An Efficient Technique to Control Road Traffic Using Fuzzy Neural Network System

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Abstract— Conventional road traffic controlling systems are dependent on human operators for most of the decisions. Such human operators have experienced a wide variety of incidents and traffic congestions. But even the most experienced operators fail to control traffic efficiently during non-recurrent situations. Non-recurrent situation is a situation which has not been seen earlier by a human operator prior to its occurrence. Controlling traffic flow in such a situation is a complex task as it demands quick reaction and expert knowledge. This paper proposes a novel and efficient approach to control traffic flow in non-recurrent traffic situations. The proposed approach uses multiple techniques, most of which are borrowed from Soft Computing such as, NN (Neural Network), FL (Fuzzy Logic) and GA (Genetic Algorithm). This approach involves clustering imprecise data, in the form of Gaussian mixtures, into fuzzy sets using Expectation Maximization algorithm. The approach also includes minimizing the initial population of chromosomes in Genetic algorithm using a novel algorithm. The proposed algorithm used in identification of valid rules for fuzzy system reduces space and time complexity of the process. The proposed approach has been validated using METANET.

Key Words—road traffic control, non-recurrent traffic congestion, Soft computing, Fuzzy system, Genetic algorithm, data clustering, Expectation maximization, Gaussian mixture.

I. INTRODUCTION

THE need for transportation is growing continuously and this is causing a huge increase in the flow of road traffic day by day. As the traffic flow increases, cities are faced with number of serious problems due to road traffic congestion. Road traffic congestions account for significant economic losses due to the wastage of productive time. There is an increase in the number of road accidents, environment pollution and the loss of fuel. Moreover, staying for long hours in congested road traffic causes stress, health issues and reduces the quality of life. Therefore road traffic control centers are being set up to tackle these problems. There is a wide variety of advanced technologies that are being used in such traffic control centers.

Conventional control strategies used in traffic control centers involve the use of camera, detectors and some environment sensors which record the traffic state related variables in real time. Most commonly recorded variables include speed, density, flow, demand, queue length, flow-speed, flow-density, speed-density etc. Moreover, along with camera and detectors, control centers also use complex dynamic control equipment such as VMSB(Variable Message Sign Boards), DRIP (Dynamic Route Information Panel) and Ramp Metering. Figure 1 shows a typical infrastructure consisting of Camera, DRIP, VMS and some Sensors [19].

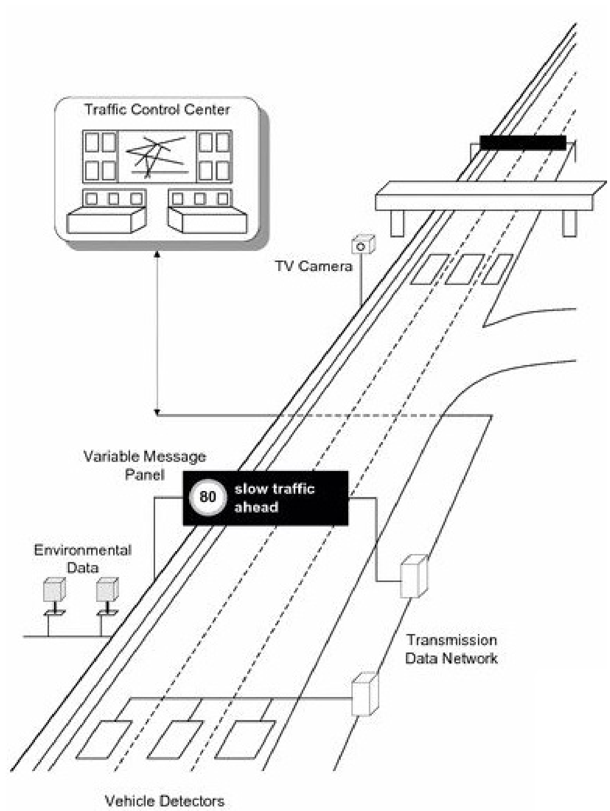

Fig. 1. Conventional traffic control network [19]

Traffic control centers are dependent on human operators for most of their decisions. Such human operators have wide variety of experiences in traffic control facilities. But even the most experienced operators fail to efficiently control traffic in a non-recurrent congestion situation .During such a situation, human operator has to evaluate the harshness of the situation, figure out the most likely transformation of the state of the network and choose the most effective control action quickly.

