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Travel Time Prediction Intelligent System for Rural Road Transportation Based on the Neural-Fuzzy Network

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Abstract

One of the major travel characteristics is time which may vary with respect to changes in travel conditions. The aim of this research is to present an intelligent system for prediction of travel time in rural roads. This topic is important because it could influence the accurate planning and organizational, social and personal management tasks. This article deals with travel time prediction by using the neural-fuzzy network, this network implements 5 fuzzy parameters as input. Presentation of the new parameters (such as the days-of-the-year parameter), a procedure for Intelligent making of the system, route blocking and using neural-fuzzy network are among the innovations of this research. The obtained results validate the possibility of using this neural-fuzzy network based on the presented parameters.

Keywords: travel time prediction, intelligent system, neural-fuzzy network, days -of- the-year parameter, route blocking

Introduction

The intelligent system for travel time prediction, with regard to conditions such as climate, holidays and traffic volume, deals with estimation of the least travel time between two points within the rural transportation network by the vehicle. Generally, if the travel conditions to be normal, the least travel time between two points is obtained by dividing the route length by the maximum allowed speed. But in case that each of the travel conditions like climate changes then the travel time could be increased.

The importance of determining accurate travel time helps not only the people involved in the transportation network but also those who use it. Knowing the travels ahead improves transportation management. The users also could delay or avoid their unnecessary travels and by more accurate planning the traffic load is reduced and the consumption pattern is modified.

The research question is that whether we can design a model or system which intelligently to be based on different travel conditions and can predict its duration and gradually enhance its precision?

The research method utilized here is a combination of mathematical analysis methods, programming and artificial intelligence knowledge. This approach could be useful in development of the intelligent transportation system. For example a program could be designed for cell phones that at any moment and with a high precision could predict the travel time between two cities.

Background of Study

Khordebinaan brothers (2010) having accurate data at hand concerning traffic of various vehicles, carried out some studies which based on different conditions and type of the road, have categorized and suggested the most suitable electronic devices for traffic detectors in the rural road transportation system of Iran.

Zheng et al. (2009) presented a model for travel time prediction which was based upon input-output linear model ARIMA[1] and Kalman filter. The information source for this model was the floating-car in which the information on the time and location of the vehicles were recorded by GPS[2]. The floating–car often diminishes the shortcomings of traffic detectors.

Rosaset al. (2010) analyzed recorded information at intelligent toll collection facilities which resulted in a model for estimation of travel time and automatic identifying of the events. When a vehicle passed a toll collection station, the start and end time of the travel was recorded. On the other hand this time was predicted based on the previous patterns. Deviation from the predicted time was a sign of an incident occurrence at the route.

Battiti (1994) for the first time discussed the issue of FRn-k with the aim that from a set of entries with n classes of data, one could select k classes in a way that would yield most information concerning the input set.

This issue later took the orderly form entitled the best input data algorithm so that by obtaining the relationship between entries and outputs existing redundancy among data is reduced and the data which has most relevance to the output is selected (Vahhabi et al. 2007).

Mutual information between previous data and selecting best data for operation, while reducing the amount of calculations also increases the prediction accuracy. Therefore, using it in the design of a short term prediction model of traffic speed seems reasonable. To calculate MI between two stochastic variables the joint probability density function between those two variables should be estimated (Hosseini et al. 2012).

The training algorithm for fuzzy systems was presented in1993 because creating a powerful fuzzy system requires numerous try and error attempts. As neural networks have good capability in learning, the idea of neural-fuzzy networks was introduced and Mr. Jung proposed its first application in estimation of model functions (Jang et al. 1993).

Mohammad Taha et al. (2012) noticed that while a lot of researches have been carried out on the application of fuzzy logic but concerning traffic simulation, fuzzy logic has not been used. To examine and assess the fuzzy logic application based on the traffic management system they produced a simulated environment where the input parameters for it included the density, volume and speed and at the end the user by entering proper values could simulate the environment they desired. The results show that proper fuzzy control patterns could solve traffic problems in a good manner.

The proposed approach by Gaxiola et al (2013) was based on training the network using type-2 fuzzy weights. The appropriate solution for this was using a set of 3 neural networks which by merging their mean, the final result could be obtained. It should be noted that adjusting the network weights is based on type-2 fuzzy weights. The results showed that while the training time is longer but the number of trainings is lower.

