

TOWARDS AN EFFICIENT TRAFFIC CONGESTION PREDICTION METHOD BASED ON NEURAL NETWORKS AND BIG GPS DATA

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ABSTRACT: The prediction of accurate traffic information such as speed, travel time, and congestion state is a very important task in many Intelligent Transportations Systems (ITS) applications. However, the dynamic changes in traffic conditions make this task harder. In fact, the type of road, such as the freeways and the highways in urban regions, can influence the driving speeds and the congestion state of the corresponding road. In this paper, we present a NNs-based model to predict the congestion state in roads. Our model handles new inputs and distinguishes the dynamic traffic patterns in two different types of roads: highways and freeways. The model has been tested using a big GPS database gathered from vehicles circulating in Tunisia. The NNs-based model has shown their capabilities of detecting the nonlinearity of dynamic changes and different patterns of roads compared to other nonparametric techniques from the literature.

ABSTRAK: Ramalan maklumat trafik yang tepat seperti kelajuan, masa perjalanan dan keadaan kesesakan adalah tugas yang sangat penting dalam banyak aplikasi Sistem Pengangkutan Pintar (ITS). Walau bagaimanapun, perubahan keadaan lalu lintas yang dinamik menjadikan tugas ini menjadi lebih sukar. Malah, jenis jalan raya, seperti jalan raya dan lebuh raya di kawasan bandar, boleh mempengaruhi kelajuan memandu dan keadaan kesesakan jalan yang sama. Dalam makalah ini, kami membentangkan model berasaskan NN untuk meramalkan keadaan kesesakan di jalan raya. Model kami mengendalikan input baru dan membezakan corak trafik dinamik dalam dua jenis jalan raya yang lebuh raya dan jalan raya. Model ini telah diuji menggunakan pangkalan data GPS yang besar yang dikumpulkan dari kenderaan yang beredar di Tunisia. Model berasaskan NNs telah menunjukkan keupayaan mereka untuk mengesan ketiadaan perubahan dinamik dan pola jalan yang berbeza berbanding dengan teknik nonparametrik yang lain dari kesusasteraan.

KEYWORDS: *neural network; traffic congestion prediction; big GPS traces*

1. INTRODUCTION

An Intelligent Transportation System (ITS) application can be efficient only if the quality and the accuracy of the provided traffic information are guaranteed. This is particularly true for Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS) because travelers, traffic managers, and transportation agencies need reliable information about the state of road congestion, travel time, and travel speed.

Considering the nonlinear characteristic of congestion and traffic conditions on the roads, the task becomes harder. However, the increased deployment of sensors in this century provides available data that helps researchers to achieve their purposes. In the literature, many techniques to predict traffic congestion states have been explored to fit all sorts of collected data [1]. Most of studies are based on fixed sensors such as the inductive loop detectors [2-4] to infer the travel time in some road links. Other works in the computer vision field based their studies on video detectors [5] or web camera sensors [6] to forecast traffic information. While this alternative can give more information about the number of cars in a place, they require high costs of installation and maintenance. Moreover, they should be installed everywhere in the city to give more accurate results. Therefore, other researchers preferred using data gathered from vehicles and smart-phones equipped with GPS systems to predict traffic speed [7] and congestion state [8].

Several techniques have been applied in the traffic forecasting field. Some statistical parametric approaches, such as the historical smoothing algorithm [9] and smoothing techniques [10], have been developed to predict traffic flow. Different variants of Autoregressive Moving Average (ARMA) models have been widely applied to forecast future values of a traffic parameter based on the previous data such as Autoregressive Integrated Moving Average (ARIMA) [11] and Seasonal ARIMA (SARIMA) [12]. Since the appearance of ARM models, the traffic prediction performance was improved whereas, the computation cost becomes very high even for small databases [13]. Non-parametric techniques have been also developed to solve the traffic forecasting problem including K-Nearest Neighbor (K-NN), Support Vector Machine (SVM) and Neural Network (NN). K-NN is the simplest algorithm. It was used to predict traffic flow on a Shanghai expressway using historical traffic variables [14]. Another work [15] applied this algorithm to forecast traffic flow based on the upstream and downstream road information. Yao et al. [16] introduced a traffic speed forecasting model in an urban corridor based on the SVM technique. Fan et al. [17] introduced the parallel random forests in order to forecast travel time in a highway in Taiwan. Some other works performed hybridizations between some machine learning algorithms to forecast traffic variables such as the hybridization of the Genetic Algorithm and Cross entropy in [18] to predict inferred congestion on a freeway in California. The ANN and the decision tree provided by Elleuch et al. [8] was used to infer the congestion state based on anomalous events. Concerning the NNs, they are able to infer complex relationships between nonlinear variables in the inputs and outputs. Therefore, they have been used in forecasting traffic variables [19,20]. Sharma et al. [19] have proposed a traffic flow forecasting model based on a single back-propagation ANN in an undivided two-lane highway. Ciskowski et al. [20] have tested the performance of ANN in forecasting traffic flow variables on some highways in India. The inputs of this model contain vehicle categories.

