Travel Time Prediction under Egypt Heterogeneous Traffic Conditions using Neural Network and Data Fusion

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Abstract

Cairo is experiencing traffic congestion that places it among the worst in the world. Obviously, it is difficult if not impossible to solve the transportation problem because it is multi-dimensional problem but it's good to reduce this waste of money and the associated waste of time resulting from congestion. One way to accomplish this is to provide driver or passenger with current traffic information throughout their trip . Travel time prediction is becoming increasingly important and it is one of the most important traffic information for both drivers and passengers. It is difficult to measure the travel time directly so the present study estimates the travel time using the speed. In this paper we present a model based approach for travelling time prediction. It will provide both passenger or driver with the fastest routes depending on the travel time. The proposed method uses DSmT (Dezert-Smarandache Theory) as a fusion technique and Artificial Neural Network as mining tool . The estimates are corroborated using actual values and the results show the model performing well and gave us acceptable prediction.

Keywords: *Travel time prediction, DSmT, Artificial Neural Network*

1. Introduction

Increase in vehicle population in the recent years has resulted in serious traffic congestion in Egypt especially Cairo as a capital city of Egypt. Traffic congestion reduces the efficiency of the traffic system and increases the travel time. The direct traditional approach to reduce congestion is the expansion of infrastructure. However, infrastructure expansion is of limited scope because of its high expense and large space requirement. One way to overcome this situation is to go for better management of the existing infrastructure such as by using Intelligent Transportation System (ITS) applications. Intelligent Transport Systems (ITS) are advanced applications which aim to provide innovative services relating to different modes of transport and traffic management and enable various users to be better informed and make safer, more coordinated, and 'smarter' use of transport networks. One component of Intelligent Transportation Systems (ITS) is Advanced Traveler Information Systems (ATIS) and a major component of ATIS is travel time information. Travel time prediction can be used in various application it is a key input for the dynamic route guidance system, travel time information enables the generation of the shortest path (or alternative paths) connecting the origins (or current locations) and destinations. Usually, there are many alternatives to travel from A to B. It is very useful to inform both driver and passenger with the predicted travel time on each alternative road .In this case, many drivers or passenger may be willing to modify their routes or departure times to avoid delays due to congestion or incidents. Travel time, being a spatial parameter, is difficult to be measured directly from field. Direct measurement of it needs either vehicle tracking devices or vehicle reidentification feature. However, majority of the vehicle tracking or reidentification techniques available such as automatic vehicle locators (AVL) and automatic vehicle identifiers (AVI) require participation, which limits the sample size .Also most of the direct travel time measurement techniques are expensive, immature, or involve privacy concerns and hence majority of the studies depend on indirect methods for travel time estimation. Most of the indirect travel time estimation and forecasting methods can be grouped under extrapolation techniques [1], regression models [2, 3], pattern recognition techniques [4], time series analysis [5], use of filtering techniques [6, 7], neural networks [8], methods based on traffic flow theory [9–10], data fusion techniques [11], and combination of above methods [12–13].For the above studies travel time data were obtained through various sources, such as loop detectors, microwave detectors, radar, intelligent cameras, GPS or cell phone tracking, Bluetooth identification, ..etc. Nowadays, information about traffic status is broadcasted via news on radio and TV, or via mobile phones. Actually in Egypt there are systems view the traffic status as Bey2ollak* and Wasalny* both depend on user reports about traffic conditions. The data from these different sources are characterized by different formats, resolution, and accuracy. Also there is a big conflict between the observations . Moreover, each source of data individually may be insufficient to determine the traffic state completely. One method to address these problems is to apply the data fusion approach and make use of these available data for more accurately than if they were used separately .The present study develops a methodology for estimating the travel time for an urban arterial using the spreaded news about traffic status on social media resources (i.e. Bey2ollak and Wasalny) as cheap, reliable and available data sources. This approach known as data fusion (DF) is not explored under Egypt traffic conditions.

2. Literature Review

Data fusion is a broad area of research in which data from several sensors are combined to provide comprehensive and accurate information [14]. The advantages of using data fusion include increased confidence, reduced ambiguity, improved detection, increased robustness, enhanced spatial and temporal coverage, and decreased costs [14–15]. Data fusion is used in many fields of engineering other than transportation, such as weather forecasting, battle field assessment, target classification and tracking [16]. The basic idea of data fusion is to estimate parameters by using more than one measurement from different sources or sensors. This may be due to lack of availability of enough data from a single source or to capture the advantages of different data sources. There are different methods to fuse data ranging from a sample arithmetic mean to a more complex DF approach. More precisely, a three-way split could be suggested:

- Statistical approaches: weighted combination, multivariate statistical analysis and its most up-to-date form data mining engine [17]. Among statistical techniques, the arithmetic mean approach is the simplest which is used for information combination. This approach is not suitable when the information at hand is not exchangeable or when estimators/classifiers have dissimilar performances [18–19].