Kumar et al. (2013) in a research used Multi- Layer Perceptron (MLP) networks for prediction of traffic flow in the next 15 minutes by using data from 45 past minutes and for comparing implemented the MSE,MAE, NMSE and R errors. The input parameters in this model are traffic volume, speed, density, time and day of the week. To choose the input parameter of speed, the speed corresponding to each class of the vehicle is assumed with respect to the previous reported studies and the average of each section is chosen separately as the input.

Lei Wang et al. (2014) proposed a method which includes two phases, in the first phase the RBFNN2 model is used for training and approximating the nonlinear relationships among previous

[1]Auto Regressive Integrated Moving Average
[2]Radial Basis Function Neural Network

data and in the second phase the realistic method is used, therefore, first, by using the applied information the results predicted by RBFNN network are modified, next the system designs a map that yields a summary of the structure and components of the system. In this article using the concept of Mutual Information (MI) states the relations between ATPS[3] and ATIS[4] in the intelligent transportation system and it is concluded that this information prevents accumulation of a large number of the passengers in the stations and helps the operators control the system well. In this research the used data includes number of the passengers who have got on and got off, the delay time, the speed, and the staying time between two routes which in the first phase are introduced to the network and for consistency of the model, the instantaneous speed is used in real time.

Design of intelligent system for travel time prediction by using neural-fuzzy network

In this section structure of the proposed system and its performance are explained.

General structure of the travel time prediction intelligent system

This system is comprised of a control center which is in contact with the road network and users.

