MODELLING SMART ROAD TRAFFIC CONGESTION CONTROL SYSTEM USING MACHINE LEARNING TECHNIQUES

A. Ata[*] *M.A. Khan*[†] *S. Abbas G. Ahmad A. Fatima*[‡]

Abstract: By the dramatic growth of the population in cities requires the traffic systems to be designed efficiently and sustainably by taking full advantage of modern-day technology. Dynamic traffic flow is a significant issue which brings about a block of traffic movement. Thus, for tackling this issue, this paper aims to provide a mechanism to predict the traffic congestion with the help of Artificial Neural Networks (ANN) which shall control or minimize the blockage and result in the smoothening of road traffic. Proposed Modeling Smart Road Traffic Congestion Control using Artificial Back Propagation Neural Networks (MSR2C-ABPNN) for road traffic increase transparency, availability and efficiency in services offered to the citizens. In this paper, the prediction of congestion is operationalized by using the algorithm of backpropagation to train the neural network. The proposed system aims to provide a solution that will increase the comfort level of travellers to make intelligent and better transportation decision, and the neural network is a plausible approach to find traffic situations. Proposed MSR2C-ABPNN with Time series gives attractive results concerning MSE as compared to the fitting approach.

Key words: *neural networks, prediction, backpropagation, MSR2C-ABPNN*

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1. Introduction

Smart system is a novel concept of designing a smart and better lifestyle by adopting modern technological advents. Smart systems incorporate neural network and communication technologies for better utilization of public resources, increase quality and reducing the operational cost of services offered to the citizens. Smart city perspective provides simple, unified, and economic access to public services for

[*]Ayesha Ata; School of Computer Science, NCBA&E, Lahore & Dept of Computer Science, GCU, Lahore, E-Mail: ayesha.ravian@gmail.com

[†]Muhammad Adnan Khan – corresponding author; Sagheer Abbas; Gulzar Ahmad; School of Computer Science, NCBA&E, Lahore, E-Mail: madnankhan@ncbae.edu.pk, dr.sagheer@ncbae.edu.pk, Gulzar.phd@ncbae.edu.pk

[‡]Areej Fatima; Department of Computer Science, LGU, Lahore, E-Mail: areejfatima@lgu.edu.pk

citizens. This concept has brought numerous advantages in management and optimization of public services as well as availability, efficiency, and transparency to the service offered by the local government such as, security and surveillance, maintaining the public property and cultural heritage, waste management, smart traffic management system, etc. According to research conducted by Pike on smart cities, smart city market is estimated at hundreds of billion dollars by 2020, with an annual expenditure of about 16 billion (mention the currency?). Smart city market connects major industries like smart governance, smart building, smart utilities, smart environment, and smart transportation, etc.

2. Related works

This paper focuses on the substantial advantages smart city market has not elevated yet because of political, technical and financial hurdles and barriers [1].

Chong et al. proposed that traffic congestion is another problematic issue; it happens when the number of automobiles on roads increases from the road capacity which is also called saturation [2].

Rising population, immense export of vehicle and lack of an efficient public transportation system is the foremost reasons for traffic saturation [3].

Safe and smooth traffic flow by developing smart traffic management systems are the main concerns and study areas in the smart cities literature. The smart and intelligent transportation management system is an advanced approach to integrate the Internet of Things and communication technologies for designing future smart cities framework [4].

The smart transportation system has multiple applications like enhancing road safety and security, monitoring of traffic flow, saturation detection, reduce travel time, alternate routing, route weather condition, reducing pollution and greenhouse gas emission, efficient fuel consumption, emergency management, noise monitoring, etc. [5].

Conventional solutions include monitoring of vehicles speed by CCTV cameras and speed trackers, traditional traffic control lights, continuous pollution check, human tracking, etc. but the theses classical traffic management techniques had failed to ensure operative traffic flow because of increase in vehicular density on roads [6].

Modern automobiles have equipped with many different types of electronic control units, e.g. power steering, rear view cameras, braking systems, etc. today the automobile industry is no longer mechanical. Instead, it is automated and electronic [7].

