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Research Article

Artificial Neural Network Adaptive Path Time Prediction on a Road Network

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Abstract: This study proposes a time prediction approach to predict trip time from Cairo airport to the tourist sites in Cairo at different conditions. The proposed approach automatically predict the trip time based on different factors such as whether, roads network type, speed and connected edge length. The proposed time prediction approach is adopted using Artificial Neural Network (ANN) techniques with Radial Basis Function Neural Networks (RBF) model and Multilayer Preceptor (MLP) model. Experimental results show that ANN time prediction approach based on two models gives promising prediction time with a powerful alternative for bus arrival time prediction. MLP model has the better-predicting performance with more accurate results than based on RBF.

Keywords: Artificial neural network, multilayer preceptor, path time prediction, radial basis function, road networks

INTRODUCTION

Tourism has become the world's largest industry as its growth shows a consistent year to year increase. The World Tourism Organization (WTO) (2005) predicts that by 2020 tourist arrivals around the world would increase by 200%. Consequently, Tourism has become a highly competitive business for tourism destination over the world. Tourism is an information-based business, tourists have to leave their daily environment for consuming the product. At the beginning of the 21st century, the structure of demand and supply in the tourism industry is undergoing significant changes. Social and economic changes, for instance, age profile, lifestyles and organization of work, together with the fast distribution of the Internet, increasing e-business and the availability of online public services have had a strong impact on the demand for tourism products and their modes of provision (Kim *et al*., 2007). The competitiveness and success of the tourism industry depend on the impact of social, economic and technological changes within society as a whole. Key among these global trends is the increase in the use of electronic services (Werthner and Ricci, 2004). Today, tourism service suppliers are a group of many different users, most of them offering electronic services. Focusing on Egypt, Tourism represents one of the most important human activities; it plays an important role in the social structure of tourism areas in Egypt and is responsible for social stability in these regions as it creates millions of direct or indirect jobs for the Egyptians. Therefore, Tourism sector plays a major role in the structure of the national economy of Egypt. Tourism is affected by main factors and auxiliary factors. The main factors associated with the tourist such as time, money and tourist interests. The auxiliary factors influent the tourism program, such as climate and political situation and services (roads, accommodation and transportation .... etc) and provide a suitable tourism program for tourists.

As the transit travel more and more frequently, they spend more time on transportation for that reason it becomes a critical concern to find an optimal path. The transit travelers spend more frequently time on transportation for that reason find an optimal path have a critical interest to maximize the advance of available transit time. The problems regarding the planning of the traffic path were considered as the shortest distance problem regarding the path problems. However in a real urban traffic system considering physical distance only is not practical impact (Feng *et al*., 1999). Shortest path algorithm was used to get the shortest route but roads type, whether or traffic congestion needs much more time to go through. Therefore, get shortest time route that takes shortest travel time from the beginning to the end is a good choice (Wang *et al*., 2005; Halpern, 1977).

In recent years, various sophisticated techniques and algorithms have been developed to predict bus travel time. There has been a growing interest in applying neural networks to many areas of science and engineering, such as control systems, medical

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application, image analysis, computer vision and time prediction systems (Yamamoto and Nikiforuk, 2000). The intelligent data processing ability of human brains is encouraged to imitate by ANN, ANN has been reported to be especially useful for finding solutions to complex non-linear problems (Chien *et al*., 2002).

Millions of people travel around the globe for business, sightseeing, vacations, or other reasons and spent a huge amount of money on tickets. Most of those travelers spent a transit time in airports. This research aims to exploit the waiting time of transit tourists in the country, due to a proposed approach that automatically predict the trip time based on different factors and adopted using ANN techniques with RBF and MLP models.

LITERATURE REVIEW

Predicting trip time between connected edges is a recognized problem in the transportation industry that has been studied by many in recent years. Kalman 29 Filters (Cathey and Dailey, 2003), Support Vector Machines (Bin *et al*., 2006) and K-Nearest Neighbors (Tiesyte and Jensen, 2008) were used to create 30 models for trip time prediction between connected edges. K-Nearest Neighbors and Kernel Regression were used to predict bus arrival time using GPS measurements (Sinn *et al*., 2012).

