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Forecasting of vehicle travel time prediction for Jaipur-Delhi Route using FTLR Neural Network Model with Gamma Memory

Vineet Kumar Goyal[1], Dr. Ranjana Dinkar Raut[2], Abhishek Raut[3]
[1](*Student, Ph.D. EC&E dept., MJRP University, Jaipur, Rajasthan, India)*
[2](*Associate Professor, SGBA University, Amravati, Maharashtra, India)*
[3]*Eighth sem BE E&TC PRMIT&R Badenera*

ABSTRACT: *Public Transport Corporations in any country rely on reliable and accurate broadcast information to transit users to achieve better service quality. Forecasting of vehicle travel and arrival time prediction has become one of the many challenging tasks due to the fact that vehicle operation variables and parameters are highly conjectural. This paper provides a case study on forecasting of travel time prediction for Jaipur-Delhi route, RSRTC India which gives results very rich non-linear dynamics using a focused time lagged recurrent (FTLR) neural network (NN).This is an optimal NN model and a highly non-linear complex dynamical system for the travel time prediction which is not currently available. This paper compares the performance of MLP NN and the proposed FTLRNN models and a standard static back propagation algorithm with momentum term has been applied for both the NN configurations. It is investigated that the estimated dynamic NN model comprising of a gamma memory (GM) filter followed by a MLP NN clearly outperforms the static MLP NN in correlation coefficients, NMSE and regression characteristics on the cross-validation (CV) as well as testing datasets. In addition, the outputs of the proposed FTLRNN model reasonably follow the desired outputs of the forecasting of travel time prediction for the testing and CV exemplars. This also means that most of the information about the rich non-linear dynamics of the system has been extracted satisfactorily from the training dataset and that the proposed model approximates the given system with realistic accuracy. In the result, it shows that the proposed FTLRNN model has a remarkable system prediction capability.*

Keywords: *Focused time lagged recurrent NN, Gamma memory, Non-linear system, Multi-layer perceptron NN, Back propagation algorithm, Rajasthan State Road Transport Corporation(RSRTC) and Intelligent Public Transport System (IPTS).*

I. INTRODUCTION

This paper is concerned with the forecasting of travel time prediction, which is a Single input Single output (SISO) system. As the essential process is highly complex, exhibiting rich non-linear dynamics, linear system forecasting techniques cannot be applied. However, it is possible to develop a learning machine based on a well-known static multi-layer perceptron (MLP) NN model that can learn from the available experimental data. From input/output experimental data, a NN model can be constructed by estimating the unknown parameters which is called system prediction [1].

Neural Networks have the capability to learn from experience. They are vehicles that in a basic sense can learn complex non-linear mappings from a set of observations. In particular, the static MLP network has gained massive popularity in system prediction. From many researches published over the past, decade, there seems to be significant evidence that MLP definitely possesses an impressive ability. There have also been some theoretical results that explain the reasons for this success [2, 3]. However, there are some limitations of this static NN configuration. It cannot deal with the rapidly changing non-linear dynamics. Therefore, it is required to use a NN configuration that can learn the sequential variation or time structure underlying the data in a true sense. With this consideration, dynamic modeling will indeed help to improve the learning and generalization ability. Hence, in this research, it is proposed to use a dynamic NN topology such as FTLRNN, designed to explicitly include time relationships in the input-output mappings.

1.1 Prediction of Bus transport:

For the system considered in this paper, the input/output experimental data has been obtained from RSRTC, India. This paper considers the forecasting of travel time prediction of RSRTC Jaipur Delhi route bus transport.The data constitutes 365 samples. This process is a SISO one. The first 292 samples (1:292) are used for training; the next 36.5 samples (293: 328.5) for CV and the last 36.5 samples (328.6: 365) are used for testing and model comparison purpose.

In this research, it has been observed that a large predicting lead time does not necessarily imply a larger prediction error. That depends on the data variability for the different periods of the day and the kind of model at hand. This also confirms the inability of even the best-chosen predictors for the suggested RNN committees in understanding the rich nonlinear (random components) dynamics underlying the time structure (active hours) of the different seasonal data. This implies that, even the best-chosen RNN models could not cope up with the subtle nonlinearities underlying the different original (raw) seasonal P.T.S. data. In order to have precise prediction, the wavelets have been embedded into the RNNs. The various combinations of wavelet and lone RNN are examined rigorously. The results found were still not satisfactory. This outcome is primarily due to the fact that lone RNN could not perform reasonably on different frequency bands because of their distinctly different characteristics. In order to overcome these problems, the wavelet-RNN committees are developed comprising of different meticulously designed RNN predictors. The exhaustive experimentation is accomplished to explore the best predictors for a committee on different frequency bands according to the characteristics of each band and finally, prediction is achieved by adding the predictions of best predictors on different frequency bands. The proposed technique offers reliable and encouraging results.