- Probabilistic approaches: for instance, Bayesian approach with Bayesian network and state-space models [20], maximum likelihood methods and Kalman filter based DF [21,22], possibility theory [23], evidential reasoning and more specifically evidence theory [24–25] are widely used for the multi-sensor data fusion. This later technique could be viewed as a generalization of Bayesian approach [26–27].

- Artificial intelligence: neural networks and artificial cognition including artificial intelligence, genetic algorithms and neural networks. In many applications, this later approach serves both as a tool to derive classifiers or estimators and as a fusion framework of classifiers/estimators [17,28].

Some specific applications of data fusion in the field of transportation engineering are discussed below.

Kwon et al. [29] proposed a linear regression model for travel time prediction by combining both loop detector and probe vehicle data. They showed that linear regression on current flow, occupancy measurements, departure time, and day of week is beneficial for short-term travel time prediction while historical method is better for long-term travel time prediction. Zhang and Rice [30] used a linear model with varying coefficients to predict the travel time on freeways using loop detector and probe vehicle data. The coefficients vary as smooth functions of departure time. The coefficients have to be estimated offline and stored and after that the model can be used real-time. El-Faouzi et al. [31] put forward a model based on the Dempster-Shafer theory. They used travel time from loop detector and toll collection data to estimate travel time. The model required the likelihood that the data sources are giving the correct data. El-Faouzi [15] carried out a similar work using Bayesian method using travel time data from loop detector and probe vehicle to estimate travel time. The results showed that the travel time estimate using data fusion approach was better than the estimate obtained if the data sources were used individually. Chu et al. [32] used simulated loop detector and probe vehicle data to estimate travel time using a model based approach with Kalman filtering technique. Ivan [33] used the ANN technique to detect traffic incidents on signalized arterials using simulated travel time data from loop detector and probe vehicle data. Another simple analytical model that uses readily available count data from upstream and downstream ends of a link for the estimation of travel time is the cumulative counts (input-output) method [9, 10, 14, 34, 35]. However, a major drawback of the input-output method is its dependency on the accuracy of flow counts for travel time estimation [9, 35]. Some of the other reported approaches include traffic flow theory based [36, 37, 38]. It can be seen from the above literature review that majority of the models discussed above are limited to freeways, and it may not be feasible to apply them directly on urban networks without further calibration due to differences in behaviour of traffic on the freeway and urban facilities .Also by reviewing the above studies on data fusion, it can be seen that most of them were carried out under homogeneous traffic conditions. However, the traffic prevailing in many countries including Egypt is highly heterogeneous composed of vehicles of different types and characteristics and less lane disciplined. The availability of data is also very limited in most of these countries.

3. Data collection

As we mentioned previously we will use both Bey2ollak and Wasalny sites as data sources . Both sites depend on user reports about traffic conditions. The system basically works by taking the average of the reports and displaying it on the routes front page.

- Bey2ollak is traffic updates website which is powered by Vodafone. It is available in web version and as an application for Blackberry and iPhones. It can be viewed in a mobile-friendly mode from any other mobile brand. Also it can be followed on Twitter for instant updates. The traffic status is rated in an amusing way; varying from '7alawa' with a green symbol, meaning perfectly flowing traffic and zero congestion, to 'mafeesh amal' in an alarming red circle, meaning you should avoid that route if possible.

- Wasalny is traffic updates web site which is powered by Etisalat. It is also available on twitter in addition to an application for Blackberry, Nokia and Android phones, along with a mobile-friendly website for iPhone and other mobile phone brands .The traffic status is also rated from green meaning no congestion to red which means the route is blocked.

Before choosing any route as a case study some conditions are taken into account these conditions are listed below:

- The route(from source to destination) must be common between Bey2ollak and Wasalny.
- The route (from source to destination) must have many alternatives .
- The length of the route must not be long to avoid the change in the status, which happens along the route it means that the status that will be spreaded about the route on both sites will represent the status of the whole route form source to destination.

The selected route is shown in Figure 1 and Figure 2 .It was identical for all the previous conditions and it is represented by source and destination as the following (From kobry El matar to kobry El Glaa). It is located in Cairo and had two alternatives to travel from its source to its destination the alternatives are :

- Slah Salem road.
- 6 October Bridge .