Based on the ability of NNs in learning complex and nonlinear relationships, NNs have proven interesting performance in forecasting traffic variables [21]. However, we notice that the road type has not been studied in previous research. Only a single type has been considered, i.e. highway or an urban region. In addition, the researches provided in [22] proved that the time and the day of the week affect the traffic congestion duration. Therefore, we present in this paper a new NNs-based model to handle this variation and forecast traffic congestion levels.

In this paper, we carried out some statistics to investigate the speed changes in urban regions and on highways. We notice that it is crucial to create a model that is able to take into account the traffic changes. The proposed methodology in this paper is different from previous technologies used in other research. We present an overview of the major aspects

developed to implement our system. We solve the problem using a NNs-based model to learn various traffic situations on highways and in urban regions at different times of day, capture different patterns over several weeks, as well as to forecast traffic congestion states of roads in future time periods. Based on our knowledge, there has not been any work in the literature that has studied dynamic traffic variation and the different traffic patterns on highways and in urban regions where the speed interval is totally different. Researchers focused on a single type of road. They did not investigate the different traffic conditions in urban regions and on highways. Our system helps drivers to detect the eventual congestion state in order to find another way to overcome this problem. Furthermore, it provides information about the congestion for transportation managers to locate the frequently congested locations to solve this issue.

The remaining parts of this paper are organized as follows. Section 2 provides an overview of the GPS traces collection step with some analysis. Section 3 presents the proposed system and highlights the process of the model development. The experimentation and results were introduced and explained in section 4. Finally, we conclude our paper in section 5 and present some perspectives.

2. BIG GPS TRACES COLLECTION

To develop an accurate system, it is essential to use an accurate and real database for test and validation of this system. With the lack of public GPS databases, we developed a GPS tracking system to gather GPS traces. This system is mainly composed of GPS satellites and GPS receivers mounted in cars. The GPS satellites send signals to the earth in order to calculate orbit positions. To get more precise positions, it is crucial to use more than three satellites. However, the GPS receivers provide the car's position and send the GPS traces to the database through GPRS network connection. In this section, we present an overview of the collected GPS traces. Moreover, the pre-processing and map-matching steps are provided to filter the noisy data and guarantee the high quality of GPS traces.

2.1 Overview of the Collected GPS Traces

Due to the developed GPS tracking system, we gathered big GPS traces from cars on the roads of Tunisia. The volume of data reached more than 100 GB of raw GPS traces. The GPS traces are based on the GPRMC sentence type [24]. This type of sentence is used because it indicates the speed of the car, which is an important feature in our case. We provide an example of GPRMC sentence to explain the role of each feature. The transmission of the data is performed about every minute. The following sample of a GPRMC sentence is provided to give an idea about the collected data.

\$GPRMC, 160533.00, A, 3445.5029, N, 01046.8838, E, 037.8,255° C, 071214, 00.0, W, 000CA .Each feature in the GPRMC sentence is presented in Table 1.

In the feature extraction step, the main extracted features from the GPRMC sentences are the ID of the car, the timestamp information, the position coordinates and the speed of the car. We gathered the GPS traces from about ten thousands cars and trucks. This number allows us to collect a big GPS database. We provide more details on the GPS database in [25]. In the transmission process, some problems can be encountered such as the lack of four satellites, which can easily cause the deformation of the GPS trace. A filtration step is developed to overcome this problem and remove the noisy data and outliers [26]. An outlier is detected if the validity value in the GPRMC sentence is set to V. Then, a map-matching step is carried out to verify the accuracy of the collected GPS

traces. Figure 1 presents the results of map-matching step of an example of GPS traces of car ID 43712 to a digital map.

