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Public transport Bus Arrival Time Prediction with Seasonal and Special Emphasis on Weather Compensation changes using RNN

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Abstract - ***Intelligent Transportation Systems is an application of current information and communications technologies to the transportation area. Bus arrival times are influenced by various factors, (e.g. weather conditions, traffic congestion and natural disasters etc) resulting delay in predefined schedule and inconvenience for passengers due to waiting times for buses. In this research, a set of ANN models, predicting bus arrival times based on seasonal changes, are developed through mining historical data for Jaipur – Delhi route, India. The results obtained are accurate, reduce average waiting and help in developed models which can be used to estimate bus arrival times. Recurrent neural network (RNN) techniques are applied to build an arrival time estimation model. The model exhibits a functional relation between real-time traffic data as the input variables and the predicted bus travel time according to weather conditions as the output variable.***

I. INTRODUCTION

As one of the most famous approaches presently used for solving complex problems, ANNs have been recently ahead popularity in transportation studies [1 -2]. Due to their ability to complex non-linear relationships solutions, artificial neural network models (ANNs) have been developed for transportation [3-6]. In the present study, a real-time bus arrival time prediction scheme under different weather conditions considering delays explicitly into account has been developed with helping Recurrent neural networks (RNN).

RNN are neural networks with one or more feedback loops [7]. The feedback can be of a local or global kind. For a multilayer perceptron as the basic building block, the application of global feedback can take a variety of forms. One may have feedback from the output neurons of the multilayer perceptron to the input layer. Another possible form of global feedback is from the hidden neurons of the network to the input layer. When the multilayer perceptron has two or more hidden layers, the possible forms of global feedback expand even further. The recurrent networks have rich architectural layouts. A typical recurrent network has concepts bound to the nodes whose output values feed back as inputs to the network. So the next state of a network depends not only on the connection weights and the currently presented input signals but also on the previous states of the network. The network leaves a trace of its behaviour; the network keeps a memory of its previous states. Basically, there are two functional uses of recurrent networks such as associative memories and input-output mapping networks. In addition, an issue of particular concern in the study of recurrent networks is that of stability. By definition, the input space of a mapping network is mapped onto an output space. For this kind of application, a recurrent network responds temporally to an externally applied input signal. We may therefore speak of the recurrent networks considered in this work as dynamically driven recurrent networks. Moreover, the application of feedback enables recurrent networks to acquire state representations, which make them suitable instruments for nonlinear prediction, modelling and load forecasting. As such, recurrent networks offer an alternative to the dynamically driven feed forward networks. Because of the beneficial effects of global feedback, they are capable to handle these types of applications. The use of global feedback has the potential of reducing the memory requirement significantly. Recurrent neural networks can model finite state automaton. Difficult questions to deal with, when using recurrent networks, are: Synchronization is needed in order to achieve proper timing when propagating the signals through the network. It is difficult to express in a

ISSN : 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 6, August 2012

linguistic form or in a formula the time-dependence learned in a recurrent network after training, that is, the balance which the network has achieved between forgetting previous states and remembering new ones.

II. RESEARCH APPROACH

In this research the proposed technique has been implemented on real world data of year 2011 for RTDC bus arrival timings between Delhi and Jaipur route. The arrival load time series pertaining to these data sets. Statistical information about the load demand is shown in Table 1.

Table 1: Summary of the load data for the year 2011

Statistical parameter	Load in Hours
Maximum	1.58
Minimum	0.20
Average	0.57
S. D	0.25

A. *Traffic Load Patterns:*

The weather in the area is very hot in the summer, moderate cool and dry in winter whereas moderate humid and dry in rainy season which will impact traffic and vehicles speed. Figure1 shows hourly load averages for each day of the week in the year 2011.

Table 2: Group of months based on load profile

Season	Months
Summer	Mar, Apr, May and June
Rainy	July , Aug. and Sept.
Winter	Jan, Feb ,Oct, Nov, Dec.

It also gives an idea about how the traffic load varies from hour to hour and day to day. From the close visual inspection of the graph, it is seen that the days from Monday to Saturday have similar load pattern. Sunday has a different load pattern than the other regular week days. Depending on the load pattern, for the purpose of analysis, the seasonal groups are defined in Table 2.