The approaches for trip time prediction can be classified as follows (Shalaby and Farhan, 2003): Statistical Models: Using a set of independent variables to form a function that predicts the trip time (Suwardo *et al*., 2009). Historical Approach: calculate the average travel time for the same period over different days to predict the travel time at a particular time. Real-Time Approach: estimating the trip time at the subsequently time interval to be the same as that in the current time interval. In this approach, the trip time trend alters within a narrow range which is impossible for actual traffic trend (Lin *et al*., 1999). Model-Based Approaches: using Kalman Filter algorithm that updates the travel time continuously as new observations became available. This algorithm is better than all other developed models in terms of accuracy and representing the dynamic ability to update itself depending on new data of the transit operating environment. Machine Learning Techniques: the most common Machine Learning technique for traffic and trip time prediction is Artificial Neural Network (ANN) because it solves complex non-linear relationships (Chien *et al*., 2002; Padmanaban *et al*., 2010).

Recently, Niu *et al*. (2015) propose online-traffic-prediction based route finding mechanism, which organically utilizes large-scale taxi GPS traces and environmental information. This mechanism extracts nonlinear, random and high-dimensional characteristics from the traffic flow changes and reflects the dynamic patterns in the transportation network. It tries to find the fastest route based on online route computing using a dynamic weighted classifier fusion approach, while it doesn't take into consideration the factors that affected on trip time.

A crucial part for the real-time computation of the path travel time in a time-dependent traffic network is the prediction of link travel times. There are many techniques solving this problem based on Bayesian network models (Sun *et al*., 2006), single link models (Pan *et al*., 2012), or traffic incident models (Pan *et al*., 2013). None of these techniques incorporate the inherent uncertainty of the predicted values, while Yang *et al*. (2013) proposed to utilize spatiotemporal hidden Markov models for this purpose. Moreover, this approach is hardly applicable in the real-time setting due to the cost of model construction and the current situation in the network doesn't include in the prediction process. Hence, it arises a robust need for a model that automatically predict path time on a road network and taking into consideration solving the previous problems.

PROPOSED APPROACH

The objective of the proposed approach is to help the transit tourist to have a suitable trip with the lowest predicted cost time to assess the overall transit tourist trip system. Although, there is a significant development of GIS applied inroads networks and there are some problems for obtaining the shortest time path. The most significant problem is the unreliable results in just searching the shortest path by its length without concerning the conditions that affected on the vehicle speed pattern. The factors that must be concerned in calculating the shortest time for a trip path between two nodes is the concerned edge length, road type, vehicle speed and weather.

The proposed approach aims to choose the predicted trip cost time for the overall suggested trips and overcome the indicated above problems. The innovative aspects of the proposed approach are supplementing the path trip time with a sequence of phases and develop a proposed approach to automatically predict the path trip time. First, we classify the roadway network of the concerned edge the focus of this study within ring road and Suez road areas that connecting all external cities in the Greatest Cairo (Nakat and Herrera, 2010). Moreover, the second phase in the proposed approach is concerning on determining the factors and conditions that affected in calculating the shortest path between two nodes. Finally, we automatically predict the path trip time using Artificial Neural Network (ANN) with two different network structures Radial Basis Function (RBF) and Multilayer Preceptor (MLP) taking into consideration the previous sequence of steps to increase the efficiency of the proposed approach. The following subsection illustrates the proposed approach phases in detail.

Table 1: GCMA zones network types (Nakat and Herrera, 2010)

Area	Local	Urban primary street	Urban expressway	Regional primary highway	Inter urban primary highway
South Giza					
Helwan					
10th of Ramadan					
6th of October					
Giza					
Imbaba Markaz					
Maadi					
Khaleefa					
Dokki					
CBD					
Shoubra					
Nasr City					
Ain Shams					
Masr Al Gadida					
Salam City					
Shoubra El Khima					
Qanater					
Qalioub					

Roadway network classification: Since roadway network types and characteristics seriously affected on driving and speed patterns. Also, it helps the passenger to predict the estimated trip time that we need to build a complete suitable trip with the lowest cost of time. Roadway networks in the Greater Cairo Metropolitan Area (GCMA) are classified to 5 road types (Nakat and Herrera, 2010) which will be listed as follows, Inter-Urban Primary Highway, Regional Primary Highway, Urban Expressway, Urban Primary Street and other (local) as illustrated in Table 1. Moreover, in the proposed approach the number of lanes in the road was taken into consideration. The number of lanes in the GCMA roads will be classified as follows, local roads having one lane in each direction, the ring road contains 4 lanes and the number of lanes in other main corridors is commonly limited to 3, or even 2 (Nakat and Herrera, 2010). This classification is essential and affected on estimating the path trip cost time.