Table 1: Features provided by the transmitted GPRMC sentence

Feature	Information
\$GPRMC	Type of the transmitted sentence
160533.00	Time (hhmmss.msms)
A	The validity of the transmitted sentence (if V=Invalid)
3445.5029	Latitude coordinate in the format ddm.mmm
S	North/South orientation
01046.8838	Longitude coordinate in the format ddm.mmm
E	East/West orientation
037.8	Instantaneous Speed (mile/hour)
255°	Travel direction
071214	Date in the format DDMMYY
00.0	Magnetic variation in degree
W	Magnetic variation orientation (E/W)
000CA	Checksum to verify the transmitted frame accuracy

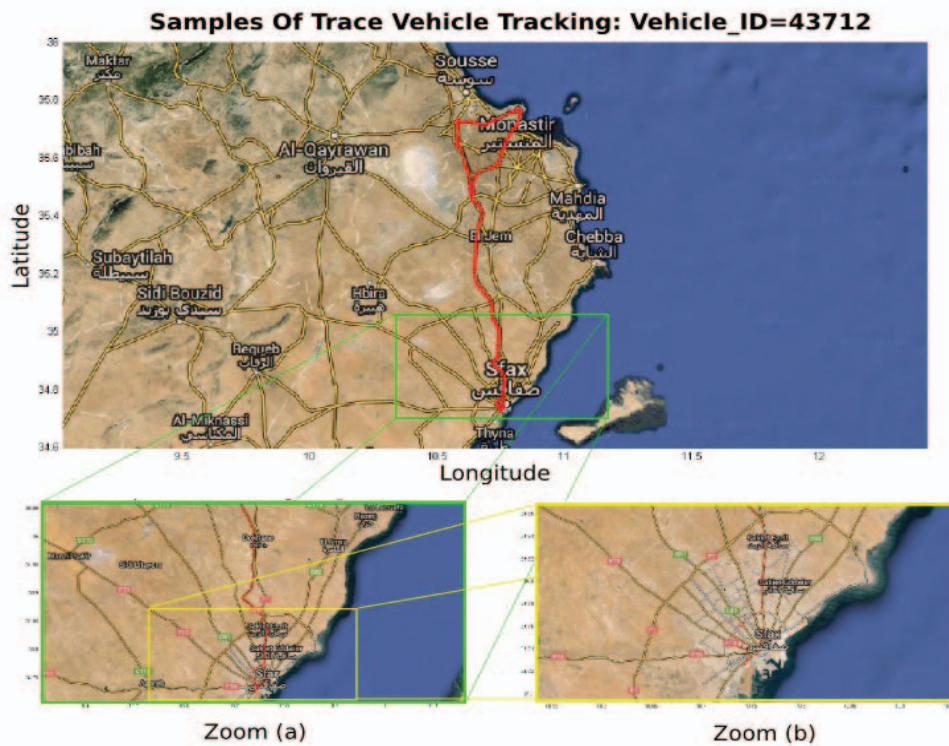


Fig. 1: Map-matching of GPS traces sample.

Figure 1 shows the GPS traces of a car that traveled from Sfax city to Sousse city through the freeway linking these two cities. We performed a zoom in Sfax city to compare the precision of our traces to the digital map. As it is shown in sub-figure (b), the red line and the yellow line of the digital map are completely superimposed which proves the accuracy of our GPS traces.

2.2 Preliminary Analysis

Predicting the traffic state of a road is a very delicate task because traffic congestion is a dynamic event. Traffic conditions depend on several components such as the time of day, the day of the week, and the road location. Therefore, in the development of a reliable system able to forecast the congestion state, we should take into account the different traffic changes. To achieve our purposes, we analyzed some statistics using our data. We computed the average speed of the cars in different places and in different periods of the day to discover the relationship between speeds, time periods, and places including highways and freeways. We provide Fig. 2 and Fig. 3 to explain the traffic speed changes along a journey in two different chosen study areas.