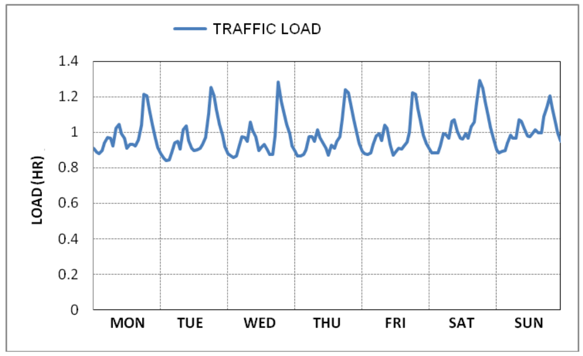

Figure 1: Hourly load averages for each day of the week from year 2011

B. *Computer Simulations for one Day-ahead Traffic load demand prediction using original (RAW) Seasonal Load:*

For one-day-ahead load demand prediction analysis, first of all the data sets have been clustered into three groups according to the seasons specified in table 2. This analysis is performed for summer, rainy and winter seasonal load series. For this analysis, different RNNs are proposed comprised of 3 different recurrent neural network architectures such as Elman, Jordan, and FRNN based on gamma memory filter was formed. All possible variations for the models such as number of hidden layer, number of PEs in each hidden layer, different supervised learning rules, transfer function of output layer and number of input variables are investigated in simulation. For the BPTT and quick propagation learning rule, further step size and learning rate are gradually varied from 0.1 to 1.0. The additive, multiplicative and smoothing factors are gradually varied from 0.1 to 1 for an adaptive delta-bar-delta algorithm. Specifically for Elman and Jordan networks, transfer functions of PEs in the context units are meticulously designed. The various parameters of the short term memory structure such as coefficient of gamma parameter and taps at the front end of the FRNN models are optimally designed.
A rigorous experimental study has been undertaken in order to determine the transfer function and multiplicative time constant in context unit for Elman and Jordan NN with respect to the various seasonal load series. Again for the chosen transfer function, each one of the next suggested RNNs are trained/ retrained for 5 times with different random initialization of connection weights with respect to the default value of time constants (usually 0.8). Then the trained RNN is tested on a day which is to be forecast. Further, along with the chosen optimal transfer function, RNN is trained on different value of time constant (typically from 0 to 1 in the interval of 0.1).

ISSN : 2278 – 1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 1, Issue 6, August 2012

For FRNN, scrupulous experimental study has been carried out in order to determine the optimal value of gamma coefficient with respect to the default value of tap (typically default value of tap equals to 6). The gamma parameter is gradually varied from 0 to 1 in the interval of 0.1. For each value of gamma parameter, RNN is trained five times with different initialization of connection weights. Optimal selection of the parameters is decided on the basis of minimum error on prediction data set in the different seasons. For the selected optimal value of gamma coefficient, next the careful computer simulation is carried out with respect to different taps. The number of taps is gradually changed from 1 to 10 in the interval of 1. Optimization of number of taps is selected on the basis of minimal value of error on prediction dataset.

C. *Selection of Best RNN Predictor*

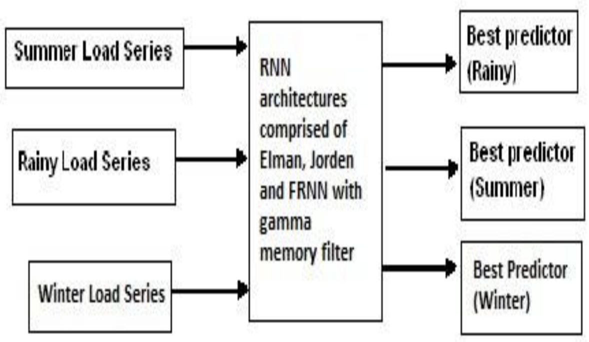

Figure 2: Working block diagram showing the best predictor from RNN committee on original seasonal load series.

Figure 2 shows the functional block diagram showing the best load predictor for one day ahead load demand prediction in different seasons for suggested RNNs. The proposed RNN predictors are optimally designed and developed for different seasonal load demand series. Next day predictions are performed for every day of the week. The training windows of regular weekdays for a particular season, is shifted 24-hour-ahead and the prediction for the next day is evaluated. This test procedure is repeated for the different seasonal load series. Finally, best predictor on each season is explored on the basis of their performance measure with respect to the performance of MSE, NMSE, r and MAPE on the prediction data set.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

Table 3 figures out the performance measures in terms of MSE, NMSE, r and MAPE for next day load demand prediction in summer, rainy and winter seasons. From the results depicted below, it is clearly seen that Elman NN as a load predictor performs reasonably better in summer and winter season, whereas Jordan NN emerges as a best load predictor.