Factors affected on traffic flow: However, the traditional algorithms only concern the speed and Euclidean distance considerations. According to the previous roadway classification and the number of lanes in the GCMA roads, driving conditions and driving preferences will be considered and observed. Also, dense regions such as big cities and the congestion costs according to determine the rush hours must be observed. Different factors describing the characteristics of traffic flow and affected on estimating the optimal path (shortest path with the lowest cost of time). Based on the previous survey these factors include roadway network type, the number of lanes in each road, weather and speed (Nakat and Herrera, 2010; Goodwin *et al*., 2015; Mehar *et al*., 2013). These factors were taken into consideration to the next phase to improve the accuracy of the path trip time prediction.

ANN path trip time prediction: We will demonstrate some properties that should be taken into account

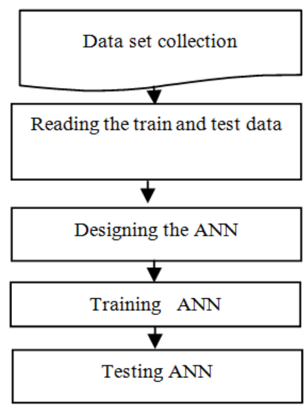

Fig. 1: The proposed time prediction approach

before applying this phase for connected edges. The fastest route between the connected edges nodes should be selected according to the roadway classification as illustrated in Sub-Section A. The selected route should be supported by all the concerned factors that affected on the trip time (roadway network type, number of lanes in each road, weather and speed) as illustrated in Sub-Section B. Finally, we use the ANN in the condition of real-time traffic to automatically predict the path trip time with RBF network and MLP network. Figure 1 illustrates an overview of the proposed time prediction approach.

Designing the ANN models for the RBF and MLP networks compromises of three stages, constructing the network, training the network and testing the network performance.

Stage 1: Constructing the network: In this stage, the network has been structured for trip time prediction application. The proposed approach has been implemented in MATLAB platform using ANN matlab toolbox and the built-in functions. For ANN models the maximum number of iterations equal 1000, the weights and biases are automatically initialized. The number of