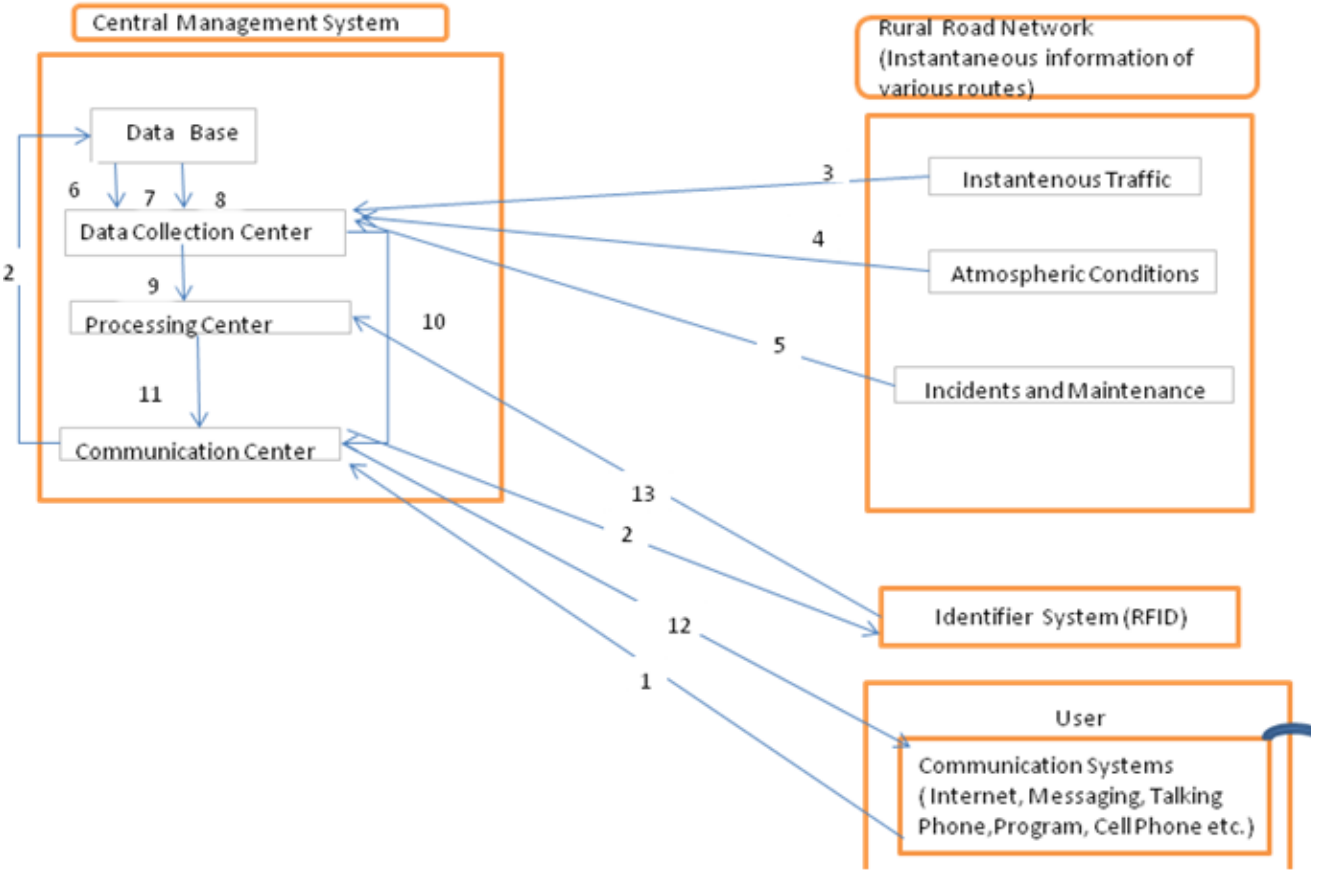

Figure 1: General structure of the travel time prediction intelligent system

For this, it takes a series of input parameters like instantaneous traffic volume, atmospheric conditions, injuries and travel start hour from the specified route (within the transportation network) and on the other hand using the available data base in the control center obtains such information

[3]Advance Public Transportation System
[4]Advanced Transportation Information System

like coefficient of the days of the year, the standard travel time in the intended route, and travel time in a similar scenario in the past, then transfers the collected data to the processing center. By using a neural-fuzzy network, the travel time is predicted and the output of this section is sent to the user. The user through internet connection, messaging system, talking phone system, software installed on the cell phone or other proper devices could contact the control center and get information about travel time predicted for the intended route. This structure is shown schematically in Fig. 1.

The interpretation of Fig. 1 and the numbering order is as follows:

1- Declaring the intended route for travel time prediction
2- Declaring the route and travel start time
3- Declaring instantaneous traffic volume for the intended route
4- Climatic condition
5- Crashes and closure of part of the line width for maintenance reasons
6- Declaring days of the year coefficient
7- Declaring standard travel time for the intended route
8- Travel time in similar conditions of the previous periods
9- Input vector for neural-fuzzy network
10- Instantaneous descriptive information of the route
11- Declaring predicted travel time for the route
12- Declaring predicted time and descriptive information for the required route
13- Declaring real-time travel

Blocking various routes of the rural network

As type of the road (highway, main road, bypass road, etc.) and type of the region (mountainous, hills, plain) and geometrical condition of the route (radius, longitudinal slope, transverse slope, etc.) directly affect travel quality, the maximum allowable speed in each segment of the route is determined based on these features. To increase the accuracy of the calculations it is necessary to divide the route into smaller segments which are called blocks. Therefore, the block is part of the route in which features of the route and maximum allowable speed are constant.

Table 1: The route from the City A to the City B

Name of the block	Length of the block (km)	Maximum allowable speed (km/h)
b_1	15	95
b_2	3	70
b_3	18	100
b_4	5	60
b_5	22	95
b_6	7	75
b_7	6	60
b_8	10	80
b_9	12	95
b_{10}	13	80
Total	111	-

The lengths of the intended blocks are not necessarily equal. The standard travel time (minimum allowable time) in a block is obtained by dividing the block length (L_i) to the maximum allowable speed in that block (V_i). So:

$$T_{i0} = \frac{L_i}{V_i} \tag{1}$$

The standard time for the total length of the route is:

$$T_0 = \sum_{i=1}^{n} T_{i0} \tag{2}$$

In this article, the route from the City A to the City B is divided into 10 blocks. The related information is given in Table 1.

The standard travel time could be determined for each block by using the equation (1). For example, the standard travel time in the first block is 9.47 minutes. On the other hand, by using the equation (2) the travel time for total route is calculated 78.15 minutes.

The intended statistical universe for prediction of travel time

This article deals with the prediction of travel demand for the general scope of the society. However, there are two deciles of the community that changes in the travel parameters do not significantly affect the travel demand for them. These two deciles are:

First decile: Persons that because of economic conditions, diseases, etc. are among the classes with low travel cases. Persons that, due to the lack of job in most days of the year have free time for travel and because of economic problems, may have less travel opportunities and special holidays do not have special effect on creating travel opportunities for them.

Second decile: Persons that, because of their special governmental, industrial or service responsibilities, may be busy in their profession in all days of the year even in holidays, these persons are generally grouped in the following groups:

People involved in transportation networks (pilots, sailors, rural road drivers, road and traffic police, custom authorities and personnel, railway, airport and port personnel, etc.).

