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NEURO-FUZZY AND ROUGH SET BASED TRAFFIC FLOW PREDICTION

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Abstract

With the rapid growth in urban population and vehicle ownership, traffic congestion has become a severe problem everywhere in the world and is only expected to rise. This problem can be avoided by knowing the traffic situation in advance which is achieved with the help of traffic flow prediction. In the proposed work, traffic flow is predicted on short term basis using neuro-fuzzy hybrid system in combination with rough set. The neuro-fuzzy hybrid system combines the complementary capabilities of both neural networks and fuzzy logic. The work has attempted to study the effect of aggregation intervals and past samples on the prediction performance using MSE threshold variation. Rough set is used as a post processing tool. The objective is to improve prediction accuracy. Data from highway of Chennai, India is used for the analysis. It is found that use of rough set results in considerable improvement in the prediction performance as indicated by performance measures like MSE, RMSE etc.

Keywords:

Intelligent Transportation Systems (ITS), Rough Set Theory (RST), Short Term Traffic Flow Prediction, Neuro-fuzzy Hybrid System

1. INTRODUCTION

As there is a fast growth in the economic development and the increased urbanization, road transportation has become a critical issue. Moreover because of the limitations in the infrastructural growth due to space and economic constraints, solution is to develop new innovations in the field of transportation with the aim to adjust the demand and capacity imbalances and many more. One of the solutions is traffic flow prediction which can provide useful information to the transport users and in turn makes the transport network safer, smarter and more coordinated. The information is provided to the travelers through ATIS in one of the three ways: real time, historical and predictive. Real time uses current values obtained from the system for prediction, historical uses archived data whereas predictive performs the prediction of future values calculated using above two i.e. real time and historical information [1]. Accuracy of traffic flow prediction is important as the transport users are required to take the decision based on this information.

Rapid changes in traffic demand are reflected by short term prediction. Thus short term prediction forms an essential component of controlling traffic in real time and management system. It predicts the next time interval traffic flow count where time interval nearly ranges from 5 to 30 minutes.

There are many research studies in the area of traffic flow prediction. In this context, different time series [2] [3], SVM model [4] [5], ANN models [6] and fuzzy neural systems [7] [8] have been developed. After review of literature it was observed that use of different soft computing tools in prediction is explored but use of rough set [9] - [12] along with these tools to improve its prediction performance was not touched upon which defines the direction for current work. The objective of this study is to use rough set in combination with the neuro-fuzzy model to improve upon prediction performance. In the proposed work, Rough set is used to perform the validation of prediction result thereby used as a post processing tool.

The rest paper is organized into different sections as follows. Section 2 discusses the data collection details. Section 3 includes the description about the structure of neuro fuzzy system and rough set used for short term traffic flow prediction. Prediction experiment is performed and simulation results are discussed in section 5. The conclusions are given in final section.

2. DATA COLLECTION

The dataset employed in this work is acquired from IIT, Chennai. It is recorded at a location near Perungudi toll plaza in IT corridor in Chennai for 6 days continuously for 24 hours from Monday to Saturday, April 2014. The device used to measure the traffic flow count is The Infrared Traffic Logger (TIRTL) [13]. It is installed on opposite sides of the road perpendicular to the flow of traffic. It uses infrared light based technology. The data were reported at every time instant the vehicle passed through the detector section [14].

Fig.1. Location map of study area

The Fig.2 shows the system architecture which describes the data collection and processing details. Before preprocessing, data available in CSV format is converted into required time format with the help of script. The recorded data includes date, time, speed, velocity, vehicle classification, trigger class, trigger list and axle details etc. But some parameters are relevant only at some specific installations. As we are concerned with traffic flow count only, these fields do not contribute in the prediction performance. So preprocessing is carried out in order to save the time in processing of invalid and redundant data so as to speed up the computation time. So data preprocessing is done to delete null and redundant entries and also to arrange the available data in 1 min time interval. After preprocessing, the final data is available as aggregated data of 5 min, 10min and 15 min interval. Finally post processing using rough set is done on predicted result.