This is a highly complex task. It requires one to have expertise in traffic control, which requires hefty training. Simulation models exist and are used in many cases. But eventually when it comes to simulating multiple traffic situations for a number of control actions, simulation models tend to be very time consuming [20]. Determination of the right control action in non-recurrent situation can be arduous for most operators. Therefore, there is a need of a system, which can interfuse the defining variables of traffic situation with the traffic flow control application to assist human operators in determining the right decisions quickly. Fuzzy Logic and Neural Networks can be used to make such systems.

An amalgam of FL (Fuzzy Logic) and NN (Neural Network) forms FNN (Fuzzy Neural Network) System. These systems constitute a FL sub-system and NN sub-system.

FL sub-system serves following purposes [2], [3]:

i) It adapts itself using NN to define membership functions.
ii) It maps the fuzzy sub-sets to corresponding fuzzy rules.
iii) It implements de-fuzzification.

The Neural sub-system serves following purpose:

i) It serves error minimization by using the tuning mechanism of NN.

FNN System can be effective in providing real-time decision support for identification of most suitable control actions to be applied in case of non-frequently occurring traffic congestion.

In this paper we propose some enhancements to the previously proposed ITC-DSS system [1]. Inputs to the Fuzzy-Neural-Network used in this implementation are, ATDM (Average Traffic Demand), ATD (Average Traffic Density) and a list of possible Control Actions. The output of this system will be an ordered list of control actions, which can be applied to control traffic flow a given situation. The position of each control action in the ordered list will be decided by its performance in controlling traffic flow.

Rest of the paper is organized in five sections: Section II highlights Related Work done in the domain of intelligent traffic control system. Section III discusses the novel approach applied to enhance the earlier proposed ITC-DSS system [1]. Section III-A describes the first phase of the system, i.e. initialization of fuzzy membership functions using EM algorithm. Section III-B describes the second phase of the system i.e. identification of fuzzy rules using Genetic Algorithm. Section III-C references the back propagation technique. Section IV illustrates the Experimental Analysis and Results obtained. Section V highlights the Conclusion and Future Work.

II. RELATED WORK

Artificial intelligence has been the major domain of work in many advanced road traffic control systems. Different authors have proposed their systems in [4]-[13]. Some authors have used fuzzy logic [5], [6], [13] while others used neural networks [10], [12] in their decision making process. An agent-based environment called TRYS, which is based on fuzzy logic, is described in [4], [9]. Moreover, to manage road traffic, some more real time systems have also been described in [7], [8]. Hegyi et al in [5] have presented a traffic control system to manage non-repeating traffic congestions efficiently. His proposed system was based on fuzzy logic. Later De Schutter et al in [6] extended Hegyi et al's fuzzy system to propose his own multi-agent traffic control system. To improve long term traffic management policies, Almejalli et al in [13] proposed a fuzzy based decision support system. His system could assist traffic decision makers by providing policy based recommendations. Fuzzy Neural Networks as described in [14], [15] have also contributed to many traffic management tasks for e.g. controlling Traffic lights, analyzing and forecasting traffic flow etc.

In this paper we are extending the work presented in [1]. We also incorporate Expectation Maximization Algorithm to determine parameters of membership functions of Fuzzy Sets.

III. PROPOSED WORK

In this paper, we are developing a system based on fuzzy neural networks as presented in [1] and employing Expectation Maximization algorithm for initialization of fuzzy sets and membership functions. Given three fuzzy sets of traffic demand, three fuzzy sets of traffic density as precedents and five fuzzy sets each of TTT (Total Travel Time) and TDT (Total Distance Travelled); there are 1125 possible rules in the rule base. To extract and construct relevant rule base, genetic algorithms is employed as mentioned in [1].All possible fuzzy rules are encoded as chromosomes. The initial population of chromosomes is 5^{45}~$28x10^{30}$ which is too large for initial computation for the proposed model. Hence, we used a novel approach which is a variation of POP (Pseudo Outer Product), to identify broadly the most relevant rules and thus reduce the initial population of chromosomes on which GA is to be applied. The proposed approach implements a five layer structure [15] in following three phases:

A. Phase 1

The inputs of FNN System are ATDM (Average Traffic Demand) and ATD (Average Traffic Density) of current traffic situation; a set of five control actions which will help relieve traffic congestion.

The output of the system is an ordered list of control actions. Position of each control action in this list is decided by performance criteria, TTT (Total Travel Time) and TDT (Total Distance Travelled) by all vehicles in the network.