High ranking governmental authorities, special industries authorities (like power plants) and special service sector personnel (like restaurants, shops of the touristy cities, etc.).

Presenting travel time prediction function

For accurate prediction of the travel time, first it is necessary to calculate the minimum standard time by equation (2). The point that should be considered is that the constant features of the road (such as type of the road, type of the region and geometric conditions) only influence the maximum allowable speed and in consequence the standard time. On the other hand, the travel time is increased by changing the travel parameters such as atmospheric conditions, traffic volume and incidents taken place at the route. This increase is in the form of percentage or the coefficient of the standard time and in each prediction it suffices only to consider the travel parameters and not constant features of the travel. This issue has not been considered in some of the past research works like that of Tayyebi et al. (2011).

In the present research, 17 primary parameters were determined for prediction of travel time, then by using the mutual information (MI) technique, the correlation between the variables is investigated and by merging or removing some of the parameters, 5 final parameters are selected. In the next step, the probable scenarios for each parameter are identified and by examining the effect of each scenario on increase of the travel time, they were initialized.

Parameter initialization was done by using triangular fuzzy method (The most pessimistic case, the most probable case and the most optimistic case) and finally, by weighted averaging of triangular fuzzy data, the final value of each scenario is determined.

In this research the following equation is presented for travel time prediction. This time is obtained by the standard travel time in a block multiplied by a coefficient. This coefficient itself is a function of 5 parameters and for its calculation a neural-fuzzy network is designed.

$$T = \sum_{i=1}^{n} f_i(x_1, x_2, x_3, x_4, x_5) T_{i0} \quad (3)$$

f_i: is the travel prediction function with respect to 5 variable parameters
X_1: is the days-of-the-year-effect parameter,
X_2: is the atmospheric condition,
X_3: is the instantaneous traffic volume with respect to the capacity,
X_4 is the instantaneous- incidents or line- closure parameter
X_5 is the travel- start- hour parameter

The days-of-the-year-effect parameter

In all countries of the world in special days of the year, people are more inclined towards travel. These days could be summer holidays, traditional or ancient holidays (Like Nowrooz or Christmas), devout holidays (Tasooa and Ashoora in Islamic countries), etc. On the other hand, there are seasons of the year in which people because of their job or education have fewer opportunities for travel. If there are continuous holidays, people prefer to take advantage of this opportunity for travel. This common and simultaneous inclination results into increased traffic load and consequently the travel time. Therefore, it is essential to predict in what season or kind of holiday schedule travel. In most research works or software prepared for travel time prediction, the day -of- the- year parameter has not been taken into account while the results of this article confirm the necessity to consider this parameter.

The effect-of-atmospheric-conditions parameter

Rural travels are directly influenced by atmospheric phenomena such as temperature, raining, air darkness, visual and auditory phenomena in the atmosphere and other phenomena at the ground level. In this case, each of these phenomena goes out of their normal situation, they would increase the travel time. Thus, considering them in travel time prediction is indispensable.

The instantaneous -traffic-volume parameter with respect to the capacity

When the traffic volume in the road is less than 60% of its nominal capacity (Tabibi et al. 2011), various vehicles without having significant effect on each other could travel with maximum allowable speed. In case that traffic volume exceeds this value, it causes the reduction in speed and increase in the travel time. The road traffic volume could exceed even the nominal capacity, in this case the travel time increases enormously. Here the instantaneous traffic volume should be considered.

The instantaneous incidents or line closure parameter

During a crash or other road incidents part of the road width is occupied for a time. Rescue and relief operations as well as the attention drawn toward the incident scene decrease the real capacity of that line in that moment. Therefore, the travel time prediction would be accurate in case that it can examine whether there is any road maintenance operation or not at the moment of incident.

The travel-start-hour parameter

The traffic congestion is not homogeneous in different hours of the day. In some hours of the morning and evening, traffic congestion is higher and traveling at those hours would be longer, thus, it is essential to consider this parameter as one of the five input parameters in the neural-fuzzy network. The final parameters are given in detail in Table (2).