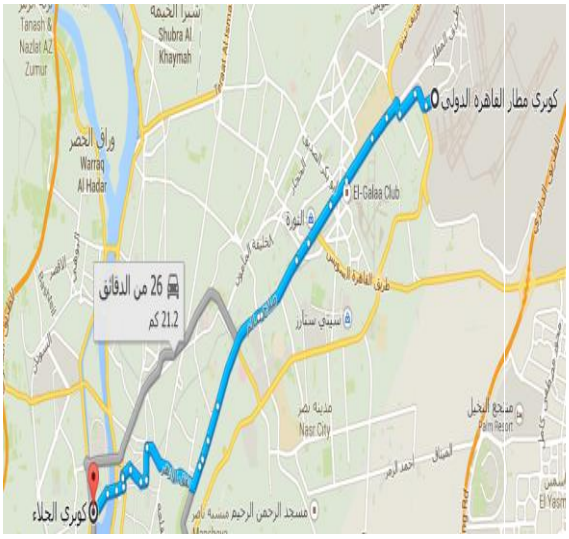

Figure 1. (From El matar to kobry El Glaa) through Slah Salem road

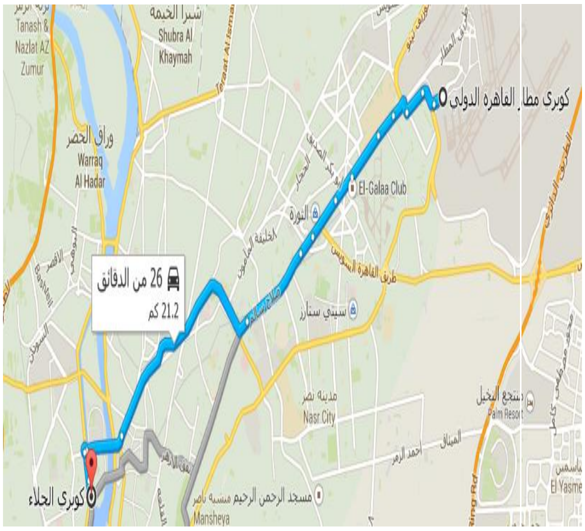

Figure 2. (From El matar to kobry El Glaaa) through 6 October Bridge

The first alternative route (From kobry El matar to kobry El Glaa). through Slah Salem is 21.1 km and the second alternative route through 6 October Bridge is 24 km .The data were collected from both sites about the two alternative routes during weekdays (i.e. Sunday ,Monday,..,Thrusday) beginning 02:00:00 PM for one hour (i.e. from 02:00:00 to 03:00:00) because it is a rush hour and the rate of users' report is very high .These data were collected for three months from January 1, 2014 to March 30, 2014 the data consists of the traffic status observation according to the user report plus the actual speed corresponding to these observation. It is noticed that the update occurred on the two sources (Wasalny and By2olk) in average every 15 min . So this hour appear as four segments .In each segments we collected the most recent observation (within 5 min).The following figures represent the samples from Bey2ollak and Wasalny observations.

Figure 3.By2olk observation sample

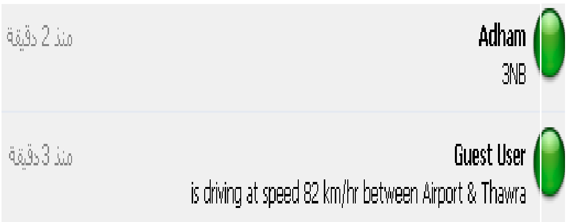

Figure 4.Wasalny observation sample

These data as it is shown are not consistent and are characterized by different formats, resolution, and accuracy. This was one of the difficulties that we have encountered in our research .These data were needed to some preprocessing to make them consistent and meaningful. There were 3 main information needed to be extracted from both sites these information are traffic condition(Block,Normal,Perfect), the time of observing this condition, the trusting level of the user who report this observation. The trusting is given in By2olk as (0 for not trusted user and 1 for trusted user) but in wasalny the trusting is represented by scores and for each route there is a mayor who has the highest score Figure 5 and Figure 6 represent the data after extracted and preprocessing from both sites .

ID	Day	Date	Grouping	Status	Timing	Score
1	Sunday	1/5/2014	1	Block	2	0
1	Sunday	1/5/2014	1	Normal	4	0
1	Sunday	1/5/2014	1	Block	5	0
1	Sunday	1/5/2014	2	Normal	2	1
1	Sunday	1/5/2014	2	Normal	5	0
1	Sunday	1/5/2014	3	Block	1	1
1	Sunday	1/5/2014	3	Block	3	1
1	Sunday	1/5/2014	3	Normal	4	0
1	Sunday	1/5/2014	3	Normal	5	0
1	Sunday	1/5/2014	4	Normal	3	0

Figure 5.By2olk collected data sample

ID	Day	Date	Grouping	Status	Timing	Score
1	Sunday	1/5/2014	1	Block	1	513
1	Sunday	1/5/2014	2	Block	3	19109
1	Sunday	1/5/2014	2	Normal	4	2049
1	Sunday	1/5/2014	3	Block	1	6056
1	Sunday	1/5/2014	3	Normal	2	11036
1	Sunday	1/5/2014	3	Block	3	19072
1	Sunday	1/5/2014	3	Block	4	3095
1	Sunday	1/5/2014	3	Normal	5	15572
1	Sunday	1/5/2014	4	Block	1	2397
1	Sunday	1/5/2014	4	Normal	4	6265

Figure 6. Wasalny collected data sample

4. Methodology

As mentioned above the main components of our frame work are data fusion using Dezert-Smarandache Theory (DSmT) and mining using Artificial Neural Network. In this section we first introduce some basic concept about these main components that were used in our proposed framework.

