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Short Term Load Forecasting of a Region of India using Generalized Regression Neural Network

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Abstract

In this paper the Generalized Regression Neural Network is used for short term load forecasting (STLF) of Rajasthan region, India. It is a powerful technique to schedule plant maintenance, power system control and load flow. Rajasthan state has rich cultural and geographical diversities. It is the biggest state of India and its land area is 342,239 km^2. The actual data of load and temperature have been collected from Load Dispatch Center, Rajasthan and Meteorological Center Jaipur, Rajasthan, for the duration from January 2008 to December 2008. Load is forecasted with help of Artificial Neural Network and Generalized Regression Neural Network (GRNN) based models for summer, monsoon and winter seasons. Last 24 hours load, maximum and minimum temperature, season code, day type and effect of social celebrations are used as input of the networks. Results have been obtained for different patterns of load. Results show that both models have good performance and reasonable prediction accuracy. Their comparison demonstrates that GRNN model is much faster, more reliable and accurate for effective STLF of Rajasthan region, India.

Index terms— short term load forecasting, ANN, GRNN, MAE, MAPE.

1 INTRODUCTION

lectrical load forecasting is important for the power industries in the deregulated economy. Operative forecasting is essential for generation control and power dispatch [1]. Operational decisions in power systems, such as unit commitment, economic dispatch, automatic generation control, security assessment, maintenance planning, and energy trading depend on the forthcoming trends of loads [2]. Accurate short term forecasting results in better economic and trouble free operations. The improved efficiency and accurate load scheduling, decreases power system reserves [3]. Short-term load forecasting plays an important role in reliability of power grid, prevent overloading and reduce the occurrence of blackouts [4]. Load forecasting have many applications such as energy trading, power generation, load flow and infrastructure development [5]. It plays an important role to take decisions relating to electrical network. STLF is required for power system control, unit commitment, security assessment, planning spinning reserve,

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energy exchange, inputs to load flow studies and contingency analysis resulting in predictive assessment of the security of the power system in which effect of loss of each generator on each transmission circuit is evaluated. The accuracy and reliability of load forecast have considerable effect on economics of power system operation [6,7,8]. Load forecasting can be categorize in very short term forecasting, short term forecasting, medium forecasting and long term forecasting [9]. Economic load dispatching requires the minute to minute load allocation to the generating units, to meet the varying demand at minimum cost and appropriate degree of system security. It is essential to minimize the cost function, subjected to a large number of operating units, plant characteristics and transmission system limits. There are a number of factors which effects STLF such as temperature variations, climatic conditions, social celebrations, agricultural load demand and tariff structure. Load forecasting remains

a difficult task because the system loads generally display periodicity and seasonality at multiple time scales and beside this there are many outside variables, such as weather conditions. Therefore it is concluded that there is not a single forecasting model which can give accurate results for all power systems [10].

Out of many of STLF techniques, in recent years, ANN based techniques are being used due to their good characteristics for high-speed computation, potential methodology for modeling hourly and daily energy consumption, their ability to perform better during rapidly changing weather conditions and the short time requirement for their development. ANN based methods uses a functional relationship between load and affecting factors, and estimate the functional coefficients by using historical data [11]. Neural network based models have mainly the drawback of using simple neuron having summation and sigmoid as transfer functions. These requires large numbers of neurons and hidden layers for complex function approximations and takes large training time and have problem of convergence. Use of the sigmoidal transfer function and ordinary summation or product as problems [12, **??**3].In this research the Generalized Regression Neural Network (GRNN) based model is used for short term load forecasting of Rajasthan state in India. GRNN is related to radial basis function of network and is based on standard statistical technique called Karnel regression. It is a powerful method to solve problems like forecasting, control, plant operation and fault identification and it does not provide negative estimation and approximates the training data with less error [14][15][16]. Rajasthan region has large variations in climatic, social and geographical conditions. A big part of region is desert which has very low rainfall in comparison of south east part of province. Most of the load is agricultural and domestic and therefore load profile is dependent on temperature variations, rain fall, social celebrations, type of crop and crop cycle.