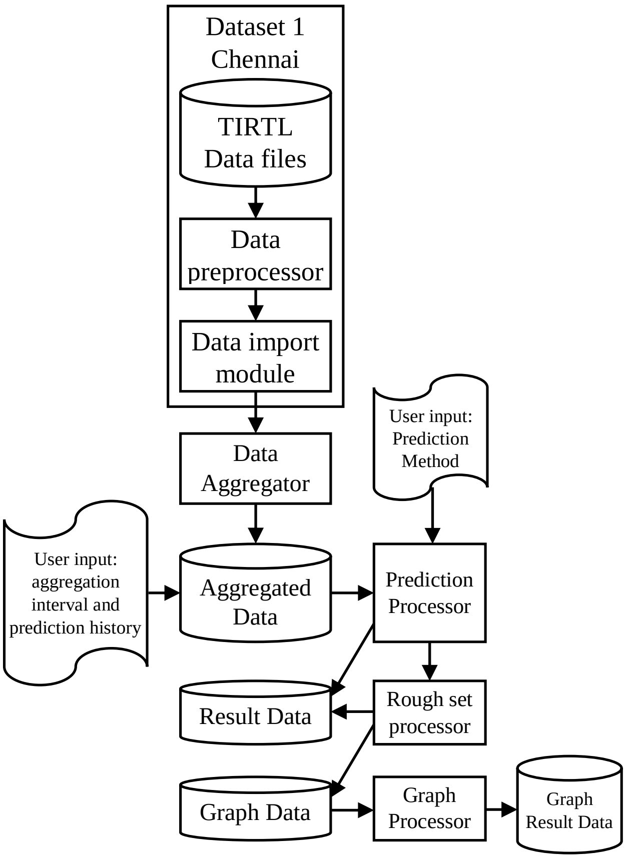

Fig.2. System Architecture

Traffic flow pattern of TIRTL based recorded data from IIT, Chennai presents the vehicle count on per minute basis. It is plotted by taking into account data of 3 days which is equal to 3 days × 24 hours × 60 minutes = 4320 minutes. It is observed that there are certain time intervals when no vehicles are recorded and peak traffic flow intervals also can be observed, thus providing idea of the recurrent pattern of the daily traffic profile.

3. METHODOLOGY USED

3.1 NEURO-FUZZY MODEL

Neuro-Fuzzy systems is the combination of artificial neural network with fuzzy systems. The neuro-fuzzy hybrid system combines the complementary capabilities of both neural networks and fuzzy logic. It allows the final system to be easily translated into a set of if-then rules and fuzzy system to be viewed as a neural network structure.

The Fig.4 shows the structure of neuro-fuzzy system for (2,1) case where 2 indicates the number of past vehicle count samples considered and 1 indicates the aggregation interval. The input to the system are the traffic values for the past 2 aggregation intervals while the system provides output which is the vehicle count prediction for the next instant.

The steps used to initiate training process on the model are as below:

Step 1: Normalize input and target values as per maximum vehicle count.

Step 2: Training data used percentage = 85%.

Step 3: Sugeno type FIS structure is generated from the training dataset.

Step 4: Grid partitioning is used on the data with no clustering.

Step 5: Optimization method = 1 (hybrid) least square method + back propagation using gradient descent.

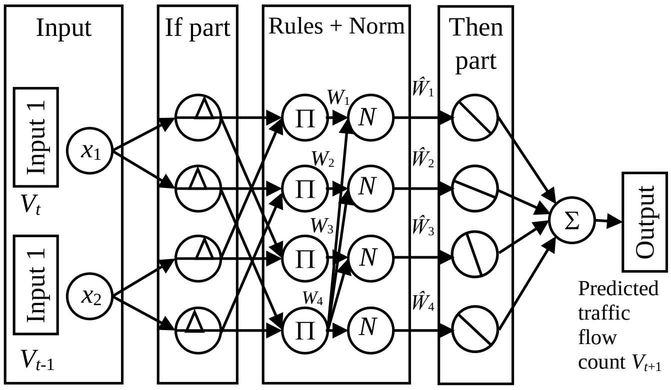

Fig.4. Structure of Neuro-Fuzzy System

So the combination of above two algorithms is used for searching optimal parameters effectively. Membership functions associated with input and output variables for the entire FIS can be edited and displayed using the Membership Function Editor. Here Gaussian bell membership function is used for input variable and linear membership function for output variable.