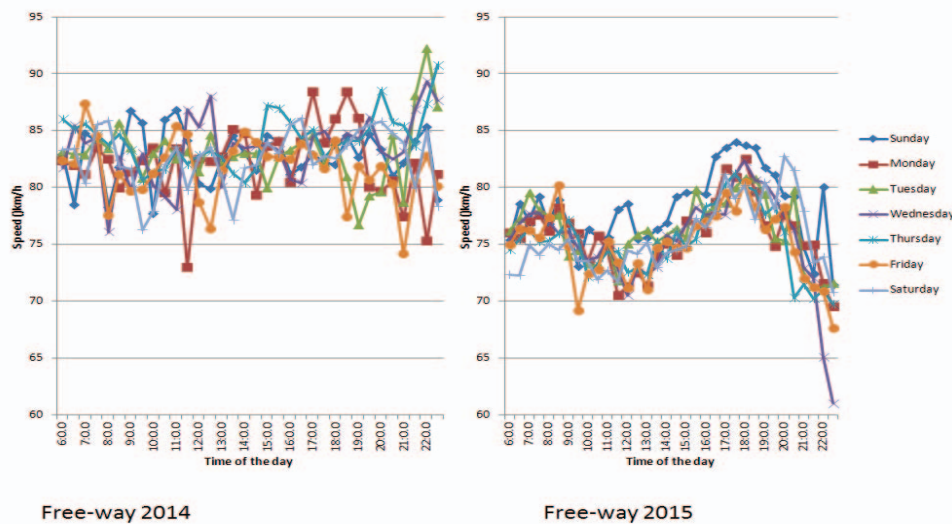


Fig. 2: Comparison between the average vehicles' speed measurements on the first week of March on the same freeway in (a) 2014 and (b) 2015.

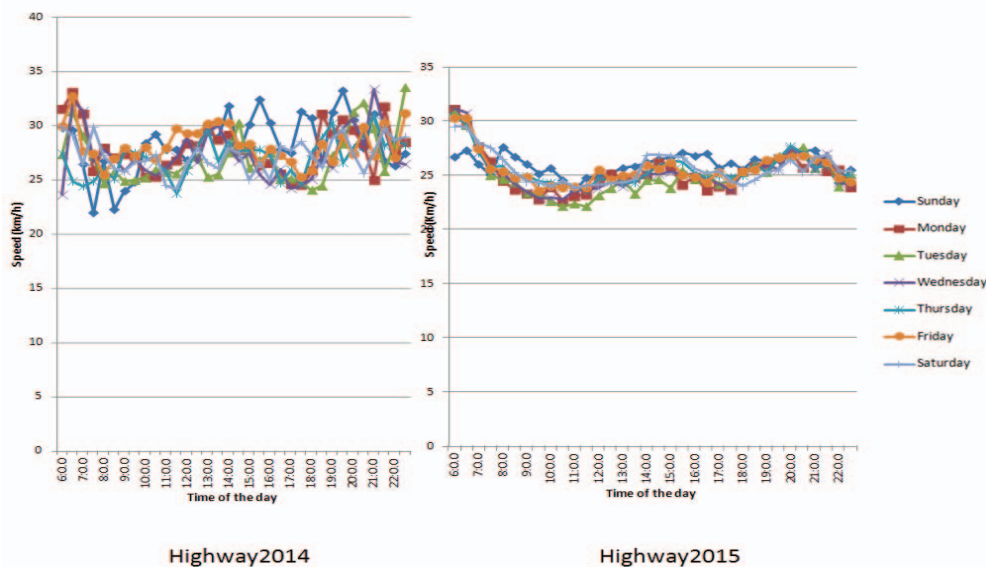


Fig. 3: Comparison between the average vehicles' speed measurements on the first week of March on the same highway in (a) 2014 and (b) 2015.