4.1. Brief introduction about Dezert-Smarandache Theory (DSmT)

As introduced in [39] ,the development of the Dezert-Smarandache Theory (DSmT) arises from the necessity to overcome the inherent limitations of Dempster-Shafer's Theory (DST), which are closely related to the acceptance of Shafer's model these limitations can be summarized as following:

- The DST considers a discrete and finite frame of discernment θ based on a set of exhaustive and exclusive elementary elements θ.
- The bodies of evidence are assumed independent and provide their own belief function on the power set θ but with same interpretation for θ.

So in most of practical fusion applications based on the DST, some ad-hoc or heuristic techniques must always be added to the fusion process to manage or reduce the possibility of high degree of conflict between sources. Otherwise, the fusion results lead to a very dangerous conclusions or cannot provide a reliable results at all. DSmT provides a new mathematical framework for the fusion of quantitative or qualitative beliefs, which appears less restrictive and more general than the basis and constraints of DST and is able to combine information even in the presence of large conflicts and constraints.

- **The Classical DSm rule of combination (DSmC) is based on the free model**

$$m_{f(\theta)}(A) = \sum_{X,Y\in D^{\theta}, X\cap Y=A} m_1(X)m_2(Y) \qquad (1)$$

When the free DSm model cannot be applied due to the nature of the problem under consideration that requires some known integrity constraints to be taken into account, one has to work with a proper hybrid DSm model.

- **The Hybrid DSm rule of combination (DSmH)**

The hyper-power set of θ (i.e. the free Dedekind's lattice) denoted D^{θ} [39] is defined as:

1) Ø, θ 1, . . . , θ n ∈ D^{θ}
2) If A,B ∈ D^{θ}then A ∩ B and A ∪ B
3) No other elements belong to D^{θ}, except those obtained by using rules 1 or 2.

If | θ |= n then $|D^{\theta}| \leq 2^{2^{n}}$. Since for any finite set θ, $|D^{\theta}| \geq |2^{\theta}|$, we call D^{θ} the hyper power set of θ. For example, if θ = { θ 1, θ 2}, then D^{θ}= { Ø, θ 1 ∩θ 2, θ 1, θ 2, θ 1 ∪θ 2}.

From any finite discrete frame θ, we define a belief assignment as a mapping $m(.):G^{\theta} \rightarrow$ [0, 1] associated to a given body of evidence B which satisfies

$$m(\emptyset) = 0 \text{ and } \sum_{A\in G^{\theta}} m(A) = 1 \qquad (2)$$

m(A) is the generalized basic belief assignment/mass (bba) of A. The belief and plausibility functions are defined as:

$$\mathrm{Bel}(A) \triangleq \sum_{\substack{B\subseteq A \\ B\in G^{\theta}}} m(B) \text{ and } \mathrm{Pl}(A) \triangleq \sum_{\substack{B\cap A\neq\emptyset \\ B\in G^{\theta}}} m(B) \qquad (3)$$

DSm hybrid rule (DSmH) for k ≥ 2 independent sources is thus defined for all $A \in D^{\theta}$ as [39]:

$$m_{DSmH}(A) \triangleq \emptyset(A).[S_1(A) + S_2(A) + S_3(A)], \qquad (4)$$

$$S_1(A) \triangleq \sum_{\substack{X_1,X_1,\ldots,X_1 \epsilon D^\theta \\ (X_1 \cap X_1 \cap \ldots \cap X_{k)=A}}} \prod_{i=1}^{k} m_i(X_i) \quad (5)$$

$$S_2(A) \triangleq \sum_{\substack{X_1,X_1,\ldots,X_1 \epsilon \emptyset \\ [u=A] \vee [(u \in \emptyset) \wedge (A=I_t\ )]}} \prod_{i=1}^{k} m_i(X_i) \quad (6)$$

$$S_3(A) \triangleq \sum_{\substack{X_1,X_1,\ldots,X_1 \epsilon D^\theta \\ (X_1 \cap X_1 \cap \ldots \cap X_{k)=A} \\ (X_1 \cap X_1 \cap \ldots \cap X_{k)\epsilon \emptyset}}} \prod_{i=1}^{k} m_i(X_i) \quad (7)$$

S1(A) corresponds to the classical DSm rule on the free DSm model ,S2(A) represents the mass of all relatively and absolutely empty sets in both the input gbbas, which arises due to non-existential constraints and is transferred to the total or relative ignorance; and S3(A):transfers the sum of masses of relatively and absolutely empty sets, which arise as conflicts of the input gbbas, to the non-empty union of input sets.

4.2. Brief introduction about Artificial Neural Network

Artificial neural network (ANN) is one of the most commonly reported techniques for traffic prediction mainly because of their ability to solve complex non-linear relationships. Neural networks are statistical models of real world systems, which are built by tuning a set of parameters. These parameters are seen as inputs to an associated set of values: the outputs. The process of tuning the weights to the correct values – training – is carried out by passing a set of examples of input-output pairs through the model and adjusting the weights in order to minimize the error between the answer the network gives and the desired output. Once the weights have been set, the model is able to produce answers for input values, which were not included in the training data [40, 41].