Internet and its future are integrated with automobiles, and vehicles are in the era of future technological transformation. Drivers use a verity of different electronic devices while driving, for example, smartphones for sending text messages, watching videos, internet surfing, navigation, listening radio, etc. as a smartphone is a single complete package of all these utilities. Herein, the portability of the mobile phone is a key reason why these communication devices are highly usable in automobiles. Nowadays cars and mobile internet have more positive combination, especially after integrating GPS with mobile phone technology makes a possibility of changing the dilemma of navigation technology [8].

Smart transportation management system integrates information technology, artificial intelligence, transportation management etc. to develop an effective transformational service system [9–15].

This paper focuses on the accuracy of the neural network, which depends upon different iterations which include three different parts of the neural network structure, and it's working, i.e. input layer, hidden layers, and an output layer. This paper concludes the accuracy of the neural network when there is one hidden layer including many neurons in the hidden and input layer is equal [14].

Al-Dweik et al. proposed (SERSU) Scalable Enhanced Road Side Unit, having contamination recognition, the arrangement of versatile traffic control and climate data framework, SERSU utilized radio recurrence, and remote correspondence organize. SERSU modules were put on the roadsides at various interims, catching created sensor motions by another module of vehicle sensors [5].

Goggin briefly inspected present-day innovations of web, vehicles and their relationship, detail history of use of electronic gadgets in social ramifications and cars of these advances [8].

Chong et al. have given the sensors which depend on an Infrared framework, which catches the radiation of infrared transmitted via vehicles on the outside of the street, to watch the stream of traffic and gives the other traffic steering way to drivers for the aversion of traffic blockage [2].

Thakur et al. proposed motioning of Density-based used to conquer the issues raised by settled time motioning for instance in stable time flagging methodology the traffic lights have predefined intermittent time framework proposed by Thakur et al. offers canny motioning by appointing greener flag to thick traffic area to escape blockage by relentless surveying the thickness of traffic [9].

Ramchandra et al. proposed a comparative framework which controls the traffic lights progressively as indicated by the mass of traffic utilizing the normal speed of vehicles? In the proposed framework, every vehicle is fitted out with locally available gadgets (OBD) which gain vehicular speed information process and disperse information to unify server utilizing Zigbee convention [1].

To lessen the clog of traffic and increment the consistency to traffic signals Chowdhury et al. proposed a smart traffic light framework for correspondence between crisis vehicles to the foundation. The proposed framework considers that the significance of vehicle relies upon the sort of episode and shielded signs from hacking [16].

Ou et al. pointed out a few weaknesses in the customary insightful transportation framework and examined to incline toward the (RFID) radio recurrence distinguishing proof, correspondence advancements and sensor system to conquer common smart transportation frameworks issues [8, 9]. In unique situations, the precision of the expectation, the reaction can't be adjusted to current conditions [17].

3. Proposed MSR2C-ABPNN system model

this article has proposed a new Modeling Smart Road Traffic Congestion Control using Artificial Back Propagation Neural Networks (MSR2C-ABPNN) for an intelligent traffic system.

The whole process of the proposed MSR2C-ABPNN system is shown in Fig. 1. herein, the sensory layer contains the input parameters which shall go to the neural network learning that was trained using an algorithm and predict the congestion point. If the congestion point is found, the vehicles will receive the message in their LCD's using RFID sensors, and after that google map is used to find the alternate route. Once again find the congestion in that particular point similar in the case if congestion not found, traffic moves further and finds continuous congestion points. Proposed MSR2C-ABPNN based model predicts the point of congestion with the help of a neural network using the backpropagation algorithm.

In proposed MSR2C-ABPNN, system application is further divided into two sub-layers, prediction and performance layer. In the prediction layer, back propagation is used to detect the occupancy, while the performance layer evaluates the prediction layer performance in terms of RMSE, Accuracy and Miss Rate.

