_{47}	c_{48}	c_{49}
	5	c_{51}	c_{52}	c_{53}	c_{54}	c_{55}	c_{56}	c_{57}	c_{58}	c_{59}
	6	c_{61}	c_{62}	c_{63}	c_{64}	c_{65}	c_{66}	c_{67}	c_{68}	c_{69}
	7	c_{71}	c_{72}	c_{73}	c_{74}	c_{75}	c_{76}	c_{77}	c_{78}	c_{79}
	8	c_{81}	c_{82}	c_{83}	c_{84}	c_{85}	c_{86}	c_{87}	c_{88}	c_{89}
	9	c_{91}	c_{92}	c_{93}	c_{94}	c_{95}	c_{96}	c_{97}	c_{98}	c_{99}

Table 5. SVM and DNN performance comparison for fleet assignment prediction

Model	Recall	Precision	Accuracy
SVM	0.9339	0.9903	0.9868
DNN	0.9998	0.9983	0.9998

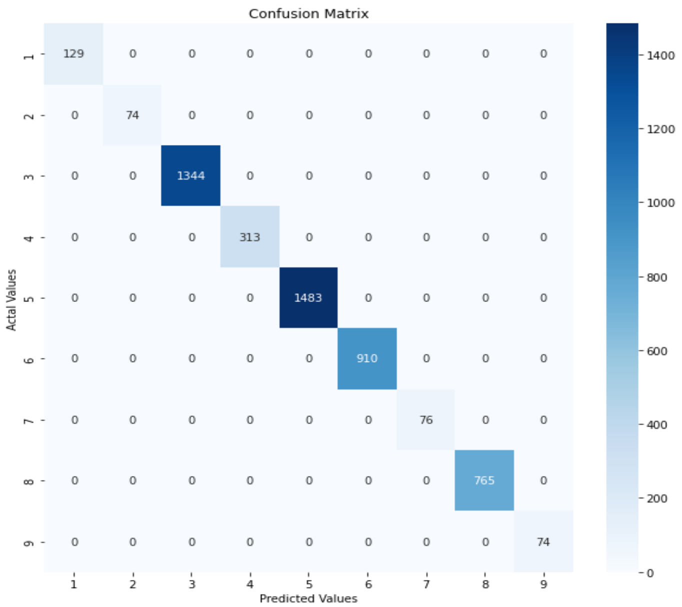
The average recall, precision, and accuracy of the SVM in our experiment are 93.39%, 99.03% and 98.68% respectively. Although the DNN for the same metrics are 99.98%, 99.83% and 99.98%. As a result, for all metrics, the DNN model performed better than the SVM.

In our case study, we continued further to defend the DNN's performance in terms of accuracy based on a variety of levels of parameters during training and testing. With the same number of features as inputs, we looked into the characteristics at various stages of model building. Table 6 displays the performance of DNN model when using different parameters during model building. We set the number of hidden layers as 2, 2, 3, 4, 5 and 6 with 2, 3,5,10, 20 and 50 neurons in each layer respectively. For the number of epochs, we used 150, 150, 200, 250, 250 and 500. We found that the accuracy was 81.42% and 80.24% when we employed 2 hidden layers, 2 neurons, and 150 epochs during training and testing respectively. However, intriguingly, the training and testing accuracy climbed to 92.51% and 92.24%, respectively, when there was a rise in the number of neurons with the same number of hidden layer and epochs. We note that the accuracy of the experiments was not significantly different between training and testing using the same set of parameters. When the quantity of neurons, epochs, and hidden layers is increased further to 5, 20, and 250, respectively. We noticed that the model reached to maximum with 99.99% and 99.98% for training and testing respectively. Increasing the number of layers above 5 or use number of epochs more than 250. The model accuracy not affected.