Given a set of training or sample data points for ATDM and ATD and assume that we know there are six fuzzy sets in the data; three for ATDM (low, medium, high) and three for ATD (low, medium, high) we need to assign the data points to the fuzzy set clusters (soft assignment) and learn the Gaussian distribution parameters for each cluster i: μ_i using (1) and σ_i using (2). The learning part is as shown in Fig. 2.

Initialize the Gaussian parameters: μ and σ randomly for each cluster and repeat the following steps until converging condition:

1) Compute for all sample data points the expected cluster membership values for each fuzzy cluster using initialization Gaussian parameters.

Gaussian mixture modeling assumes the data distribution to be a finite mixture of Gaussians. Generally, these estimates of the parameters of Gaussian distribution are computed using the maximum-likelihood (ML) approach, through an iterative procedure known as the Expectation Maximization(EM) algorithm. Once the parameter values are known, the posterior probabilities of each data point belonging to a particular distribution may be computed. Then, classifying each point into the distribution with highest posterior probability partitions the given data into respective Gaussian distributions.

This expected value is the output of the membership functions for each data point as input. For e.g.: Suppose for the fuzzy set "low average traffic density" the parameter $\mu$is 45.5 and is 0.6, then the expected value of sample data point for ATD as 50.5 will be $y=e^{-((x-\mu)*(x-\mu))/6*\sigma}$ =0.000968.This is the probability of 50.5 belonging to fuzzy set "low average traffic density". Similarly probability of 50.5 belonging to fuzzy sets medium and high average traffic density is also calculated. This is repeated for all sample data points. This is called the E-step.

2) Re-compute the parameters of each Gaussian membership function of each fuzzy set. This is called the M-step for it performs maximum likelihood estimation of parameters.

Means: $\overrightarrow{\mu_i} = \frac{\sum_{t=1}^{T} p(i|\overrightarrow{x_t},\ \lambda)\overrightarrow{x_t}}{\sum_{t=1}^{T} p(i|\overrightarrow{x_t},\ \lambda)}$ (1)

Variance: $\overline{\sigma_i}^2 = \frac{\sum_{t=1}^{T} p(i|\overrightarrow{x_t},\ \lambda)x_t^2}{\sum_{t=1}^{T} p(i|\overrightarrow{x_t},\ \lambda)} - \overline{\mu_i}^2$(2)

Where $p(i|\overrightarrow{x_t},\ \lambda)$ is probability of $\overrightarrow{x_t}$ belonging to fuzzy set i as calculated in E step. λ is the set of initial Gaussian parameters for fuzzy set i in consideration. Convergence condition occurs when:

$$|\sigma_{old}-\sigma_{new}|<=0.01 \text{ and } |\mu_{old}-\mu_{new}|<=0.01$$

B. Phase II

GA based learning algorithm is used to identify the fuzzy rules that are supported by the set of training data and is performed as shown in Fig. 3.

1) For our modeled problem, we have a total of 45*5*5=1125 possible rules out of which only 45 are relevant. All the possible fuzzy rules are encoded as chromosomes. Integer strings as chromosomes are used to represent candidate solutions of the problem. The encoding of the chromosomes is done as given in [1].