Table 3: Performance measures of predictors in various seasons (Next day predictions)

SEASON	PREDICTOR	TEST ON PREDICTION DATA				TEST ON TRAINING DATA			
		MSE	NMSE	r	MAPE	MSE	NMSE	r	MAPE
SUMMER	ELMAN	0.0053	0.3547	0.8034	9.00%	0.0051	0.3047	0.8339	8.51%
	JORDAN	0.0057	0.3777	0.7898	9.54%	0.0052	0.3149	0.8278	8.87%
	FRNN	0.0053	0.3520	0.8050	9.15%	0.0048	0.2873	0.8443	8.33%
RAINY	ELMAN	0.0034	0.1221	0.9381	7.61%	0.0012	0.0992	0.9491	5.53%
	JORDAN	0.0037	0.1335	0.9318	7.48%	0.0017	0.1413	0.9267	6.13%
	FRNN	0.0036	0.1288	0.9340	7.66%	0.0017	0.1355	0.9299	6.30%
WINTER	ELMAN	0.0053	0.3553	0.8040	9.06%	0.0046	0.2737	0.8523	7.94%
	JORDAN	0.0059	0.3156	0.8320	9.20%	0.0058	0.2378	0.8731	9.64%
	FRNN	0.0056	0.3704	0.7973	9.38%	0.0045	0.2708	0.8539	8.10%

Figure 3 shows one weeks prediction curve tracking the actual load curve. This figure demonstrates the regression ability of the proposed models on the prediction test dataset. In this figure, desired outputs are compared with the actual outputs produced by the proposed estimated models.

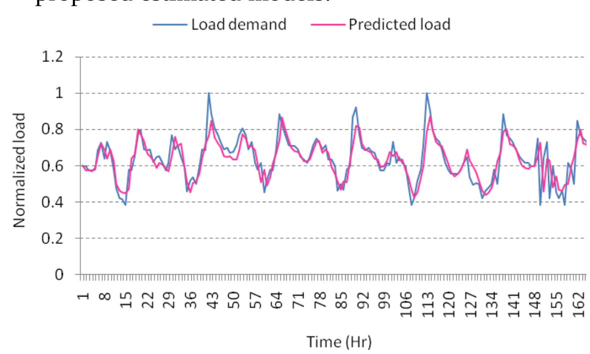

Figure 3: Actual and corresponding load prediction obtained with best predictor (ELMAN) in summer season

Table 4 shows the effect of weather parameters on performance measures of best predictor (ELMAN NN) in summer season. It indicates the degradation of the system due to introduction of additional weather inputs. From the various results depicted from table 4 it is observed that prediction accuracy is improved considerably when lone temperature and

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Vol. 1, Issue 6, August 2012

lone humidity is used as one of the input variables for the best chosen estimated model.

Table 4: Effect of weather parameters on the performance measures of the best predictor (ELMAN) in summer season. (Weather parameters, T= Temperature, H=Humidity)

WEATHER INPUT	TEST ON PREDICTION DATA				TEST ON TRAINING DATA			
	MSE	NMSE	R	MAPE	MSE	NMSE	r	MAPE
Nil	0.0057	0.3785	0.7922	9.73%	0.0051	0.3087	0.8318	8.64%
T	0.0053	0.3547	0.8034	9.00%	0.0051	0.3047	0.8339	8.51%
H	0.0054	0.3628	0.8013	9.40%	0.0052	0.3110	0.8306	8.72%
T & H	0.0053	0.3510	0.8064	9.08%	0.0050	0.3034	0.8349	8.68%

However it is noticed that if no information about weather variables fed to the neural network, prediction accuracy is degraded significantly. The aforementioned effect on a typical day in the summer season is reflected in the figures 4 to 7.

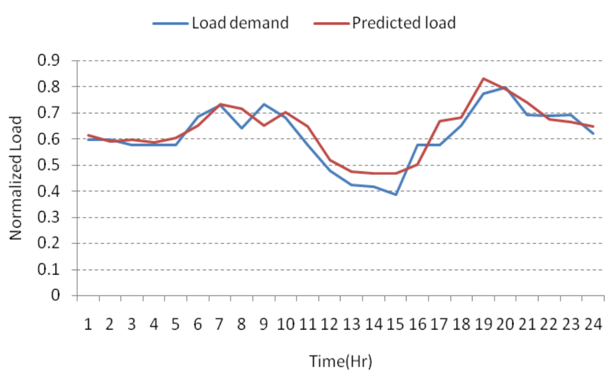

Figure 4: Actual and corresponding load prediction obtained with best predictor (ELMAN) in summer season without any additional input.

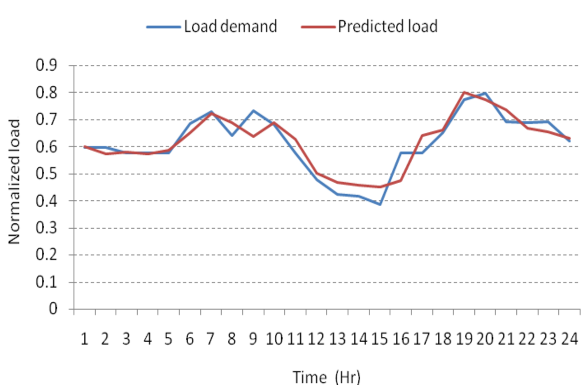

Figure 5: Actual and corresponding load prediction obtained with best predictor (ELMAN) in summer season with Temperature as an additional input.