The preliminary analysis presented in Fig. 2 and Fig. 3 were performed on a freeway linking Sfax and Sousse cities and for one of the most congested highways in Sfax city

called Taniour highway, respectively, on the first week of March for two different years (2014 and 2015). Figure 2 shows that the average speed on the freeway in 2014 is between 70 km/h and 93 km/h which is very low compared to the permitted maximum speed (110 km/h). Furthermore, in 2015 the speed is lower and reaches very low levels. This can be explained by the increase in the number of vehicles and some road works on this freeway that directly affected the traffic congestion. Concerning Fig. 3, the average speed on the highway doesn't exceed 35 km/h in the two years along the week and it becomes more serious in the rush hours (between 7 a.m -9 a.m and 4 p.m-7 p.m). As we said, this road is very congested. It contains many primary schools and child care centers. We conclude that it is necessary to handle the different patterns and traffic speeds along the highways and freeways to elaborate a robust and reliable approach able to overcome real-world conditions.

3. NEURAL NETWORKS APPROACH FOR CONGESTION PREDICTION

After the preliminary analysis, we present in this section a combined neural network approach for congestion prediction based on the gathered GPS traces able to forecast the traffic congestion in roads. The combination of two neural networks is provided to respond to the need to differentiate between traffic conditions and range of allowed speed along highways and freeways.

We present in Fig. 4 an overview of the proposed system composed of two main phases. An offline phase is carried out to collect and preprocess the GPRMC sentences gathered from cars equipped with GPS systems and to develop the neural networks-based model. Concerning the online phase, it is composed of a decision module and it is mainly based on the trained neural networks.

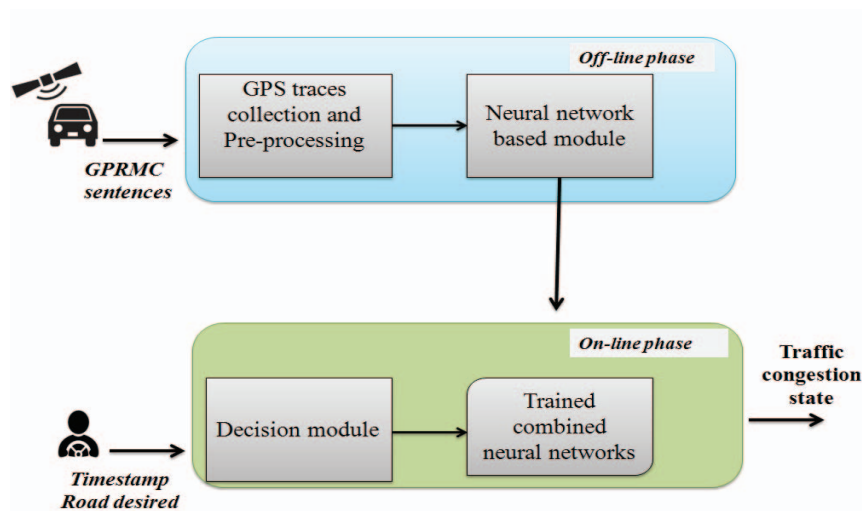


Fig. 4: The proposed system architecture.

3.1 Neural Network Based Module

This module is an important step to build our system. We applied the neural networks because it is one of the most performing tools in machine learning. The choice of the neural networks among the other techniques can be explained by their ability to deal with predictors with complex relationships. Moreover, we highlight the robust capabilities of

neural networks in forecasting the future state when they know the previous states. Furthermore, the results are mostly improved and can reach high accuracy if a large quantity of data is fed into the NN system. These criteria, such as the need for big GPS trace data, the complexity of the relationship between the input variables and the desired congested state, are provided in our case which encourage the authors to apply and test the performance of the NNs to predict the future congestion state of a road.

The common structure of all NNs is inspired by biological neural networks. They consist of many calculating units called *neurons*. Their principal components are layers. The first layer is the input layer composed of the predictors. We present in Fig. 5 the composition of our NN architecture.

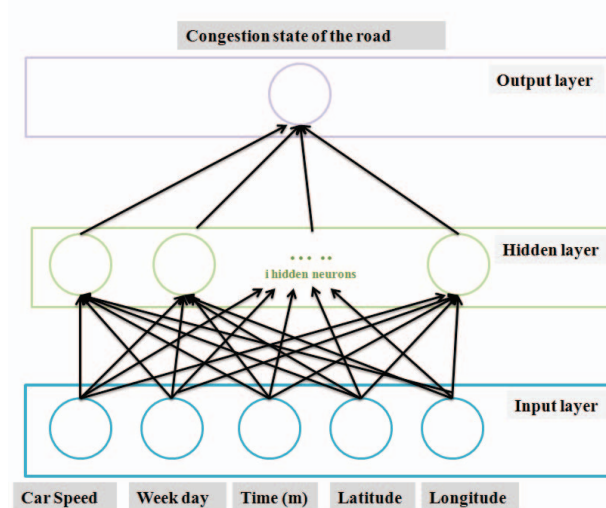


Fig. 5: Architecture of the NN based design.