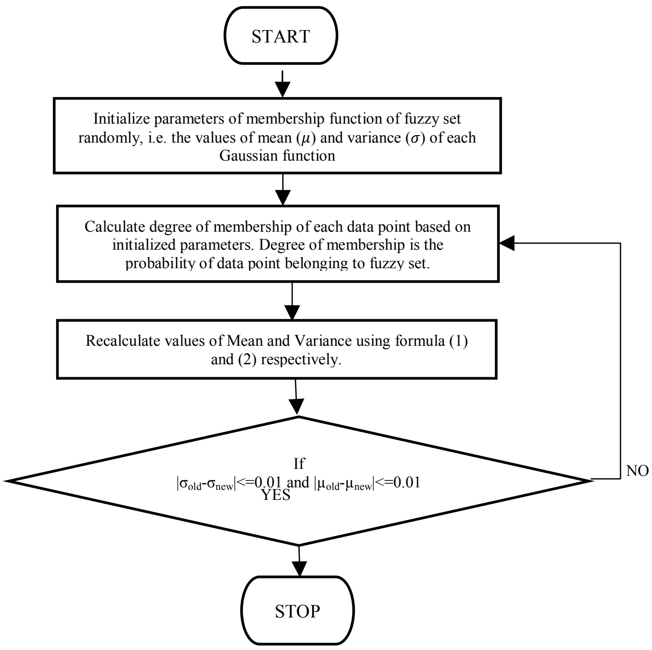

Fig. 2. Flow chart of Phase I

2) The chromosome string is given by $X_1, X_2, ..., X_i,...,X_P$ where X_i is an integer $0 \leq X_i \leq Q$ which indicates the link of neuron R_i (i.e. neurons in Fuzzy-Rules Layer) with output neurons(i.e., neurons in Consequence Layer). P is the number of neurons in the Fuzzy-Rules Layer and Q is the number of neurons in the Consequence Layer. For our example the chromosome has forty five integers, and $0\leq X_i\leq 5$. $X_i = 0$ indicates there is no link of R_i with output neuron; $X_i = 1$ indicates that there is a link with 'VL' neuron in Consequence Layer and so on.

This rule base generation using GA is done twice. Every rule has two consequent parts. These are TTT and TDT. For e.g.: IF x_1 is L and x_2 is VL, then TTT is L and TDT is L. These can be split as Type 1: IF x_1 is L and x_2 is VL, then TTT is L and Type 2 as: IF x_1 is L and x_2 is VL, then TDT is L. Once GA is run for generating rule base of rules of Type 1 and a second time to generate rules of Type 2.

3) After the chromosomes have been encoded, the total initial population of chromosomes is 5^{45}~$28x10^{30}$ which is too large for computation. To reduce this initial population, we use a novel approach on the lines of POP algorithm. In the historical or simulated data, it is known that for time instant t, average traffic demand (TDM) is x_1, average traffic density (TDN) is x_2 and the values of TTT is y_1 and TDT is y_2. For fuzzy rule R1, if TDM is low and TDN is low, the values of TTT and TDT would be high or low, that needs to be determined. In the historical data or the simulated data, find a time instant "t" when corresponding TDM value belongs to fuzzy set of "low TDM" and corresponding TDN value

belongs to fuzzy set of “low TDN”. At this time instant t, note down the values of TTT and TDT. Let them be y_1 and y_2 respectively. TTT and TDT values are also categorized into five fuzzy sets of VL, L, M, H and VH. Calculate degree of membership of y_1 and y_2 belonging to each of these clusters. For e.g. the values are shown in Table 1:

TABLE I. DEGREE OF MEMBERSHIP OF TOTAL TRAVEL TIME Y1 AND TOTAL DISTANCE TRAVELLED Y2 FOR DIFFERENT FUZZY SETS

Categories	TTT	TDT
VL	0.006	0.008
L	0.07	0.08
M	0.005	0.003
H	0.0003	0.0007
VH	0.00005	0.00006

Arrange the degree of membership values in descending order. Note down the first three values and the corresponding fuzzy sets to which these values belong. Let them be F_1, F2 and F_3.In the above e.g. For TTT, F1, F2 and F_3 are VL, L and M respectively. For TDT, F_1, F2 and F_3 are VL, L and M respectively. Now, the possible consequents of TTT part of R_1 becomes F_1, F2or F_3.Similarly for TDT part of R_1, possible consequents become F_1, F2 or F_3.Thus the neuron corresponding to R_1 in fuzzy rule layer will have possible out connections to F_1, F_2, F3 clusters of TTT and F_1, F_2,F_3 clusters of TDT in consequent layer of FNN model. Now in the encoding of the chromosome, integer for R_1 will have three different values as opposed to five earlier. Thus the initial population of chromosomes will gradually decrease to accommodate only the most relevant rules.GA is then applied on these chromosomes to find the fittest solution.

4) The goodness (3) of every chromosome is evaluated by using a fitness function [1]. We use a set of training data to calculate the fitness of each chromosome based on the following fitness function:

$$Fitness = \frac{1}{RMS(error\_i)} \quad (3)$$

where *RMS* (*error_i*)represents the root-mean square error between the fuzzy-neural network outputs and the desired outputs for the i^{th} string. The GA aims to maximize the fitness function (3) to minimize the error value (*error_i*).When pre-specified error level is achieved after running the GA over a large number of iterations or generations, we choose the best GA chromosome. This best chromosome is decoded to get the structure of the Fuzzy neural network system by keeping only the links that are indicated by the chromosome.

C. Phase III

The derived structure and parameters are fine-tuned by using the back-propagation learning algorithm [17].