Table 2: Input parameters in the neural-fuzzy network

Traffic volume parameter with respect to capacity			Days of the year parameter		
Value	Description	Scenario	Value	Description	Scenario
0	Flowing traffic	1	0	Ordinary days of the year	1
0.2	Moving congestion	2	1	Special events (Nowrooz and Tasooa & Ashoora)	2
0.6	Semi – heavy traffic	3	0.1	One or two- day summer holidays	3
1	Heavy traffic	4	0.2	One or two- day winter holidays	4
The instantaneous incidents or line closure parameter			0.3	One or two- day Spring and Autumn holidays	5
Value	Description	Scenario	0.2	3 or 4- day summer holidays	6
0	Normal (without incident or closure)	1	0.4	3 or 4- day winter holidays	7
0.6	Minor crash	2	0.6	3 or 4- day Spring and Autumn holidays	8
0.8	Incident	3	0.4	more than 5 day summer holidays	9
1	Road closure due to repair (one line)	4	0.7	more than 5 daywinter holidays	10
Travel start hours parameter			0.9	more than 5 day Spring and Autumnholidays	11
Value	Description	Scenario	Atmospheric conditions parameter		
0.2	5-7	1	Value	Description	Scenario
1	7-12	2	0	Normal (complete vision and without raining)	1
0.6	12-16	3	0.2	Minor raining or dust	2
0.8	16-22	4	0.4	Fug , rain or snow	3
0	22-5	5	0.8	Hail	4
			1	Blizzard or gravel hurricane	5

Travel time prediction by using the neural-fuzzy network

For prediction of travel time when the travel influencing parameters vary, a specified structure of neural-fuzzy network should be presented. This network includes one input vector with 5 aforementioned parameters. By investigating the various scenarios of each parameter and implementing the multiplication principle, 240 different cases are considered for each block. As mentioned before, the values of each parameter are determined by using triangular fuzzy method to account for the uncertainty. The network output is the travel time prediction function $f_i(X_1, X_2, X_3, X_4, X_5)$ which multiplying it by the standard time corresponding to each block, the predicted travel time for each block is obtained. The accuracy of this network depends highly on the proposed topological types and their corresponding weights.

The main elements of a network include the topology or network structure, type of activation functions and their parameters as well as the network weights. Therefore, this neural network has a wide range of unknowns that optimum selection of each of them could affect the accuracy of travel time prediction. To determine these unknowns a series of real data (as training data) was used. For various blocks between the two cities of A and B totally 850 combined scenarios of input vectors were implemented which their real travel time was known. The proposed network has been designed and weighted by utilizing the MATLAB software.

Design of travel time prediction intelligent system based on the neural-fuzzy network

The proposed system in this article is deemed to be intelligent in that it has self-modifying capability i.e. it continuously takes the real travel times from the transportation network predicted previously and compares them with its own predictions, then by minor modification of the neural network weights and coefficients of activation functions increases its own accuracy. Also, when the error trend seemed to be increasing or exceeded the acceptable value, major modifications would be applied in the neural network architecture, form of the activation function or its solution algorithm, so that the new network would have less prediction error. What is needed for intelligentization of the system is installation of RFID chips that by recording the travel-start and travel-end moments for the prediction system provides the possibility of comparing real and predicted travel times.

Data analysis

For travel time prediction 5 discrete parameters were defined which by examining various cases many scenarios occur from their combination, 10 samples related to these combined scenarios are given in Table 3.

Table 3: The samples related to these combined scenarios

Scenario	Days of the year	Atmospheric conditions	Traffic volume	incidents and line closure	Travel start hours
1	One or two- day summer holidays (0.2)	Minor raining(0.2)	Flowing traffic (0.2)	Minor crash (0.6)	5-7(0.2)
27	3 or 4- day winter holidays(0.4)	Snow(0.4)	Flowing traffic (0.2)	Minor crash(0.6)	5-7(0.2)
43	3 or 4- day Spring and Autumn holidays (0.6)	Dust(0.2)	Flowing traffic (0.2)	Road closure one line due to repair (1)	16-22(0.8)
79	More than 5 day winter holidays (0.8)	Hail(0.8)	Flowing traffic (0.2)	Closure one line of road (1)	5-7(0.2)
105	Special events (1)	Dust(0.2)	Semi-heavy traffic (0.6)	Closure one line of road (1)	16-22(0.8)
152	More than 5 day summer holidays (0.4)	Fug (0.4)	Semi-heavy traffic (0.6)	Closure one line of road (1)	5-7(0.2)
194	More than 5 day winter holidays (0.8)	Blizzard (1)	Semi-heavy traffic (0.6)	Closure one line of road (1)	16-22(0.8)
198	3 or 4- day Spring and Autumn holidays (0.6)	Rain (0.4)	Heavy traffic(1)	Closure one line of road (1)	16-22(0.8)
200	Special events (1)	Fug (0.4)	Heavy traffic(1)	Closure one line of road (1)	16-22(0.8)
210	Special events (1)	Gravel hurricane (1)	Heavy traffic(1)	Closure one line of road (1)	16-22(0.8)

The real travel time for all scenarios is already recorded. By using the neural-fuzzy network and MATLAB software, at first, all the available data was implemented for training the neural network and then, the designed neural-fuzzy network was used for travel time prediction of the same data, this is called over-fitting.