Total 32 different rules are constructed by Sugeno type-1 FIS structure based on the knowledge of past samples of traffic flow count for selecting the relation of antecedents and consequents.

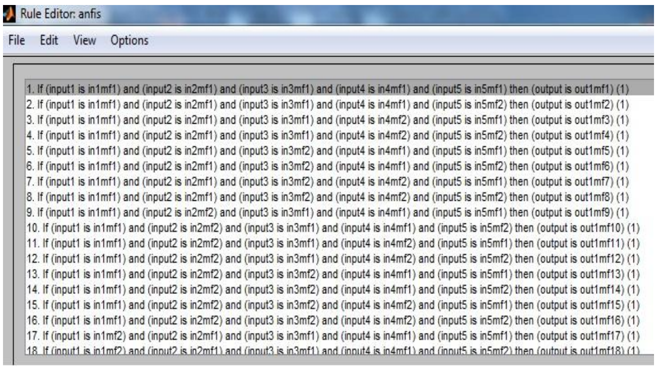

Fig.5. Rules generated by FIS

3.2 ROUGH SET THEORY

The rough set theory is defined as a formal approximation of a crisp set by a pair of sets. The main goal of the rough set analysis is defining the approximation of concept. Hence every rough set is associated with a pair of sets called lower and upper approximation.

The rough set theory proposes a new mathematical approach to imperfect knowledge, i.e. to vagueness (or imprecision). In this approach, vagueness is expressed by a boundary region of a set. In order to define rough set mathematically,

With every object in the universe some information is associated given by $I_S = (U,A)$ where U and A are finite and non-empty sets which represents data objects and attributes respectively.

For every $a \in A$, $a{:}U \geq V_a$ where V_a corresponds to value set of a. Set B which is a subset of A determines a binary relation $I(B)$ on U called indiscernibility relation. The relation is defined as $(x,y) \in I(B)$ subject to the constraint that if $a(x)=a(y)$ for every a in B. Now A and B are related by

$$X \subseteq U \text{ and } B \subseteq A.$$

The lower and upper approximations are represented mathematically by the following equations.

$$\bar{B}X = U_{x\in U}\left\{B(X) : B(X) \subseteq X\right\} \qquad (1)$$

$$\bar{B}X = U_{x\in U}\left\{B(X) : B(X) \cap X \neq \varnothing\right\} \qquad (2)$$

Thus lower approximation consists of all the members that surely belong to the target set.

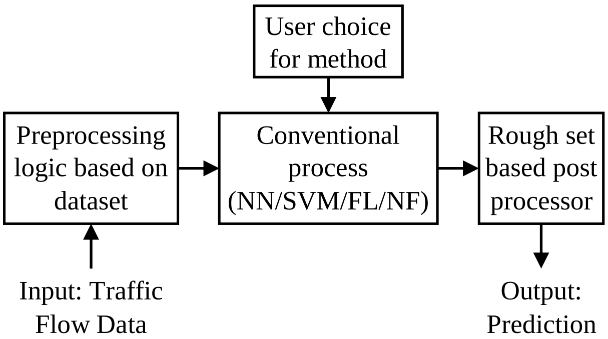

Fig.6. Rough set based model for traffic flow prediction

Lower approximation is achieved by means of non-negativity of traffic flow count thereby ensuring that set under consideration does not remain empty. Upper approximation is achieved by considering maximum road capacity for flow. This work uses a correction methodology for the predicted traffic count to be corrected by choosing a traffic count from the training set value closest to the current predicted value and belongs to the lower approximation set. If a count predicted by the method predicts a value not belonging to the training set then it is discarded and replaced by the closest member belonging to this set which has a higher probability of occurrence. Probability computation and the above mechanism is carried out by first block of Fig.6. In order to reduce the error the rough set mechanism is used as a validator for prediction results. If the prediction of the traffic count belongs to lower approximation set the error is minimal, but if it is beyond the lower approximation set then surely it will contribute to error thereby increasing it.