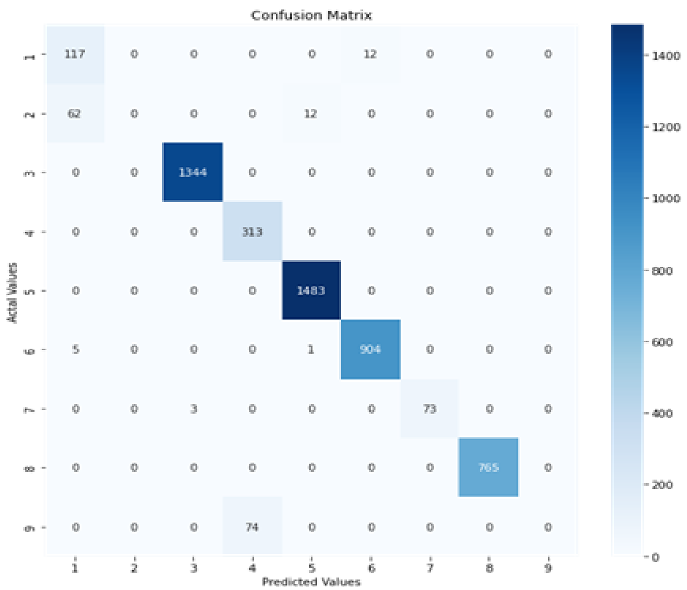
Table 6. Performance of the DNN model during training and testing with various parameter settings

No. of hidden layers	No. of neurons/layer	Epochs	Accuracy	
			Training	Testing
2	2	150	0.8142	0.8024
2	3	150	0.9251	0.9224
3	5	200	0.9697	0.9672
4	10	250	0.9799	0.9780
5	20	250	0.9999	99.98
6	50	500	0.9999	0.9998

Figure 1 dispalys the confusion matrix output for DNN model with two different parameters setting. The first one displayed in Figure(a) for the confusion matrix output with parameter values 5, 20 and 250 for the number of hidden layer, number of neurons and epochs respectively. The second displayed in Figure(b) for the confusion matrix output with parameter values 4, 10 and 250 for the number of hidden layer, number of neurons and epochs respectively. Therefore, any increasing for these parameter values above 5, 20 and 250 does not guarantee greater or better accuracy for DNN model. Also, decreasing the parameter values from 5, 20 and 250 make the model performance decreased. Consequently, we can conclude that when we set the model parameters for number of hidden layer, number of neurons and epochs to 5, 20 and 250 we get the maximum accuracy for the DNN model.



(a)



(b)

Figure 1. Confusion matrix output for DNN model with two different parameter values for (a) parameter values 5, 20 and 250 and (b) parameter values 4, 10 and 250

4. CONCLUSION

Previous researches discussed the process of fleet assignment for current fleet types according to current flight schedule for airlines. Airline companies need to add new flights to its network continuously. In this article, we implemented a multi class deep neural network to build a fleet assignment model for EgyptAir airlines to predict fleet type for new flights. To justify the DNN model accuracy we compare the results with multiclass SVM. The models trained and tested on EgyptAir actual dataset. The experiment results showed that the average recall, precision, and accuracy of the SVM are 93.39%, 99.03% and 98.68% respectively. while the DNN for the same measures are 99.98%, 99.83% and 99.98%. Consequently, on all metrics, the DNN model outperformed the SVM. Due to the great influence of parameter values on DNN performance. This article discussed the influence of parameter setting during DNN model building to determine the best parameter values that grantee the best model accuracy during fleet type prediction. The best model accuracy obtained when setting parameter values 5, 20 and 250 for number of hidden layers, number of neuron and number of epochs respectively with accuracy 99.98%. Besides, any increasing for these parameter values above 5, 20 and 250 does not guarantee a better or more accurate DNN model. Also, smaller number of hidden layers, neurons and epochs the model's performance generally declined throughout training and testing. Finally, we can conclude that Airline companies can use our fleet assignment model to predict the fleet type for new flight with desired parameter values 5, 20 and 250 for hidden layers, number of neuron and number of epochs respectively if they use the same structure for data attributes described in section 3.

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