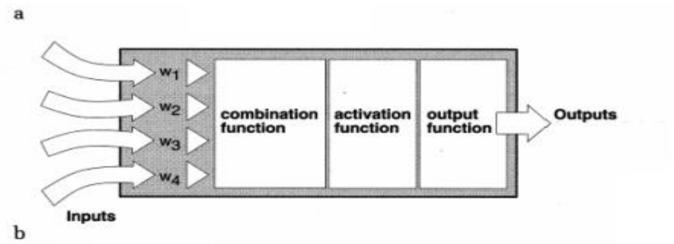

Figure 7.Neural network structure [40]

5. Proposed model

The construction of frame of discernment plays a critical role in travel time estimation based on (DSmT) evidence theory. For the two data resources By2olk and Wasalny the frame of discernment (Ω) is as follow:

θ= {θ1, θ2, θ3} = {Block, Normal, Perfect}

They are mutually Exclusive i.e. it is impossible that two θs occurs at the same time as it is shown in Figure.8 for example the road can't be block and perfect at the same time. We’ve added constraints on sets that contains union or intersections to be empty.

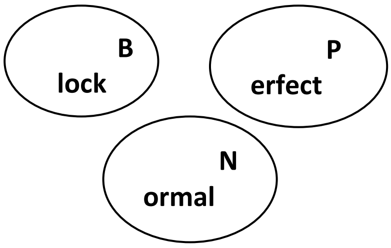

Figure 8. Venn diagram of a proposed model frame of discernment

The main challenges and difficulties encountered in this research can be summarized as the following:

- Find the effective, or optimal, implementation of the DSmH combining rule .
- How to apply the fusion rule on just some observations about the traffic status.
- How to handle the conflict between the resources .
- How to relate these observations with the speed to calculate the travel time indirectly the form the route speed .

Figure.9 represents the main structure and main processing in of our proposed frame work

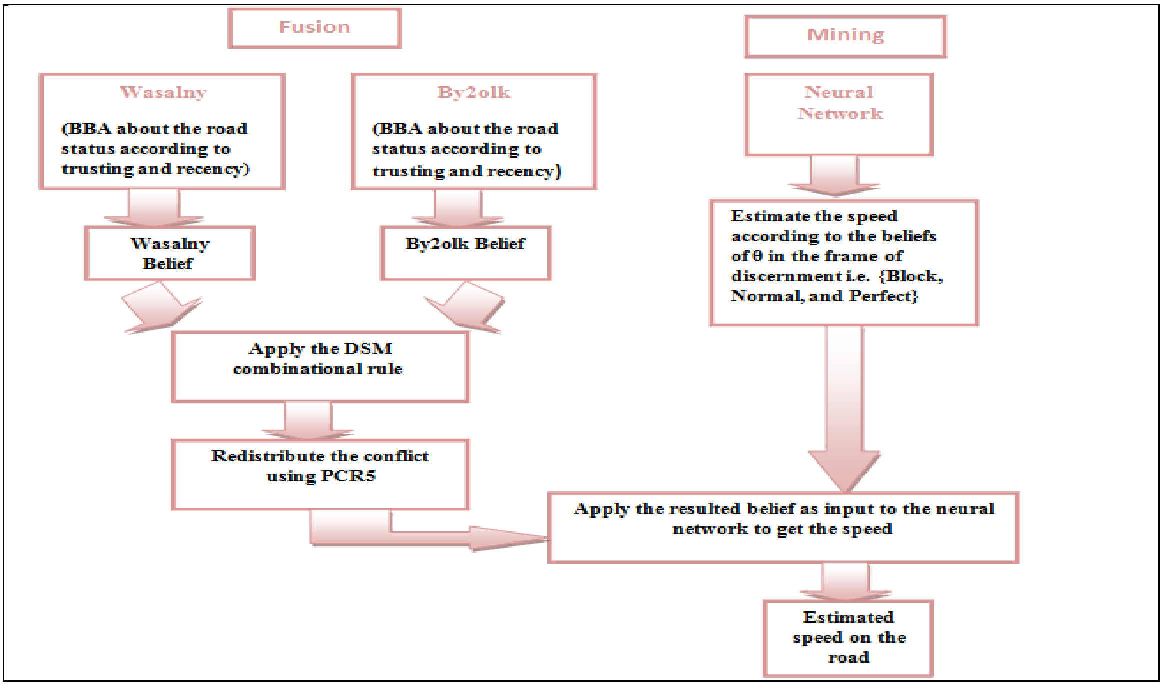

Figure 9. proposed frame work

Proposed model steps :

- **Step1**

For each route assign the basic belief for each θ in the frame of discernment (i.e. {Block, Normal, Perfect}) . It is calculated from the observations that are collected from both sources (i.e. Wasalny and by2olk) .The basic belief is calculated according to the trusting level of the observations and recently data . The trusting level in By2olk represented by a flag refer to that user is trusted or not trusted according to the user activities and number of submitted reports that were identical to the real so in our model the trusted observation in By2olk is weighted by 1 and the untrusted observation is weighted by 0.5 because it may be true or not . In Wasalny the trusting level is measured by the user scores and each route has the mayor who is the user that have the highest score ,defiantly it is the most trusted observer in this route. We deal with the trusting level in Wasalny in different manner, the trusting level for each user is the user score for each route divided by mayor score for this route. Also the time of the observation is used to calculate the belief beside the trusting level. We considered the observation that was within 5 minutes is a good representation to the traffic status and each minute within this time slot has a weight as it is shown in Figure 10.