4. EXPERIMENTS AND SIMULATION RESULTS

After preprocessing of data is done, the traffic data is aggregated into different time intervals like 5 min, 10 min and 15 minutes. Before further processing time series data is normalized so as to make them in the range from 0 to 1 using the following formula:

$$x_{tNormal} = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}} \qquad (3)$$

where x_{max} and x_{min} represent the maximum and minimum value of input sample.

The Fig.7 shows the probability of occurrence of every vehicle count for defining rough set membership. In order to establish a rough set membership function we make use of the probabilities of the presence of a particular traffic count in the training set. As the training set is a bounded set with 0 on the lower side and a maximum value (say 250) on upper side, we compute the probability of occurrence in training set of all the numbers from 0 to 250. This gives a number which is from 0 and 1. As the counts which are not present in the training set will have zero probability these are considered as non-members of the rough set of the training dataset. Values which are present have a non-zero probability including the traffic count of 0 (when no vehicles arrive on the road during the aggregation time) and hence qualify to become the member of the rough set.

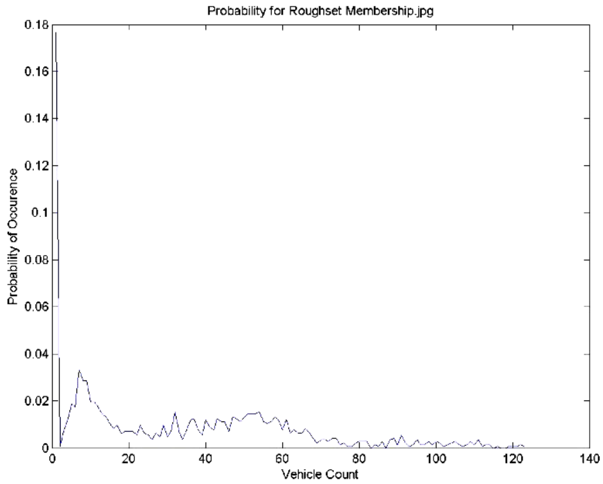

Fig.7. Probability for Rough set membership

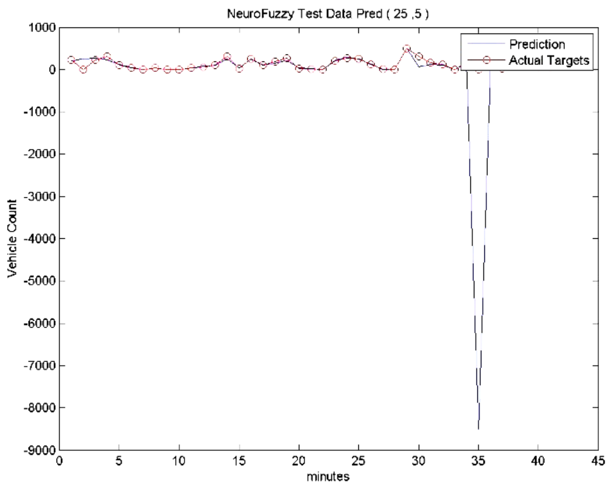

Fig.8. Actual vs. Predicted vehicle count using NF

The Fig.8 shows the prediction graph for actual vs. predicted traffic flow count where it is observed that predicted output follows actual output almost everywhere except at about 35th aggregation slot (35×5=175min) where predicted value suddenly drops to nearly -8000. This is one of the outlier point, point beyond the normal range. Due to this outlier y axis range is expanded in negative direction whereas for training predicted output follows the actual one yielding the same pattern as original waveform.

Table.1. Performance measures for different aggregation interval

Effect of Aggregation Interval with Prediction History = 5					
Neuro-Fuzzy Test	**Aggrega-tion Interval**	**MSE**	**RMSE**	**Error Mean**	**Error Std. deviation**
(5,1)	1	1.58E+3	3.97E+1	-1.41E+0	3.97E+1
(25,5)	5	1.40E+4	1.18E+2	-7.64E+0	1.18E+02
(50,10)	10	3.92E+4	1.98E+2	-1.77E+1	1.98E+02
(75,15)	15	2.18E+4	1.48E+2	-2.47E+1	1.46E+02

The Table.1 shows the effect of different aggregation interval on prediction performance where first number indicates history used and second number indicates aggregation interval in minute. With an average of 33 vehicles per minute we have the following %MSE thresholds.