The second method for making the neural-fuzzy network of the above problem is using 80% of data for training of the neural-fuzzy network in which the back propagation algorithm was implemented. The designed network predicts the travel time for the remaining 20% of data.

The third method is also similar to the second method with the difference that the solution algorithm here is different. To assess the accuracy of each method mentioned above, the mean-absolute percentage-error (MAPE) and root-mean-square error (RMSE) are used which their results are given in Table 4.

Table 4: Results of MAPE and RMSE

Over- fitting algorithm (using 100% of data for training)		Back-propagation algorithm (using 80% of data for training)		Algorithm (using 80% of data for training)	
root mean square error	mean absolute percentage error	root mean square error	mean absolute percentage error	root mean square error	mean absolute percentage error
0.0045	0.1249	0.0008	0.0240	0.0198	0.8125

As Table (4) shows Back- Propagation algorithm is more suitable for solution of this neural-fuzzy network. The schematic view of the designed neural-fuzzy network in MATLAB software is shown in Fig. 2

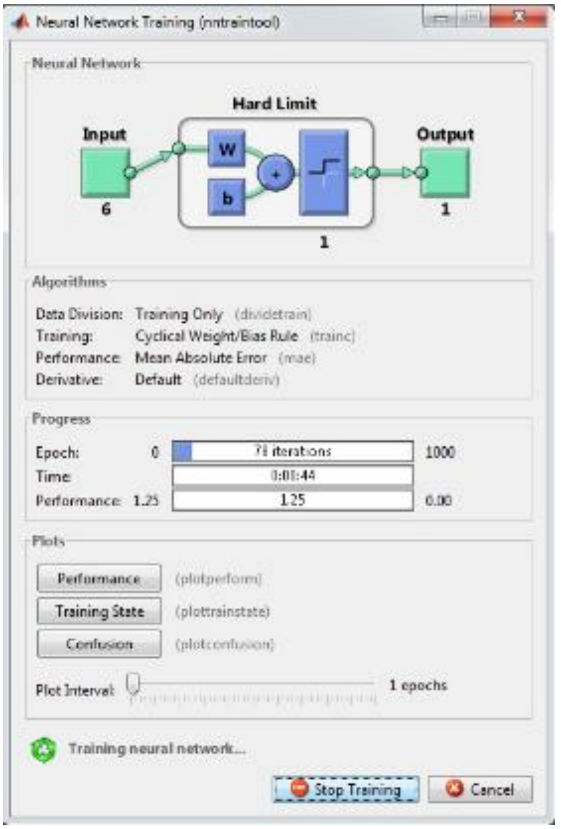

Figure 2: Schematic view of the designed neural-fuzzy network

Conclusion

In this article, with the aim of presenting an intelligent transportation system for travel time prediction, first the research is done on the topic of travel time prediction by using neural-fuzzy network and the way in which the identifier systems is implemented are briefly investigated. In continuation, a general structure for travel time prediction intelligent system is suggested. For analysis and better prediction of the travel time, the route is divided into several segments called blocks with similar maximum allowable speed property and a general function for travel time prediction is presented. Then, a neural-fuzzy network is implemented to support this system. The

neural network with 5 design fuzzy input parameters and using real data of the blocks within the route were programmed by the MATLAB software.

In this article there is the potential of designing an intelligent system for travel time prediction with high speed and precision and for its best efficiency the effective parameters such as the days-of-the-year parameter and atmospheric conditions re given special attention. Establishment of RFID technology is essential in intelligentization and self-modification of this system so that after end of the travel, the real time is made clear to the system and the system automatically and continuously, by comparing the real time and the predicted time, would apply necessary modification in the neural-fuzzy network. The results showed that using the Back- Propagation algorithm for solution of this neural-fuzzy network would yield less error.

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