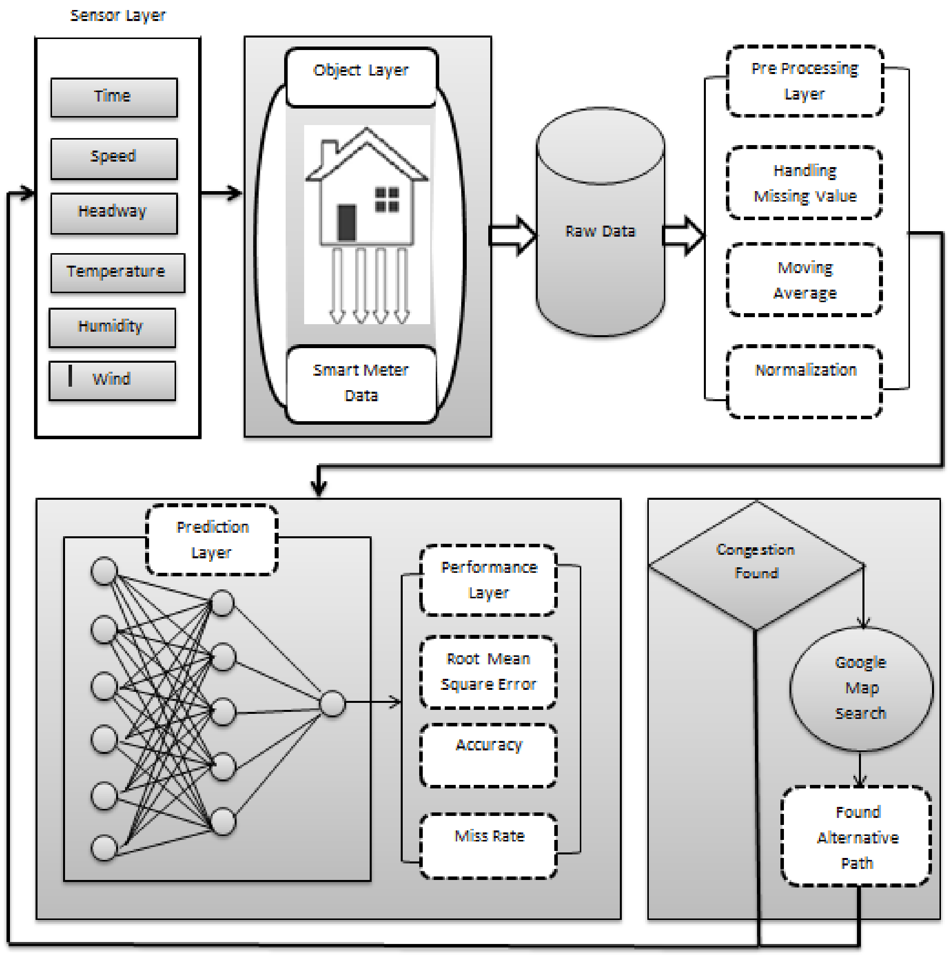

Fig. 1 *Proposed MSR2C-ABPNN system model.*

Adverse weather conditions directly affect the road traffic congestion by decreasing the visibility of the road and the condition of the road becomes worse. Adverse weather can be a combination of multiple factors such as; rain, humidity, temperature, etc. To predict the weather adversity, the previous data of the current system plays an important role.

In this paper, the dataset has been adopted from the internet which shows the weather report and traffic speed of M1 junction 37 England at the interval of 10 minutes. To predict the behavior of the network, allocate resources, dynamically [18], the experiments prove that this method allows better use of the network. The congestion variables are being defined as an input variable named as shown in Tab. I.

Sr. No	Input/Output Variable Name
Input 1	Time
Input 2	Traffic Speed
Input 3	Traffic Flow
Input 4	Humidity
Input 5	Wind Speed
Input 6	Air Temperature
Output 1	Delay Time

Tab. I *Input/output variables of the proposed MSR2C-ABPNN system.*

The neural network works as a powerful model for solving hard problems. According to the study of Smith and Demetsky, 1994, 1997 and S. Lee, 1998 due to virtuous and efficient results the Multi-Layer Perceptron (MLP) were the best model for prediction. With the help of a neural network, the mapping can be done effortlessly for input and output [19] to calculate and predict future trends — different number of methods available for calculating the uncertainty estimation [20].