1.2 Motivations of Research:

In the state of Rajasthan people residing in rural and remote areas have been experiencing severe problems and consequences of BTS since last decade. Because of the enormous increase in populations, Change in socio-economic behavior, Rapid growth of urbanization, Industrialization and agricultural demands etc. a wide gap between demand and transportation has been observed in the present era. The development of optimal RNN model for short-term bus arrival time prediction where the original bus transportation data of Jaipur -Delhi route considered for creation of necessary input-output mappings (inputs corresponding to desired outputs) for training- cross validation testing of RNNs. Table 1 discussed review of related literature based on statistical techniques.

TABLE 1

Prediction errors (MAPE) estimated by various researchers (In other predictions)

Author	Prediction interval	MAPE (%)
K.Y.Lee et al.	24-hour-ahead	2.00
A.K. Topalli et al.	24-hour-ahead	2.45
Otavio A.S. et al.	24-hour-ahead	2.03
M. Beccali et al.	24-hour-ahead	1.97
B.Satish et al.	Maximum error	4.00

II. RESEARCH METHODOLOGY

Jaipur Delhi (J-D route), Rajasthan BTS Bus arrival time prediction date of years July 2010 to July 2012 Non-weather sensitive prediction

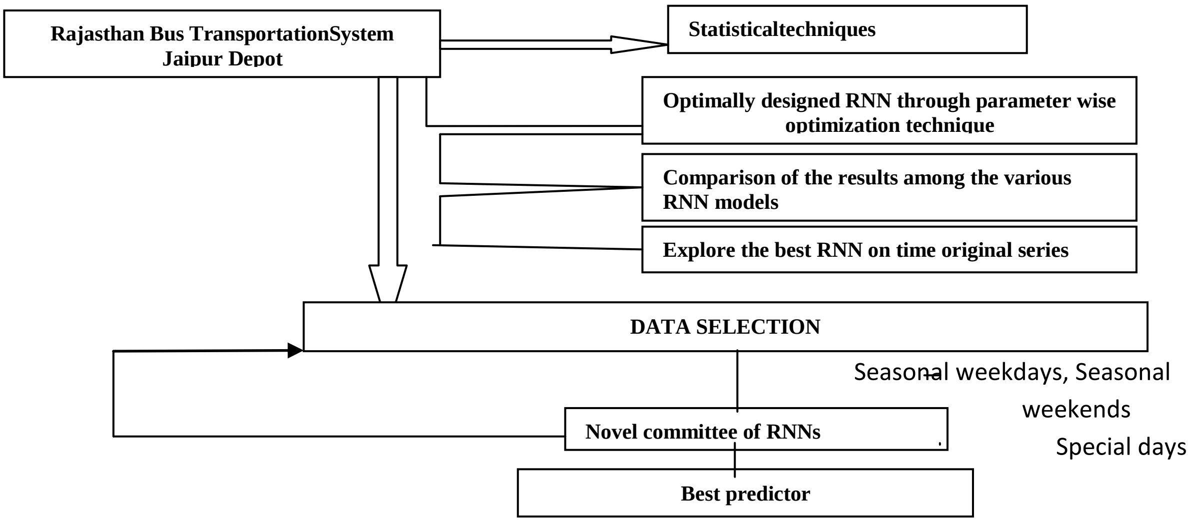

Fig1 : Flow chart of the overall research flow

As depicted in Fig 1, in the first phase, different RNNs, such as Elaman, Jordan, FTLRNN, PRNN and FRNN each with axon, gamma, laguarre and TDNN based memory structure for a proposed RNN committee is optimally designed and developed on original (raw) seasonal weekdays time series for one-hour, one-day and one-week-ahead. Weekend (Sundays) and special bus arrival time predictions. Based on the validation performance, the subtle comparison of the different RNN models are explored. The best predictor is chosen on the basis of performance with respect to the performance measures of MSE, NMSE, r and MAPE on prediction, cross validation and test data set.In the second phase, the various seasonal datasets have been undergone via MIRA in order to gain deeper insight of the time series for improving prediction accuracy.

Soft wares used:

1. MATLAB 12.0
2. Neurosolution 5.06
3. XLSTAT2012

TABLE 2

SUMMARY OF TRANSFER FUNCTION OF CONTEXT UNIT

Type	Feature
Integrator axon	Linear integrator
Tanhintegrator axon	Saturating integrator (-1/+1)
Sigmoidintegrator	Saturating integrator (0/1)
Context Axon	Linear decay
Tanhcontext	Saturating context decay (-1/1)
`Sigmoidcontext	Saturatingsd context decay (0/1)