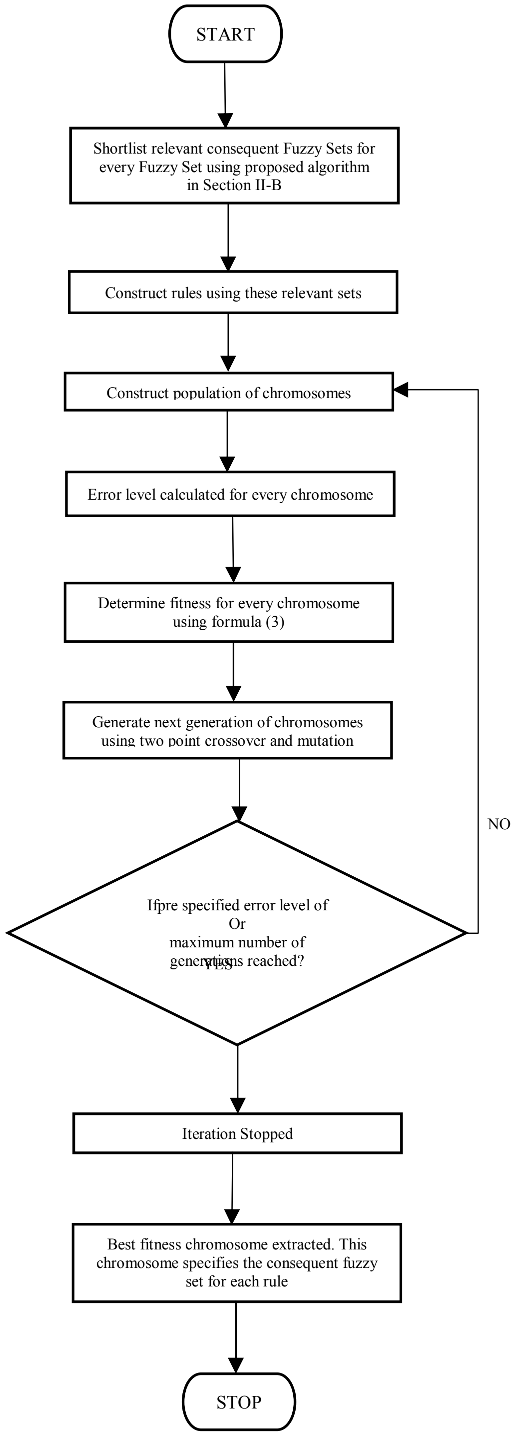

Fig. 3. Flow chart of Phase II

IV. Experimental Analysis & Results

The proposed Fuzzy neural network approach for road traffic control has been tested for a case-study of a small section of the Mahatma Gandhi Flyover in Delhi region of India as shown in Fig. 4.

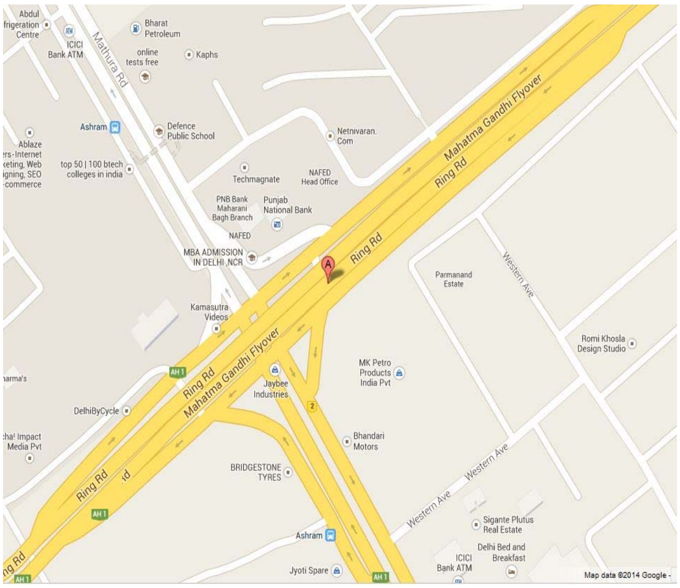

Fig. 4. Mahatma Gandhi Flyover in Delhi region of India

A. Data Set

The selected section is one of the busiest parts of Delhi as it handles all incoming traffic from Noida to Delhi and outgoing from Delhi to Noida. Here we are considering only the incoming traffic from Noida as shown in Fig. 5.