Multilayer perceptron consists of an input and output layer. The left side layer is known as input layer which receives an input signal and then transmits it into the right side, layer by layer. Back Propagation Algorithm was used to train multilayer perceptron, while the weather information and traffic flows were used to predict congestion. Furthermore, the data set was used for Traffic flow and weather gathered every 10 minutes a day.

Many factors affect the traffic speed which causes the congestion, to include weather, accidents, and construction; this paper predicts the traffic flow by using artificial neural network model named as Back Propagation (BP) Neural network. It is being used for gaining maximum accuracy in the prediction of the traffic congestion with a defined structure of a neural network having an input layer, hidden layer and output layer — the structure composed of the forward propagation and backpropagation of error. In the forward propagation, information is being processed from the input layer to the hidden layer, then finally transmitted to output layer and if the output layer cannot accept then it sends back to the process of back propagation error, in which different values of weights are adjusted in such a way to minimize error and again transferred to the forward propagation. The main objective of this article is to predict the traffic flow under the condition of adverse weather.

In this research, the input layer, hidden layer, and output layer are being used in ANN architecture with the Back-Propagation algorithm for convergence and bit per data rate. Different steps are involved in the algorithm of backpropagation including, Initialization of weight, Feedforward, Back Propagation of error and updating of weight and bias. Every neuron present in the hidden layer has an activation function like $f(x) = \text{Sigmoid}(x)$. The sigmoid function for input is written as in Eq. 1, and the hidden layer of proposed MSR2C-ABPNN System in sigmoid function is written as in Eq. 2

$$\psi_j = b_1 + \sum_{i=1}^{m} (\omega_{ij} \times r_i)\,, \tag{1}$$

$$\varphi_j = \frac{1}{1+e^{-\psi_j}} \text{ where } j = 123\ldots n. \tag{2}$$

Input is taken from the output layer shown in Eq. 3

$$\psi_k = b_2 + \sum_{j=1}^{n} (\upsilon_{jk} \times \varphi_j)\,. \tag{3}$$

Output layer activation function is shown in Eq. 4

$$\varphi_k = \frac{1}{1+e^{-\psi_k}} \text{ where } k = 123\ldots r. \tag{4}$$

Error in backpropagation written as Eq. 5.

$$E = \frac{1}{2}\sum_{k} (\tau_k - \varphi_k)^2\,, \tag{5}$$

where $\tau_k r$ represents the desired output and out_k as a calculated output.

In Eq. 6 rate of change in weight for the output, layer is written as

$$\Delta W \propto -\frac{\partial E}{\partial W},$$
$$\Delta \upsilon_{j,k} = -\epsilon \frac{\partial E}{\partial \nu_{j,k}}. \tag{6}$$

Chain rule method is written as in Eq. 6.

$$\Delta \upsilon_{j,k} = -\epsilon \frac{\partial E}{\partial \varphi_k} \times \frac{\partial \varphi_k}{\partial \psi_k} \times \frac{\partial \psi_k}{\partial \nu_{j,k}}. \tag{7}$$

After substituting the values in Eq. 7, the value of weight changed can be obtained as shown in Eq. 8.

$$\Delta \upsilon_{j,k} = \epsilon\,(\tau_k - \varphi_k) \times \varphi_k (1-\varphi_k) \times (\varphi_j)\,,$$
$$\Delta \upsilon_{j,k} = \epsilon \xi_k \varphi_j, \tag{8}$$

where

$$\xi_k = (\tau_k - \varphi_k) \times \varphi_k (1-\varphi_k),$$

$$\Delta\omega_{i,j} \propto -\left[\sum_k \frac{\partial E}{\partial \varphi_k} \times \frac{\partial \varphi_k}{\partial \psi_k} \times \frac{\partial \psi_k}{\partial \varphi_j}\right] \times \frac{\partial \varphi_j}{\partial \psi_j} \times \frac{\partial \psi_j}{\partial \omega_{i,j}},$$

$$\Delta\omega_{i,j} = -\epsilon \left[\sum_k \frac{\partial E}{\partial \varphi_k} \times \frac{\partial \varphi_k}{\partial \psi_k} \times \frac{\partial \psi_k}{\partial \varphi_j}\right] \times \frac{\partial \varphi_j}{\partial \psi_j} \times \frac{\partial \psi_j}{\partial \omega_{i,j}},$$