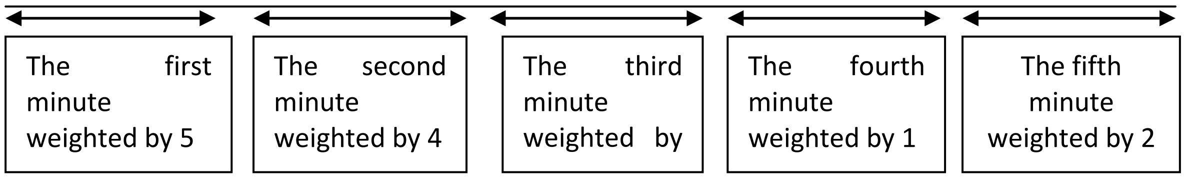

Figure 10. The weighted time slot

From above we can model the basic belief assignment for Wasalny and By2olk observation as the following :

- The basic belief assignment equation for By2olk =(Weight of the current time /5)*(User trusting level)
- The basic belief assignment equation for Wasalny=(Weight of the current time /5)*(User score/Mayor score)

Assigning the basic belief means that we success in converting the observations that are spreaded about the traffic status to a basic belief depending on very affected parameters as trusting and timing and make them a meaningful information which can be used in fusion process .

- **Step2**

Perform fusion using the Hybrid DSm rule of combination (DSmH) to get the belief of each θ in the frame of discernment (i.e. {Block, Normal, Perfect}) . As we mentioned before the data that are spreaded on both sources (i.e. Wasalny and By2olk) may have conflict so we can use PCR rules to redistribute the conflict .These PCR fusion rules work for any degree of conflict in [0, 1], for any DSm models (Shafer's model, free DSm model or any hybrid DSm model) and both in DST and DSmT frameworks for static or dynamical fusion problems.

The general principle of PCR rules is then to :

1) Calculate the conjunctive rule of the belief masses of sources ;
2) Calculate the total or partial conflicting masses ;
3) Redistribute the conflicting mass (total or partial) proportionally on non-empty sets involved in the model according to all integrity constraints.

The PCR5 rule for only two sources is defined by:

$$\mathrm{mPCR5}(\emptyset) = 0 \text{ and } \forall\, \mathrm{X} \in \mathrm{G}\theta \ \{\emptyset\} \quad (8)$$

$$mPCR5(\emptyset) = m12(X) + \sum_{\substack{Y\in G\theta\{X\}\\ X\cap Y=\emptyset}} \left[\frac{m1(X)^2\, m2(Y)}{m1(X)+m2(Y)} + \frac{m2(X)^2\, m1(Y)}{m2(X)+m1(Y)}\right] \quad (9)$$

- **Step3**

Apply the resulted beliefs as input to the neural network to get the estimated speed Figure 11 , represents the proposed neural network which consists of three layers: input, two hidden, and output layer. The Input layer of the proposed neural network has three nodes. In this configuration, a single hidden layer is used. The hidden layer has 2 nodes and the output layer has only one node. As we mentioned before we also collected the actual average speed which is corresponding to the collected observations . So the input of our proposed neural network is the basic belief for each θ in the frame of discernment and the output is the speed .

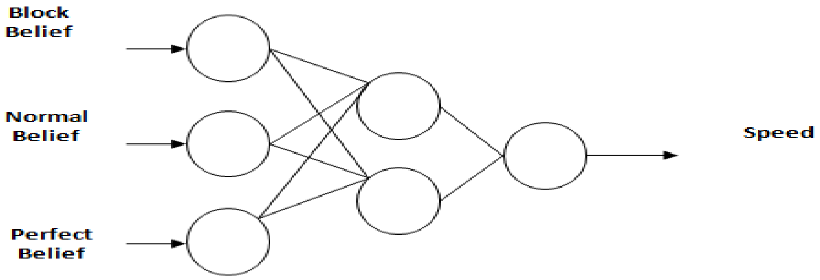

Figure 11. Proposed Neural Network

Finally by knowing the speed and the length of the route we can calculate the estimated travel time for the two alternative routes using the following equation :

$$T = \frac{l}{v} \quad (10)$$

Figure 12. represents the proposed model structure with all components and processes in details as the following