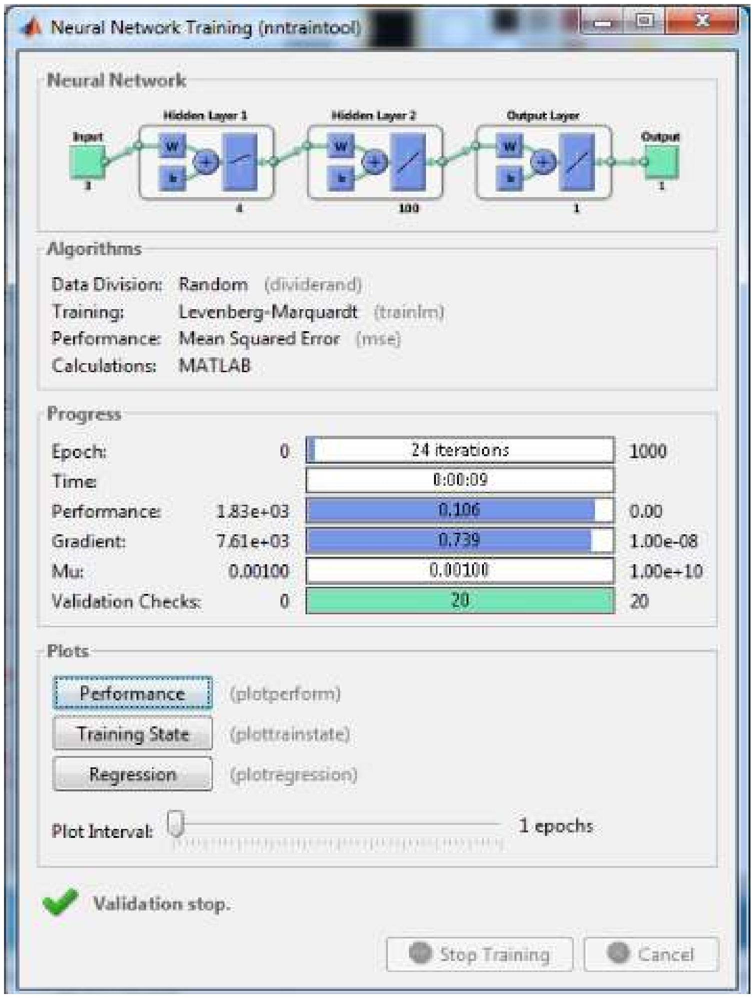

Fig. 2: Training based on MLP

neurons in the input layer is equal to 3 and one neuron in the output layer. For RBF model, the built-in function 'newrb' used for creating an RBF network using the spread of radial basis function equal to 50 and the value of the mean square error goal is ranged from 0.02 to 0.09. For hidden layer, the maximum number of neurons to add is equal to 200. In MLP model, the built-in function "newff" used for creating a feedforward back-propagation network. The network structure consists of 100 hidden layer and 4 neurons. 'logsig', 'purelin' are built-in transfer functions that are used.

Stage 2: Training the network: The training function is the same for ANN models. During this stage, the weights learning function are adjusted to minimize the difference between the predicted output of the network and actual output. To start the training process the initial weights are chosen randomly and then begin the training. Initially, on all the interconnections the weights are set to be small random numbers. Each neuron (node) were randomly initialized its weights to values between -1 and +1 (Torres-Sospedra *et al.*, 2005). Then, the ANN has been trained by exposing it to sets of existing data where the outcome is known. The ANN training is done by iteratively adjusting connection weights by the minimization of the error function that has the mean square error between target and actual outputs averaged overall training data. The training stage is illustrated in Fig. 2 and 3 for MLP and RBF models.

Stage 3: Testing the network performance: Finally, we test the performance of the developed ANN models using statistical analysis with the Root Mean Square Error (RMSE) and the Mean Bias Error (MBE) which are the short term performance parameter and the long-term performance parameter respectively. RMSE measure the variation of the predicted values around the measured data. MBE determine the average deviation of the predicted values from the corresponding measured data:

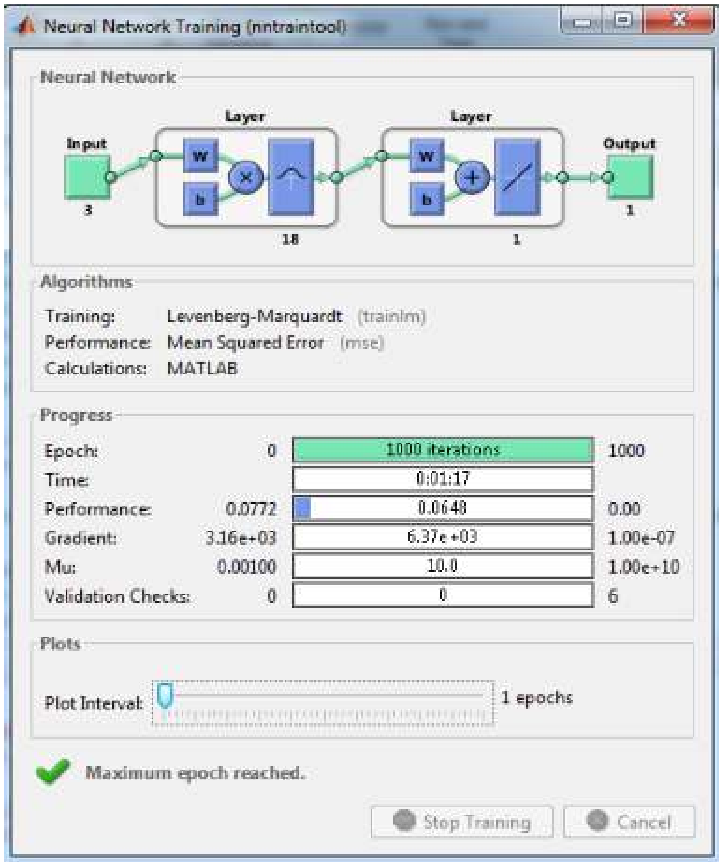

Fig. 3: Training based on RBF

Table 2: Values of the concerned factors for two examples of connected edges

Connected Edge No.	Path	Length KM	Road type	Whether	Speed KM / Hrs	Time Min.
1	Airport Rd --> Pyramids Hill Rd	46	Regional primary highway	32 clear sky	70.7	39
	Airport Rd --> Pyramids Hill Rd	46	Regional primary highway	37 clear sky	71.5	38
	Airport Rd --> Pyramids Hill Rd	46	Regional primary highway	19 rainy	42	65
	Airport Rd --> Pyramids Hill Rd	46	Regional primary highway	22 partially cloud	50.6	54
	International Cairo Airport Rd --> Cairo Tower, Zamalek	24	Inter urban primary highway	32 clear sky	35.1	41
2	International Cairo Airport Rd --> Cairo Tower, Zamalek	24	Inter urban primary highway	37 clear sky	36	40
	International Cairo Airport Rd --> Cairo Tower, Zamalek	24	Inter urban primary highway	19 rainy	20	72
	International Cairo Airport Rd --> Cairo Tower, Zamalek	24	Inter urban primary highway	22 partially cloud	29	49

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{p,i} - I_i)^2} \tag{1}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(I_{p,i} - I_i) \tag{2}$$

where,

$I_{p,i}$ = The predicted trip time in the connected edge between two nodes

I_i = The measured trip time in the connected edge between two nodes

n = The number of observations.

RESULTS AND DISCUSSION

The experiments were carried out to validate the performance of the proposed approach. This section illustrates the achieved results for both the MLP and RBF ANN models. Each model runs 8 trails in order to get best results. Table 2 represents a sample for the values of the concerned factors that affected on the trip time for two examples of connected edges from the 48 connected edges that we do our experiments on it. For MLP model in best trail Fig. 4 displays the simulation of training stage and Fig. 5 display the simulation of a