2 II. Basic Structure of Artificial Neural Network Based Model

The neural network derives its computing power through its massively distributed structure and has ability to learn and therefore generalization. The flexibility of the generalized neuron can be improved by using more number of activation functions like Sigmoid, Gaussian and straight line. This reduces the size of network. The working of ANN model is explained with the help of Fig. 1 The output of ANN, Output=f

3 Generalized Regression Neural Network Based Model

The working of GRNN model is shown in Fig. 2.

4 Design of Implementation a) Data Collection

The real data are collected from January 2008 to December 2008. For ensuring selection of most relevant data and assurance of error free data used for forecasting of electrical load of Rajasthan state, electrical load data and meteorological data are collected from concerned government agencies Rajasthan RajyaVidyutPrasaran Nigam Ltd (RRVPNL), State Load Dispatch Centre (SLDC), Jaipur and India Meteorological department, MausamBhawan, Jaipur respectively. These data are provided by these departments on concession rates applicable to research students. Two types of data have been collected for short term load forecasting of Rajasthan state:

? Every fifteen minute interval data of electrical energy consumption of year 2008 ? Maximum and Minimum temperature of the days of year 2008

The load of all four season's spring, summer, monsoon, winter is collected. As Rajasthan is a big state maximum and minimum temperature of zonal head quarter Jaipur, Bikaner and Kota are taken as temperature input.

5 b) Data Preparation

The use of original data as input to neural network may cause convergence problem. To improve (and sometimes ensure) convergence, the data must be scaled or normalize such that to unify the very different ranges of the data originally collected. Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets. Before training, the inputs and targets are normalized so that they always fall within a specified range. There is a strong correlation between the behavior of power consumption and weather variables. Here temperature (maximum and minimum = ? ? = ? ? 1) ( ) (1 i i forecast i actual

Where M is the total number of data points,) (i actual is the i th actual value, and) (i forecast is the i th forecast.

6 Mean Absolute Percentage Error (MAPE) MAPE

= % 100) ( ) ( ) (1 1 × ? ? ? ? = i i actual i forcast i actual

The MAE criterion penalizes all errors equally, whereas MAPE criterion is accepted industry standard for measuring load forecast quality.

VI.

7 Results and Discussion

The load profile is dynamic in nature with temporal, seasonal and annual variations. The load pattern is divided into four categories: week days, weekend days, holidays and social celebration days. Forecasting results of all four seasons of week days have been shown in graphical form. Actual load, forecasted load and percentage forecast error for ANN and GRNN are also shown in tabular form. VII.

8 Conclusion

This work is an effort to examine the neural network based models for STLF. ANN based load forecasting models are very attractive alternative in energy management systems due to simplicity and accuracy. From the forecasting results it is found that GRNN based model produces better performance matrices. **??**RNN [1]