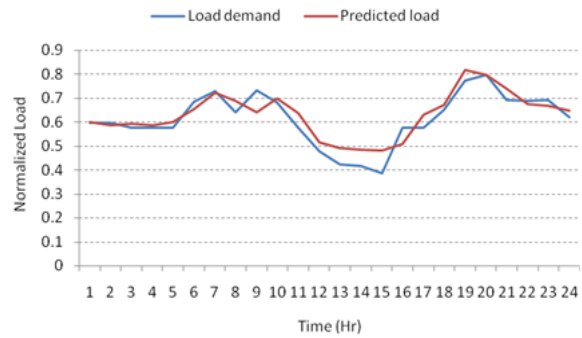

Figure 6: Actual and corresponding next day prediction obtained with best predictor (ELMAN) in summer season with Humidity as an additional input.

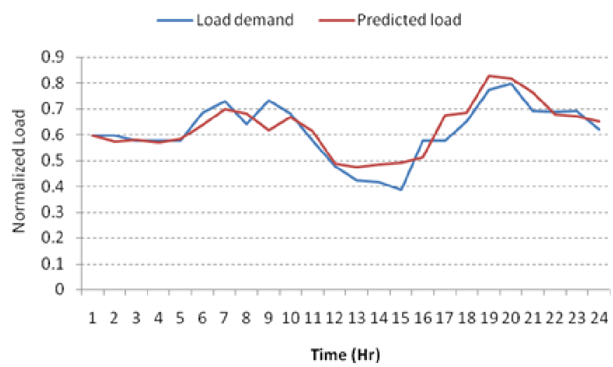

Figure 7: Actual and corresponding next day prediction obtained with best predictor (ELMAN) in summer season with Temperature and Humidity as an additional input.

IV. CONCLUSIONS

In this study, real-world historical data are used in developing bus arrival time prediction methodology with RNN, which contains a prediction model for bus travel times for different weather conditions and an algorithm to find best load predictor for different weather and conditions. Therefore, the methodology developed in this study can potentially be used for providing real time bus arrival time prediction with RNN for Jaipur Delhi route.

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REFERENCES

[1] C. H. Wei and Y. C. Chen, "Review of artificial neural network research and applications in transportation," Transp. Planning J. Quart. (Taiwan), vol. 30, no. 2, 2001.

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Vol. 1, Issue 6, August 2012

[2] M. S. Dougherty, "Guest editorial: Applications of neural networks in transportation," Transp. Res., vol. 5, 1997.
[3] Y. Ramakrishna, P. Ramakrishna, V. Lakshmanan, et al. "Use of GPS probe data and passenger data for prediction of bus transit travel time".
[4] S. I. J. Chien, Y. Ding, C. Wei. "Dynamic bus arrival time prediction with artificial neural networks". Journal of Transportation Engineering, Vol. 128, (2002).
[5] G. Chang, C. Su. "Predicting intersection queue with neural network models". Transportation Research C, Vol. 3, (1995), Proceedings of the 2007 Transportation Land Use, Planning, and Air Quality Conference, Orlando, FL,United states, Vol. 320, (2007).
[6] Chien-Hung Wei and Ying Lee "Development of Freeway Travel Time Forecasting Models by Integrating Different Sources of Traffic Data" IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, 2007.
[7] Mikael Bod´en "A guide to recurrent neural networks and backpropagation" Halmstad University, 2001.

Biography

Dr. Mrs. Ranjana Dinkar Raut has more than 25 years of experience in teaching and research. She received her BE (Instrumentation Engineering) from Government College of Engineering, Pune, Pune University in 1986, ME (Electronics and Communication Engineering) from Government College of Engineering Amravati, SGB Amravati University and Ph.D. (Electronics Soft Computing) from Amravati University, Amravati in 2009. She occupied various positions as Lecturer, Senior Lecturer, Assistant Professor (Reader) and Head of Central Instrumentation Cell (CIC) Lab at SGB Amravati University, Amravati. She has published more than 30 research papers in High Impact factor International Journal, National and International conferences and visited many countries. She has guiding a number of research scholars in the various areas.

Mr. Vineet Kumar Goyal is pursuing Ph.D. (Electronics & Communication Engineering) in Mahatma Jyoti Rao Phoole University, Jaipur under guidance of Dr. Mrs. Ranjana Dinkar Raut. He did BE (Electronic instrumentation and Control Engineering) from Global Institute of Technology, University of Rajasthan, Jaipur in 2006 and ME (Electronic Product Design and Technology) from Punjab Engineering College, Deemed University, Chandigarh in 2008. He has published two International Journals related to his research work. His area of interest in Networking, Neural Network, Wireless Communication and Embedded system.