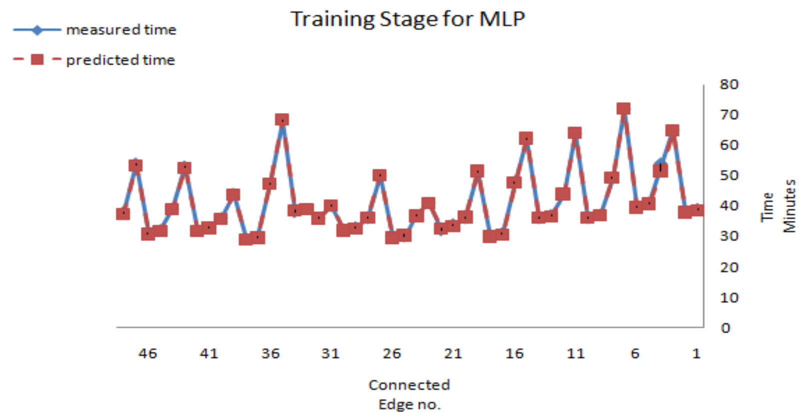

Fig. 4: Simulation of training stage for MLP

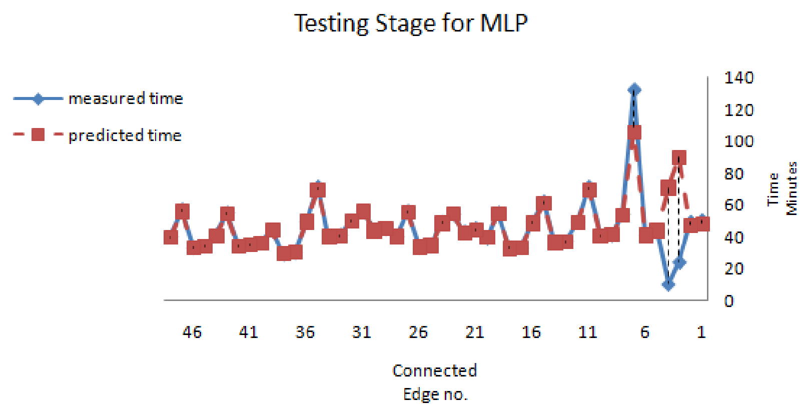

Fig. 5: Simulation of testing stage for MLP

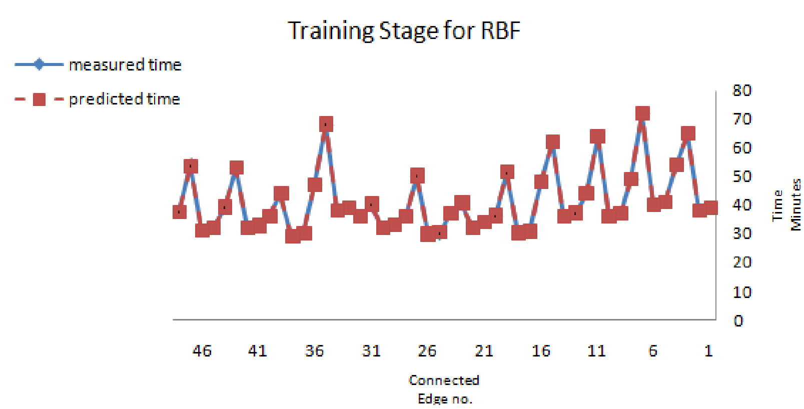

Fig. 6: Simulation of training stage for RBF

Table 3: Statistical error parameters for MLP

Trail	Iterations	Training Time (sec)	RMSE	MBE
1	43	22	13.64	2.61
2	33	12	13.52	1.64
3	34	12	13.41	0.41
4	30	10	13.82	1.57
5	24	9	2.58	0.79
6	26	10	11.48	3.83
7	181	65	13.37	2.21
8	73	27	14.52	2.62

testing stage for the best trail. Table 3 shows the computed values of the statistical error parameters RMSE and MBE for 8 trails and the corresponding number of iterations and the run training time.

In RBF model, for the best trail Fig. 6 displays the simulation of training stage and Fig. 7 displays the simulation of testing stage. Table 4 shows the computed values of the statistical error parameters RMSE and MBE for 8 trails at the different goal. A negative MBE

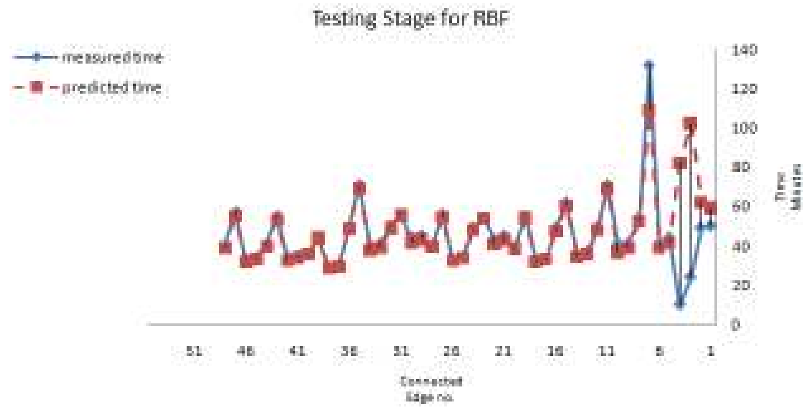

Fig. 7: Simulation of testing stage for RBF

Table 4: Statistical error parameters RBF

Trail	Goal	RMSE	MBE
1	0.02	21.13	3.11
2	0.03	7.09	-1.47
3	0.04	12.18	-1.04
4	0.05	15.95	2.17
5	0.06	13.39	1.4
6	0.07	12.9	1.41
7	0.08	12.93	1.29
8	0.09	12.93	1.29

occurs when predictions are smaller in value than observations.

From experimental results for MLP and RBF models, using the comparison between measured time and the predicted time in the training and testing stages we find that the predicted ANN models (MLP and RBF) provide a good prediction of the arrival time.

Lower MBE and RMSE values are better and more accurate. For MLP, trail number 5 satisfy the best results where the value of MBE equal to 0.79 and RMSE equal to 2.58 with minimum training time equal 9 sec. and less number of iterations equal to 24. For RBF trail number 7 and number 8 satisfy the best results where the value of MBE equal to 1.29 and RMSE equal to 12.93 using the goal value equal to 0.8 or 0.9.

CONCLUSION

This study proposed trip time prediction approach from Cairo airport to the tourist sites in Cairo at different conditions based on ANN techniques with Radial Basis Function Neural Networks (RBF) model and Multilayer Preceptor (MLP) model. Moreover, the proposed approach automatically predicts the path trip time depending on two stages in the first stage the roadway network of the concerned edges was classified. Hence, the second determine the factors and conditions that affected in calculating the shortest path time between two nodes. Ultimately, comparing MLP and RBF models demonstrates that, in MLP model we satisfy lower value of MBE with less training time and less number of iterations than RBF model so ANN based on MLP has better accuracy for predicting the arrival time compared to RBF.

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