$$\Delta\omega_{i,j} = \epsilon \left[\sum_k (\tau_k - \varphi_k) \times \varphi_k (1-\varphi_k) \times (\nu_{j,k})\right] \times \varphi_k (1-\varphi_k) \times \alpha_i,$$

$$\Delta\omega_{i,j} = \epsilon \left[\sum_k (\tau_k - \varphi_k) \times \varphi_k (1-\varphi_k) \times (\nu_{j,k})\right] \times \varphi_j (1-\varphi_j) \times \alpha_i,$$

$$\Delta\omega_{i,j} = \epsilon \left[\sum_k \xi_k (\nu_{j,k})\right] \times \varphi_j (1-\varphi_j) \times \alpha_i,$$

$$\Delta\omega_{i,j} = \epsilon \xi_j \alpha_i, \tag{9}$$

where

$$\xi_j = \left[\sum_k \xi_k (\nu_{j,k})\right] \times \varphi_j (1-\varphi_j),$$

output and the hidden layer is shown in Eq. 10 in which updating the weight and bias between them

$$\nu^+_{j,k} = \nu_{j,k} + \lambda_F \Delta \upsilon_{j,k}. \tag{10}$$

Updating weight and bias between the input layer and the hidden layer is shown in Eq. 11.

$$\omega^+_{i,j} = \omega_{i,j} + \lambda_F \Delta\omega_{i,j}, \tag{11}$$

λ_F is the learning rate of MSR2C-ABPNN. Convergence of MSR2C-ABPNN depends upon the care full selection of λ_F.

3.1 Proposed MSR2C-ABPNN system model using fitting modeling

ANN fitting application used a 2-layer feed forward network. In ANN, fitting network was trained by selecting data and dividing this data into sets as training, validation, and testing to define the architecture of the network. Performance of the network was measured by regression analysis, to evaluate the results, analyze the tool as a regression fit and mean square error. If the obtained result was not satisfactory the network re-trains with different dataset.

For neural network fitting, Levenberg–Marquardt algorithm was used to train and fit 997 sets of datasets randomly divides into 70 % of training (697 samples), 15 % validation (150 samples) and 15 % testing (150 samples).

The architecture of the Proposed MSR2C-Artifical Neural Network System consists of one hidden layer that contains 10 hidden neurons, 6 inputs, and one output to form the network.

3.2 Proposed MSR2C-BPANN model using time series modeling

ANN Time series was used to solve three types of a nonlinear problem using the dynamic network. ANN time series modelling was trained by selecting data then divide data into sets as training, validation, and testing to define the architecture of the network. Performance of the network was measured by regression analysis. To evaluate the results, analyze the tool as an error autocorrelation plot or histogram of the errors. If the obtained result not satisfied the need then the network retrains with diverse dataset.

The Proposed MSR2C-ABPNN system was assessed with Time series modelling. A neural network time-series using MATLAB technical calculation language [21] used to train and fit 997 sets of datasets using Non-Linear Autoregressive with External Input (NARX).

The architecture Proposed MSR2C-Artifical Neural Network System using Time Series which consist of one hidden layer with delays that contains 10 hidden neurons, 6 inputs, and one output to form the network in an optimal condition.

4. Results analysis

MATLAB R2017a tool is used for simulating the results, is used. In Tab. IV during training and validation Accuracy, Miss Rate and RMSE calculated and show the results.

Proposed MSR2C-ABPNN		Accuracy [%]	Miss Rate [%]	RMSE [%]
Using fitting modeling	Training	96.20	3.80	$8.261 \times 10 - 2$
	Validation	95.84	4.16	$9.807 \times 10 - 2$
Using time series	Training	98.15	1.85	$1.416 \times 10 - 3$
	Validation	97.56	2.44	$4.351 \times 10 - 3$

Tab. II *Performance evaluation of proposed MSR2C-ABPNN in validation & training.*

Tab. III shows the performance of the proposed MSR2C-ABPNN system using a fitting model and Time Series model with previous approaches given in the literature [21, 22].