Table.2. MSE thresholds validation for Neuro-Fuzzy

Method used	MSE Percentage threshold			
	5	**10**	**15**	**20**
NF Test (5,1)	-	-	-	-
NF Test (25,5)	-	-	-	OK
NF Test (50,10)	-	-	OK	OK
NF Test (75,15)	OK	OK	OK	OK

From Table.2, it is observed that aggregation interval of 15 minutes gives good prediction with MSE% threshold of 3% whereas lower aggregation intervals do not do well with MSE % threshold exceeding 10% and even more with the decrease of aggregation interval.

Table.3. Performance measures for different history samples

Effect of History with Aggregation Interval=5					
Method	**History**	**MSE**	**RMSE**	**Error Mean**	**Error Std. deviation**
NF Test (10,5)	2	1.24E+3	3.52E+1	1.56E+0	3.52E+1
NF Test (15,5)	3	3.22E+4	1.79E+2	1.10E+1	1.79E+2
NF Test (20,5)	4	2.13E+5	4.62E+2	3.07E+1	4.62E+2
NF Test (25,5)	5	1.40E+4	1.18E+2	-7.64E+0	1.18E+2

The Table.3 shows the performance measures by varying the history samples.

Table.4. MSE thresholds validation for history variation

Method Used	MSE Percentage threshold			
	5	**10**	**15**	**20**
NF Test (10,5)	-	OK	OK	OK
NF Test (15,5)	-	-	-	-
NF Test (20,5)	-	-	-	-
NF Test (25,5)	-	-	-	OK

From the Table.4, it is observed that past sample value of 2 gives good prediction with MSE (%) threshold lying within 10% whereas higher values of past samples do not do well.

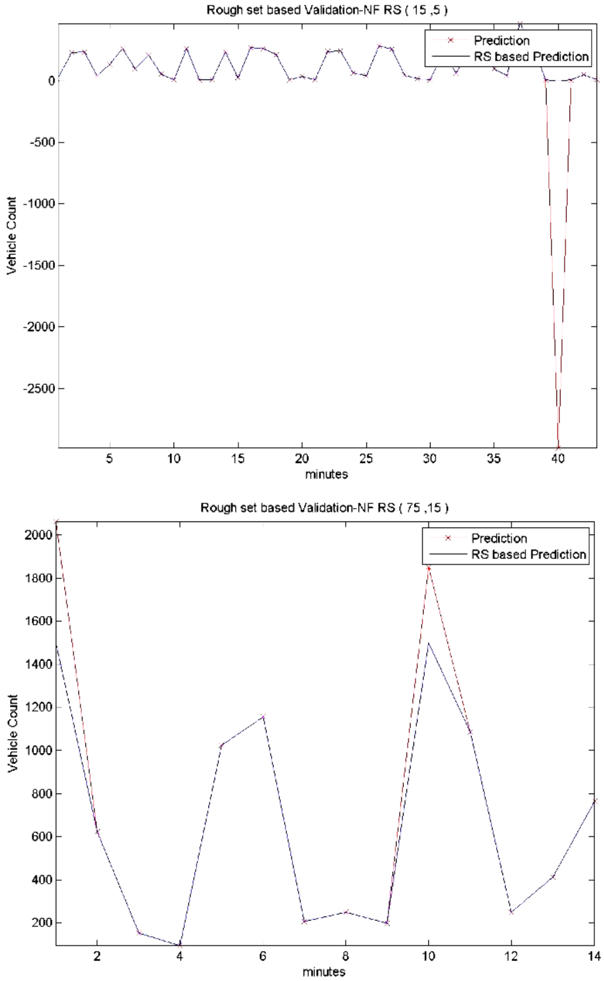

Fig.9. Rough set based validation of prediction result

The Fig.9 shows the validation of prediction result using rough set. In case of rough set we have negative numbers and numbers greater than maximum vehicle count all have a probability of zero as they are not in the initial data set. So we just replace these by nearest values which are part of the rough set.