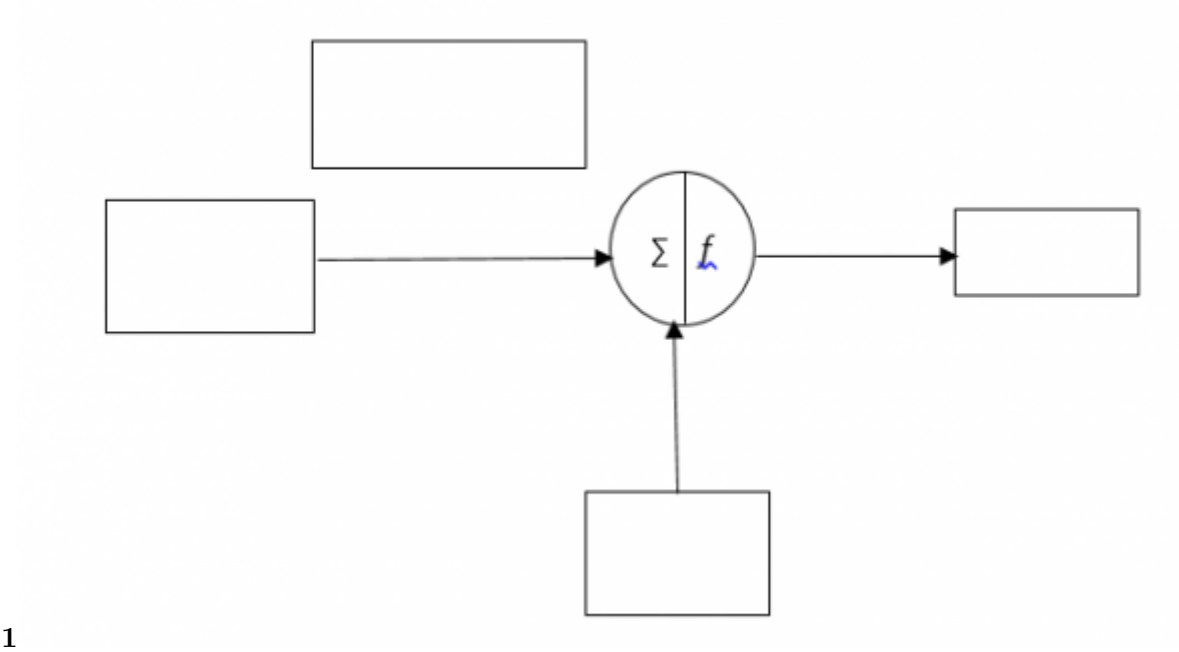

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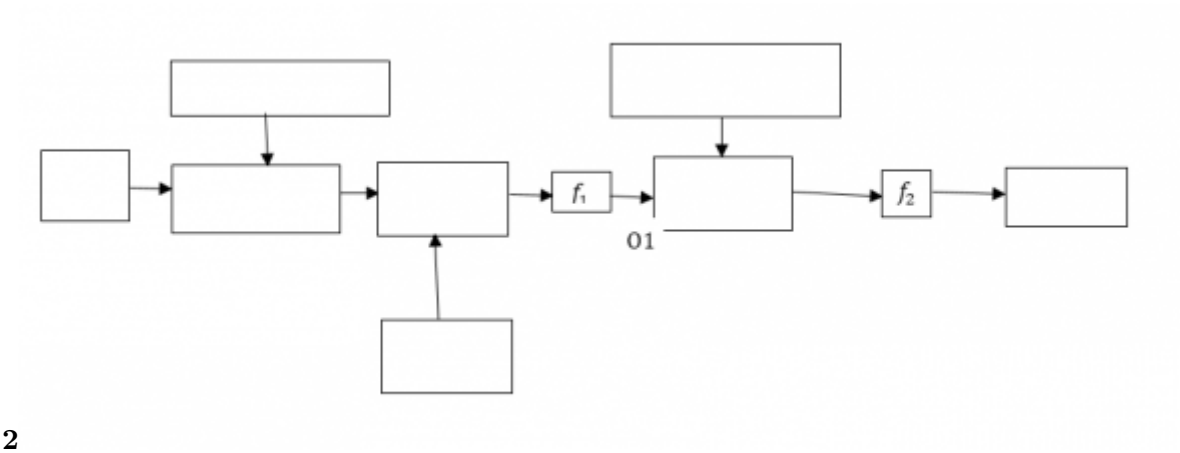
Figure 1: Fig. 1 :



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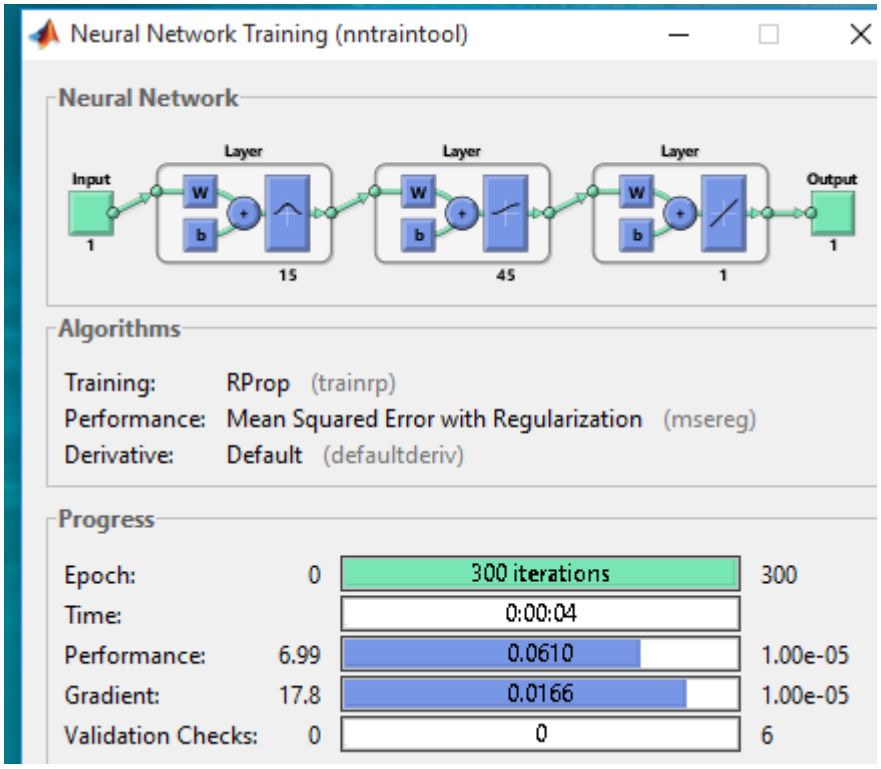