In our system, as it is presented in Fig. 5, five inputs extracted from GPS traces which are the position coordinates, the speed of the car, and the timestamp information (the number of minutes and the week day). The second layer is composed of the hidden neurons. Finally, the output layer is composed of the desired output which, in our case, is the predicted congestion state. The choice of the number of hidden neurons is defined after performing some experiments that will be discussed later. The role of this architecture is to compute the future state of the desired road using the inputs by means of a transfer function called the activation function.

The module structure relies primarily on the preliminary analysis made in section 2. In fact, the difference between traffic changes on highways and freeways has an impact on the structure of our neural network-based system. We solved this challenging problem using an architecture composed of a combined neural network. It is composed of two neural networks. Each neural network is trained with the GPS traces gathered from the correspondent type of road (freeway/highway). The output of the offline phase is the trained combined neural network that will be used in the online phase.

3.2 Decision Module

The online phase is composed of the decision module that is based on the trained combined neural network. It is performed when a driver needs to discover the traffic condition state in a specific place and time. We provide the driver with a mobile application where he can insert the details of the place and the time. We get the required

information from this application and the current traffic condition from the floating cars in this location. Our decision is taken after distinguishing if the required place is a highway or freeway. When we get this information, our system activates the corresponding neural network. Finally, the congestion state is predicted and sent to the driver.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

We propose in this paper a combined NNs system to forecast congestion state based on two NNs in order to take into consideration the traffic changes depending on several variables like the road type road and weekday, as discussed above. We present in this section some experiments and comparisons with other approaches to evaluate our proposed system.

To guarantee the high performance of our system, it is crucial to get the best configuration of neural networks. In order to realize the experiments, we used the provided data in Table 2, which contains the data repartition used in the training and test steps.

Table 2: Data repartition

Training data samples	Test data samples
3 909 756	1 366 830

We notice from Table 2 the vast amount of data used in these steps. Regarding the experiments, the input variables were fixed and the number of hidden neurons were changed. Also, in the training step, we varied the training function. Table 3 provides the Root Mean Square Error (RMSE) given by Eq. (1) of all the proposed architectures.

$$RMSE = \sqrt{\left(\frac{1}{N} \sum_{k=1}^N (C_k - \hat{C}_k)^2\right)} \quad (1)$$

where C_k is the real traffic congestion state, \hat{C}_k is the predicted one and N is the number of GPS traces fed in the evaluation process.

Table 3: RMSE of different proposed ANN architectures

Configuration	Number of Hidden Neurons	Training function	RMSE_train	RMSE_test
C1	3	Levenberg-Marquart	0.0651	0.0655
C2	5	Levenberg-Marquart	0.0935	0.0947
C3	8	Levenberg-Marquart	0.0663	0.0765
C4	13	Levenberg-Marquart	0.0659	0.0715
C5	17	Levenberg-Marquart	0.0603	0.0692
C6	3	Bayesian-Regularisation	0.0806	0.0822
C7	5	Bayesian-Regularisation	0.0637	0.0721
C8	8	Bayesian-Regularisation	0.0624	0.0636
C9	13	Bayesian-Regularisation	0.0606	0.0510
C10	17	Bayesian-Regularisation	0.0566	0.0571
C11	3	Scaled Conjugate Gradient	0.1370	0.1425
C12	5	Scaled Conjugate Gradient	0.1034	0.1073
C13	8	Scaled Conjugate Gradient	0.0931	0.0948
C14	13	Scaled Conjugate Gradient	0.1757	0.1839
C15	17	Scaled Conjugate Gradient	0.1006	0.1027