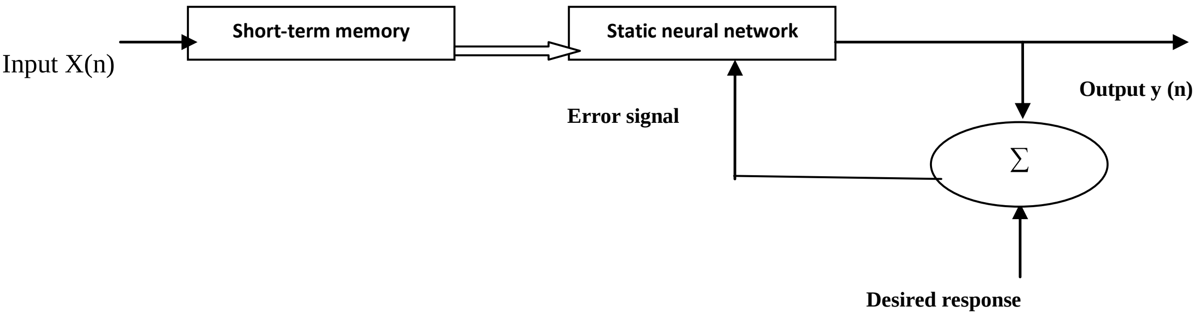

Fig2 :Focused Time Lagged Recurrent Neural Network

III. MODELING OF A JAIPUR DELHI ROUTE BUS TRANSPORT USING FTLRNN MODEL

A Bus transport is a complex non-linear dynamical system. As there is a time structure underlying the data collected after precise experimentation, dynamic modeling with surely help to improve the performance. Dynamic NNs are topologies designed to explicitly include time relationships in the input-output mappings. Time constitutes an indispensable component of the learning process and it is an ordered entity that is basic to many of the cognitive tasks that come across in system prediction. Time lagged recurrent networks (TLRNs) are MLPs extended with short term money structures. Here, a 'static' NN (for example, MLP) is capable with dynamic properties. This in turn, makes the network reactive to the temporal structure of information bearing signals. For a NN to be dynamic, it must be given memory. This memory may be classified into "short-term" and "long-term" memory. Long term memory is built into a NN through supervised learning, whereby the information content of the training data set is stored (in part or in full) in the synaptic weights of the network. However, if the task at hand has a temporal dimension, some form of "short-term" memory is needed to build the network dynamic. One simple way of building short-term memory into the structure of a NN is through the use of time delays, which can be applied at the input layer of the network (focused). A short-term memory structure transforms a sequence of samples into a point in the reconstruction space. This memory structure is incorporated inside the learning machine.

Table 3 Parameters of MLP NN

Number of exemplars: Training = 292, CV = 36.5, Testing = 36.5, Maximum epochs = 1000, Supervised learning, weight update in batch mode, number of input PEs = 1

Parameter	Hidden layer #1	Hidden layer #2	Output Layer
Processing elements	6	4	1
Transfer function	tanh	tanh	tanh
Learning rule	momentum	momentum	momentum
Step size	1.0	0.1	0.01
Momentum	0.7	0.7	0.7

Table 4 Performance of MLP NN Model

Output of prediction of Delhi arrival time	Performance metrics					
	Testing Dataset			CV Dataset		Training dataset
	NMSE	r	NMSE	r	NMSE	r
	0.790477894	0.663847181	0.549964585	0.674652396	0.410750588	0.767667772
	0.387184052	0.83779306	0.421823822	0.827262523	0.237015817	0.879803184
	0.725297328	0.545435863	0.575662749	0.656887582	0.586200576	0.64359986
	0.314835811	0.835619039	0.45411266	0.766034617	0.250064606	0.866004178

Table 5 Performance of a FTLRNN model

Output of prediction of Delhi arrival time	Performance metrics					
	Testing Dataset			CV Dataset		Training dataset
	NMSE	r	NMSE	r	NMSE	r
	0.10755199	0.971103663	0.106021719	0.949314875	0.027251145	0.986288638
	0.059687032	0.976086845	0.421823822	0.97217915	0.029715941	0.985413831
	0.080298436	0.960668459	0.087214257	0.957509801	0.042832065	0.978423369
	0.019809884	0.990600649	0.045335938	0.981317796	0.010912384	0.984532701

An exhaustive and cautious experimental study has been carried out to determine the optimal parameters of the proposed FTLRNN model. It is seen that of this model performance is optimal on the test dataset for the following parameters. The static MLP optimal parameters are already listed in Table 4.Table 5 describes the NMSE and r (correlation coefficient) for the estimated FTLRNN model on testing, CV, and training dataset.

Depth in samples = 10, Trajectory length = 70, Number of taps = 6, Tap delay = 1.

The FTLRNN model regression ability on the testing dataset is shown in Figure 2.

From the comparison of Table 4 and Table 5, it is obvious that the dynamic NN model, that is, FTLRNN and GM filter has certainly outperformed the static NN model based on MLP NN, in the sense that it has learned the complex non-linear dynamics with reasonable accuracy. It consistently performs well not only on the CV dataset but also on the testing dataset.

IV. CONCLUSION

Static NN configuration such as the well-known MLP NN model fails to cope up with the underlying rich non-linear dynamics. It cannot learn satisfactorily from the training exemplars. Results demonstrate that the FTLRNN model using GM filter works sensibly in the forecasting of a typical transport system, exhibiting fast changing highly non-linear and complex dynamics. It, thus, may act as a universal prediction for transit time. The GM produces a representation-preserving mapping onto the signal space (an embedding, provided that the size of the delay line is large enough) and the static MLP NN is able to approximate arbitrarily complex functions in the newly created signal space. This new neural topology (combination of a GM filter and a MLP NN) is highly suited for forecasting involving time signals (system prediction).

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