In Tab. III delay is estimated for evaluating the congestion in road traffic for proposed MSR2C-ABPNN system and method proposed by Tamimi and Zahoor (2010) in [18] as well as Pushpi and Dilip Kumar (2018) in [22] by considering the factors of time, speed, the flow of traffic, wind speed, temperature and humidity.

Algorithms		Training Accuracy [%]	Training Miss Rate [%]	Training RMSE [%]	Validation Accuracy [%]	Validation Miss Rate [%]	Validation RMSE [%]
Tamimi and Zahoor (2010) [18]		78.12	21.88	2.751	76.1	23.9	4.312
Pushpi and Dilip Kumar (2018) [22]		91.265	8.732	1.015	90.6	9.4	1.826
Proposed MSR2C-ABPNN System	Fitting Model	96.2	3.8	8.261×10^{-2}	95.84	4.16	9.807×10^{-2}
	Time Series Model	98.15	1.85	1.416×10^{-3}	97.56	2.44	4.351×10^{-3}

Tab. III *Comparison results of the proposed MSR2C-ABPNN system with other algorithms.*

Algorithms		Training Regression	Validation Regression
Tamimi and Zahoor (2010) [18]		0.78	0.76
Pushpi and Dilip Kumar (2018) [22]		0.91	0.90
Proposed MSR2C-ABPNN System	Fitting Model	0.96	0.95
	Time Series Model	0.98	0.97

Tab. IV *Comparison results of the proposed MSR2C-ABPNN system with other algorithms concerning regression analysis.*

A different measure of evaluation compares the proposed MSR2C-ABPNN system and the method proposed by Tamimi and Zahoor (2010) also Pushpi and Dilip Kumar (2018); Mean Squared Error (MSE) and Regression Value (RV).

Proposed MSR2C-ABPNN with Fitting & time series model system gives the results as $8.261 \times 10^{-2} 1.416 \times 10^{-3}$ MSE with 96.2 %, 98.151 % accuracy values respectively during traning, and $807 \times 10^{-2} 4.351 \times 10^{-3}$ MSE with 95.84 %, 97.56 %. Accuracy values respectively during validation.

Tab. IV shown the regression analysis of Proposed MSR2C-ABPNN with Fitting & time series model system with previously published approaches [18, 22]. Regression analysis is a powerful statistical method that allows you to examine the relationship between two or more variables of interest. The principal uses for regression analysis are determining the strength of predictors. Proposed MSR2C-ABPNN with Fitting & time series model system gives the 0.96, 0.98 regression values respectively which is more improved values as compared to methods proposed by Tamimi & Zahoor (2010) [18], also Pushpi & Dilip Kumar (2018) [22]. Regression above 0.90 considered suitable value. It means regression values shown in Tab. IV also validates the proposed MSR2C-ABPNN system model.

It is plausible to state that the proposed MSR2C-ABPNN system has provided better results than the previously mentioned methods regarding MSE as well as Regression value. It also observed that the proposed MSR2C-ABPNN model with the ANN time Series gives more accurate results as compared to ANN Fitting.

5. Conclusion

This research has used a neural network as a methodological approach to control the congestion of traffic flow. It is detected that the smart transportation system has a significant impact on smart city whereas the traditional systems do not have the flexibility to automatically control the adjacent signals timers to minimize the congestion in traffic. Therefore, a Smart traffic congestion control system was presented to manage the traffic signal timer automatically by using machine learning techniques. Different sensors implemented on different adjacent signals that collect, share traffic data and sent to a controller through IoT enabled devices. In soft real-time system like smart traffic, time is critical. Therefore, if the data received by the signal sensors in delay or too much noise, in that sense proposed (MSR2C-ABPNN) solution performance may be affected.

This article has proposed a new MSR2C-ABPNN model for an intelligent traffic system to collect data from the controller. A neural network has been presented using the fitting and time series model. Pre-processing is done on the received data from the adjacent signals. The simulation results showed that performance of the proposed both variants of MSR2C-ABPNN model gives better results as compared to the previous Tamimi & Zahoor (2010) as well as Pushpi and Dilip Kumar (2018) proposed approaches. Furthermore, it is observed that the Proposed MSR2C-ABPNN system with an ANN time series gives better results than the ANN time series.

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