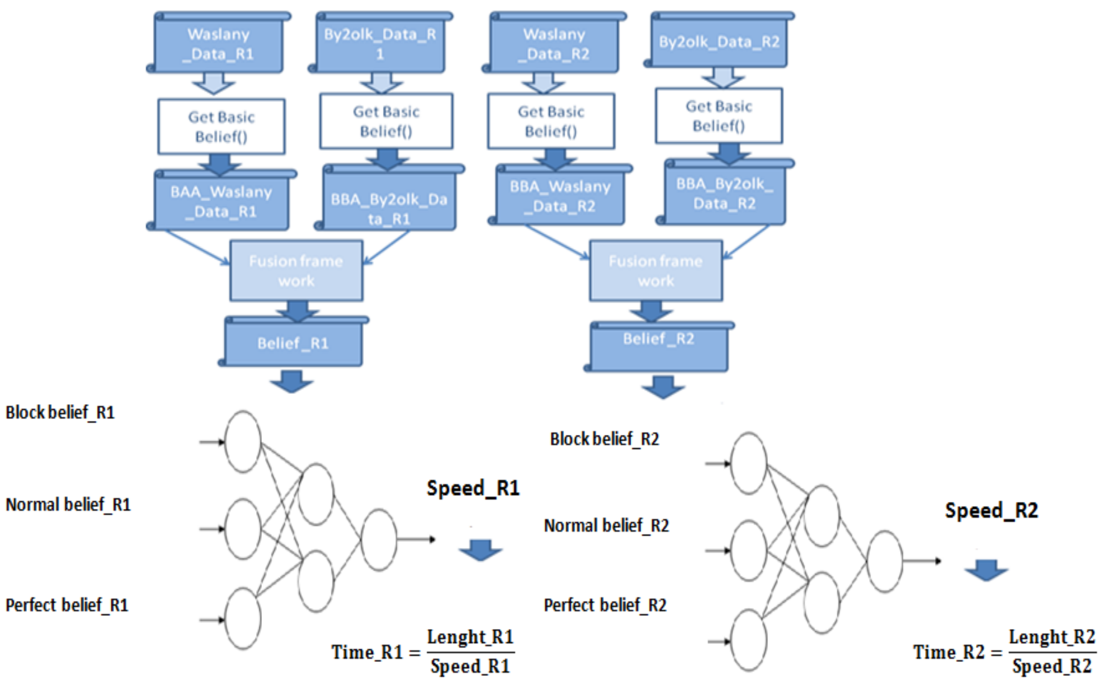

Figure 12 (Proposed model structure in details)

6. Performance and evaluation

In order to test and evaluate the proposed travel time prediction model, as mentioned before the route (From kobry El matar to kobry El Glaa) is selected as a case study. It is located in Cairo and has two alternatives one through 6 October Bridge and another through Slah Salem road. The average speed for the two alternatives were collected by two test vehicles from January 1, 2014 to February 31, 2014.Also Corresponding, traffic status are collected from both data sources (i.e. By2olk and Wasalny) ,these data were used for fusion and learning process. Also both speed and traffic status were collected from March 31, 2014 to March 31, 2014 and they were used for testing and verifying the proposed model. Three performance measures as Mean Absolute Error (MAE), Mean Absolute Percentage Error(MAPE), and Root Mean Square Error (RMSE) are used. The specific formulas of the three measures are given as following.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|T_n - \bar{T}_n| \quad (11)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_n - \bar{T}_n)^2}{n}} \quad (12)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{T_n - \bar{T}_n}{T_n}\right| \quad (13)$$

where n is the sample number, T_{ti} is the actual measured value of travel time of route i at time t and T_{ti} is the estimated value of travel time of route i at time t. The results of the proposed model is listed in Table 1. and Figure13. and Figure14 .Also Figure15 represent the comparison between two alternative routes in predicted time which is updated every 15 minutes. This comparison show that in some cases one route may take less time or equal or greater than the another route.

Table I. Performance Measures

Route	MAE	RMSE	MAPE
From El matar to kobry el glaaa) through 6 October Bridge	**2.5776**	**3.4233**	**6.8614%**
From El matar to kobry el glaaa) through Slah Salem road	**2.7245**	**3.6348**	**6.6229%**

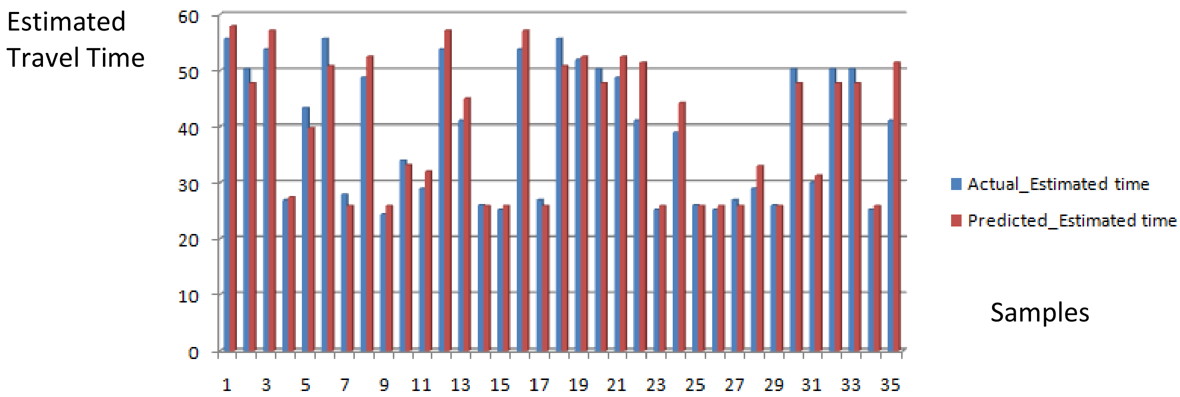

Figure 13. Comparison of actual and estimated travel time for route1 (From El matar to kobry el glaaa) through Slah Salem road