Table.5. Performance measures with and without rough set for prediction system

Method/Measure	MSE	RMSE	Error Mean	Error STD
NF Test (15,5)	3.22E+04	1.79E+02	1.10E+01	1.79E+02
NF RS (15,5)	9.46E+02	3.08E+01	4.81E-01	3.08E+01
NF Test (75,15)	2.18E+04	1.48E+02	-2.47E+01	1.46E+02
NF RS (75,15)	1.55E+04	1.25E+02	-1.47E+01	1.24E+02

5. CONCLUSION

The work proposed in this paper presented the effect of using rough set as a post processor tool on the short term traffic flow prediction performance. It was found that prediction error has been reduced considerably especially where there were outliers. As the outliers in the predicted value were limited to the rough set upper bound, the post processing using rough set leads to prediction error minimization. The study of the MSE for predicted value showed variation as the history samples and aggregation interval were varied but was limited to less than 10% thus indicating the utility of the process.

The use of rough set as a post processor for various techniques based on fuzzy as well as neural networks in the field of short term traffic flow prediction is a promising field and can be explored as a part of future work.

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REFERENCES

[1] Lelitha Vanajakshi and Laurence Rilett, "A Comparison of the Performance of Artificial Neural Network and Support Vector Machine for the Prediction of Traffic Speed", *Proceedings of IEEE International Symposium on Intelligent Vehicles*, pp. 14-17, 2004.

[2] T. Thomas, W. Weijermars and E.V. Berkum, "Predictions of Urban Volumes in Single Time Series", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 11, No. 1, pp. 71-80, 2010.

[3] M.C. Tan, S.C. Wong, J.M. Xu, Z.R. Guan and P. Zhang, "An Aggregation Approach to Short Term Traffic Flow Prediction", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 10, No. 1, pp. 60-69, 2009.

[4] Y. Mingheng and G. Ganglong, "Accurate Multisteps Traffic Flow Prediction Based on SVM", *Mathematical Problems in Engineering*, Vol. 2013, pp. 1-14, 2013.

[5] Y. Cong, J. Wang and X. Li, "Traffic Flow Forecasting by a Least Squares Support Vector Machine with a Fruit Fly Optimization Algorithm", *Procedia Engineering*, Vol. 137, pp. 59-68, 2016.

[6] Wusheng Hu, "The Short-Term Traffic Flow Prediction Based on Neural Network", *Proceedings of IEEE International Conference on Future Computer and Communication*, pp. 293-296, 2010.

[7] C. Quek and B.B.S. Lim, "Pop-Traffic: A Novel Fuzzy Neural Approach to Road Traffic Analysis and Prediction", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 7, No. 2, pp. 133-146, 2006.

[8] C.B. Ping and M.Z. Qiang, "Short-Term Traffic Flow Prediction Based on ANFIS", *Proceedings of IEEE International Conference on Communication Software and Networks*, pp. 1-8, 2009.

[9] S. Chen and P Wang, "*Computational Intelligence in Economics and Finance*", Springer, 2002.

[10] L. Shen and H. Loh, "Applying Rough Sets to Market Timing Decisions", *Decision Support Systems*, Vol. 37, No. 4, pp. 65-72, 2006.

[11] K Ang and C Quek, "Stock Trading using RSPOP: A Novel Rough Set based Neuro-Fuzzy Approach", *Proceedings of IEEE International Conference on Neural Networks*, pp. 105-112, 2005.

[12] Zhenguo Zhou and Kun Huang, "Study of Traffic Flow Prediction Model at Intersection Based on R-FNN", *Proceedings of International Seminar on Business and Information Management*, pp. 1-7, 2008.

[13] CEOS, Available at: http://www.ceos.com.au.

[14] Minal Deshpande and Preeti Bajaj, "Performance Improvement of Traffic Flow Prediction using Combination of Support Vector Machine and Rough Set", *International Journal of Computer Applications*, Vol. 163, No. 2, pp. 31-35, 2017.