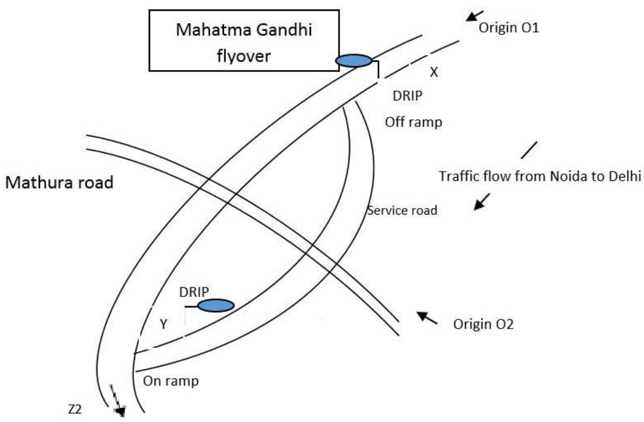

Fig. 5. Traffic Map of Mahatma Gandhi Flyover in Delhi region of India

At point X ,there is a DRIP that can display queue information, or give some alternative routes to drivers. The parameters chosen to rate the performance of control actions is Traffic demand (TDM) i.e. number of vehicles and Traffic density (TDN). The traffic control actions that can be applied on this case study are:

- C_1: Speed limitation at point X and using DRIP.
- C_2: Speed limitation at point Y and using DRIP.
- C_3: Speed limitation at both X and Y
- C_4: using VMS to display the queue information and directing traffic going to Z2 to go through on ramp.
- C_5: doing nothing.

The data needed for the training process has been generated using a traffic simulation model (more specifically, the METANET macroscopic flow model [18]). All our variables have been considered and simulated for the period from 4:00 PM to 10:00 PM.

B. Results & Analysis

In order to test the performance of the proposed technique, we have made a comparison between the results obtained from our proposed approach for fuzzy neural network system and the results obtained from traffic simulation model METANET. The comparison of results obtained from FNN System and METANET simulation model for a chosen traffic state are shown in Table1.

TABLE II. The performance evaluation of the control actions on a selected traffic state

Results	**METANET**		**FNN System**	
	TTT	***TDT***	***TTT***	***TDT***
C_1	2258.14	189700.2	2205.16	189139.22
C_2	2570.91	189756.9	2528.738	189139.22
C_3	2627.16	189645.1	2528.738	189139.22
C_4	2234.64	193770.8	2528.738	192480.96
C_5	2704.92	192721	2528.738	192480.96

We found that the results produced by our system are approximately close to the results produced by the traffic simulation model. Hence, the proposed method is validated.

The time taken by proposed method to calculate the performance of a given control action is much less than the time needed by the METANET simulation model. Calculation of total travel time and total distance travelled on METANET simulation model on application of each of the five control actions separately takes a total of 35 seconds. Whereas on running Fuzzy neural network system using proposed approach takes around 3-4 seconds, which is 85% less than the time taken by METANET simulation model.

V. Conclusion & Future Work

This paper has proposed a novel approach to improve the time complexity of existing system as described in [1] and provide a yet better decision support system to control traffic during non-recurrent congestion situations. The approach used in this paper applies EM and a novel approach to reduce initial chromosome population in addition to Fuzzy Logic, Neural Network and Genetic Algorithm. The output of the system is a ranked list of control actions which can be applied to manage traffic flow for a given geographic area and a given traffic situation. During a non-recurrent congestion situation human operator can quickly evaluate the performance of multiple control actions, for a given traffic situation, using the proposed system. We have trained the neural network using following algorithms: expectation maximization algorithm for initialization of fuzzy clusters; genetic algorithm for identification of fuzzy rules; and back propagation technique for fine tuning the neural network parameters.

The key strength of proposed approach is the reduction of initial population of chromosomes in Genetic Algorithm. To reduce the initial population of chromosomes in GA algorithm, we applied a novel approach on the lines of POP algorithm. And we were able to broadly identify the redundant rules and discard them based on the training data.

The technical feasibility of the proposed system has been tested over a small section of Mahatma Gandhi flyover near Ashram Chowk, New Delhi. The results were not just in alignment with the METANET Simulation model, but also our proposed system took 85% less time to estimate the performance of control actions.

The case study was done over a small geographical area, with limited number of control actions and small training data set. The proposed model can be used for any other geographical area with numerically varied training data set. Though the system will need powerful hardware, such as parallel processors, to perform major computations and large training data set to output accurate results.

Image processing can be used to calculate the numerical values of input variables using live image and video feed. The input variables, ATDM and ATDN, can be extracted using live satellite feed or using traffic layer feature in Google Maps.

The results of the proposed system are promising and can be further improved with more training samples. Extending this work, we plan to implement this system on a much larger network with more efficient results.

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