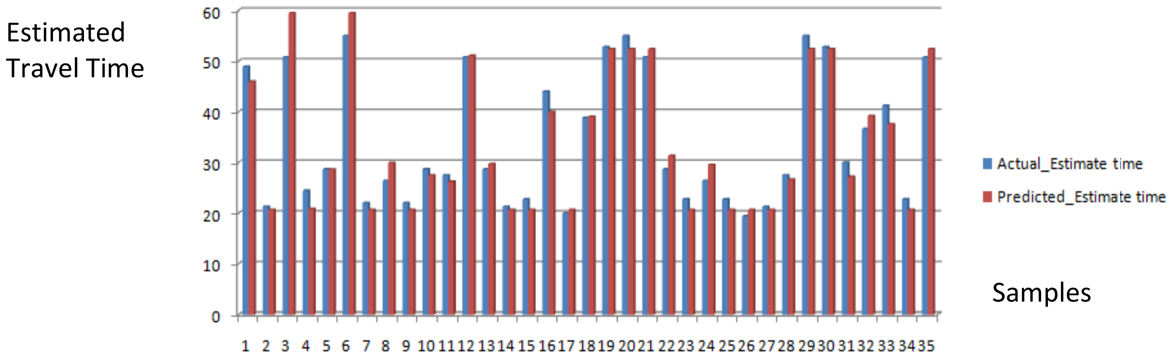

Figure 14. Comparison of actual and estimated travel time for route1 (From El matar to kobry el glaaa) through 6 October Bridge

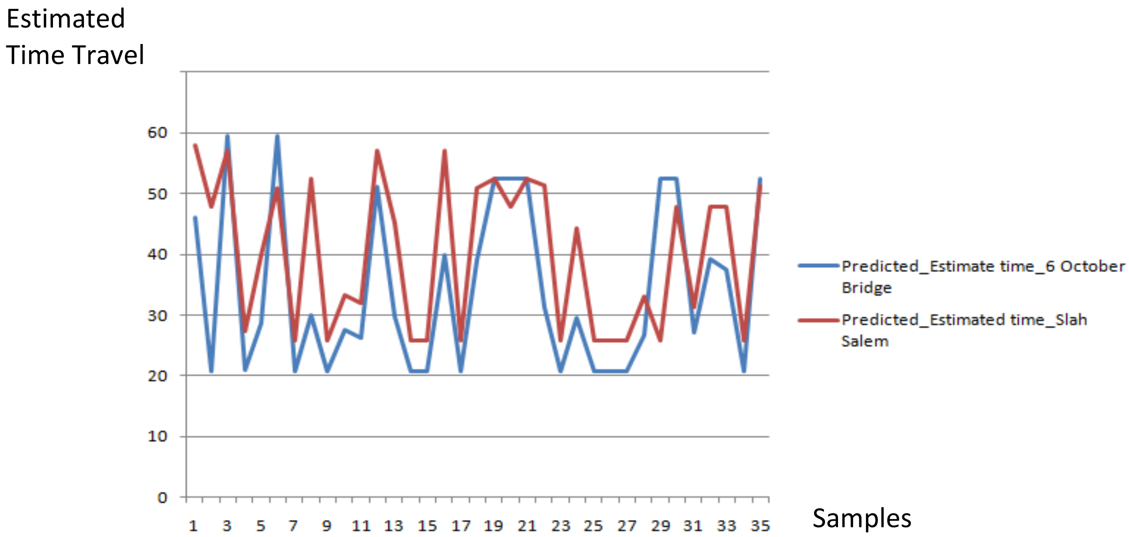

Fig 15. Comparison of actual and estimated travel time for route1&route2

7. Conclusions

This paper presents a travel time estimation which is a very important parameter in ITS .The estimation was carried out using DSmT (Dezert-Smarandache Theory) as a fusion technique and Artificial Neural Network as mining tool . The proposed uses two social media ITS resources(i.e. By2olk and Wasalny). The results obtained from the proposed system is capable of achieving satisfactory accuracy.

8. Limitations of this study

There are some limitations which we hope to be overcome in the future as traffic data collection and extraction are not yet automated. The current study is carried out on a short stretch of a roadway for selected periods of time so that the performance can be tested. More detailed studies for longer stretches of roadways and longer duration are needed to draw detailed conclusions. Future studies need to be carried with more data to evaluate the performance of the proposed method in more detail.

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