Table 3 presents the different configurations of the proposed NNs to deduce the best network. In our experiment, we performed the variation of the number of hidden neurons from 3 to 17 and the training function. In fact, we tested the most popular training functions: Levenberg-Marquardt back-propagation, Bayesian regularization back-propagation and scaled conjugate gradient back-propagation techniques. Among the NNs architectures trained with Levenberg-Marquardt back-propagation function, the best results were given by configuration C1, which has the NN architecture with 3 neurons. For those trained with Bayesian-Regularisation algorithm, we reached 94% with 17 hidden nodes. Finally, using the Scaled Conjugate Gradient, the best result is about 89% with only 8 neurons. We conclude that the best configuration is given by the Bayesian-Regularisation algorithm with 17 neurons. We applied this configuration to the combined neural networks for highways and freeways.

The second experiment sets were performed to compare the NN techniques to other nonparametric techniques such as SVM and k -NN. Figure 6 presents the results given by these three algorithms.

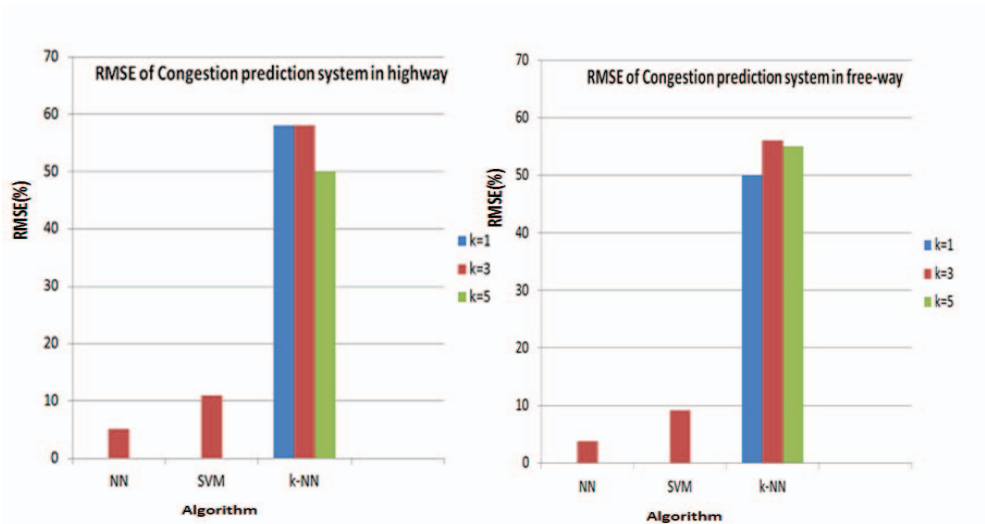


Fig. 6: RMSE of Congestion prediction system in highways and freeways.

As shown in Fig. 6, the best performance was given by our proposed system, which is based on NNs on the two types of road. The k -NN gives the worst results even if we change the value of k . The SVM provided acceptable results, especially in freeways because of its similar composition to NN. We notice that our system, which is composed of a combined NNs, is reliable and provides very interesting results on freeways and in urban regions. These experimentations demonstrate the efficiency of our proposed system which validated our model.

5. CONCLUSION

We presented in this paper a NNs-based model to predict the congestion state of roads. Our model helps drivers to preplan their trips to avoid congested roads. Also, it can be efficient for transportation managers to find solutions for congested roads.

Our model takes into account several traffic changes, spatial patterns in particular. We provided some statistics to analyze the impact of the road type on traffic conditions. We infer that driving speeds are very low on highways in urban regions but very high on

freeways. Based on this analysis, the structure of our model was built using a combination of two NNs, one to process highways and another for freeways. Thanks to the NNs structure, our proposed model has proven its capabilities to deal with several variables and successfully detect the nonlinear relationship between them. It was tested using a big GPS database gathered from a huge number of vehicles circulating in metropolitan Tunisia. Furthermore, our model has shown very high performance in forecasting congestion state compared to other nonparametric techniques.

In future studies, we would like to analyze the effect of other parameters such as holidays and workdays on driving speed in a dynamic environment to gather other eventual inputs to our model in order to improve the results. We would like to explore more techniques such as deep learning techniques and perform more experiments based on these huge datasets to obtain a more reliable traffic congestion prediction system.

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