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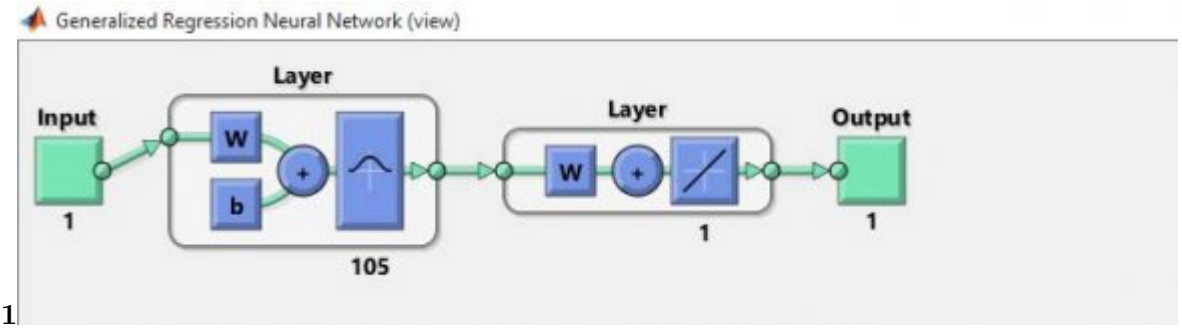

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Figure 4: Fig. 3 : 1 ?F

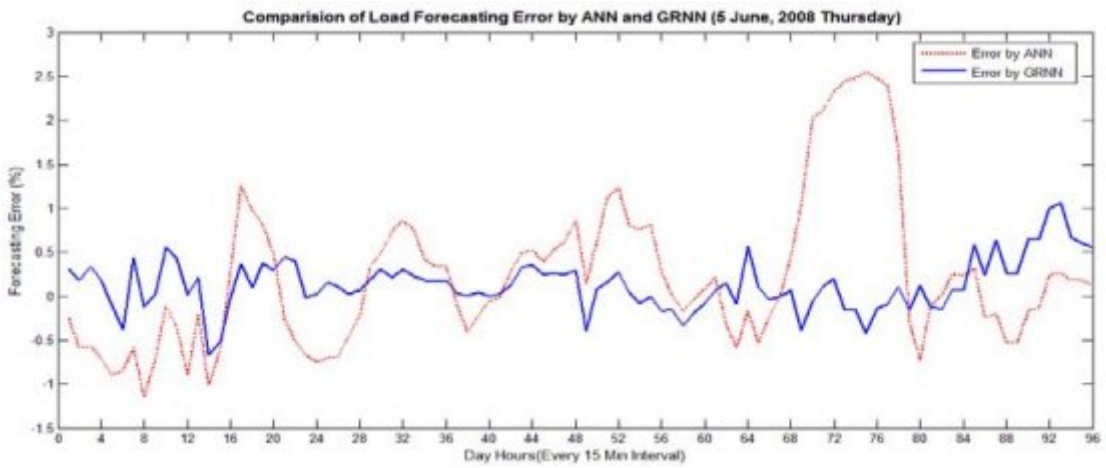

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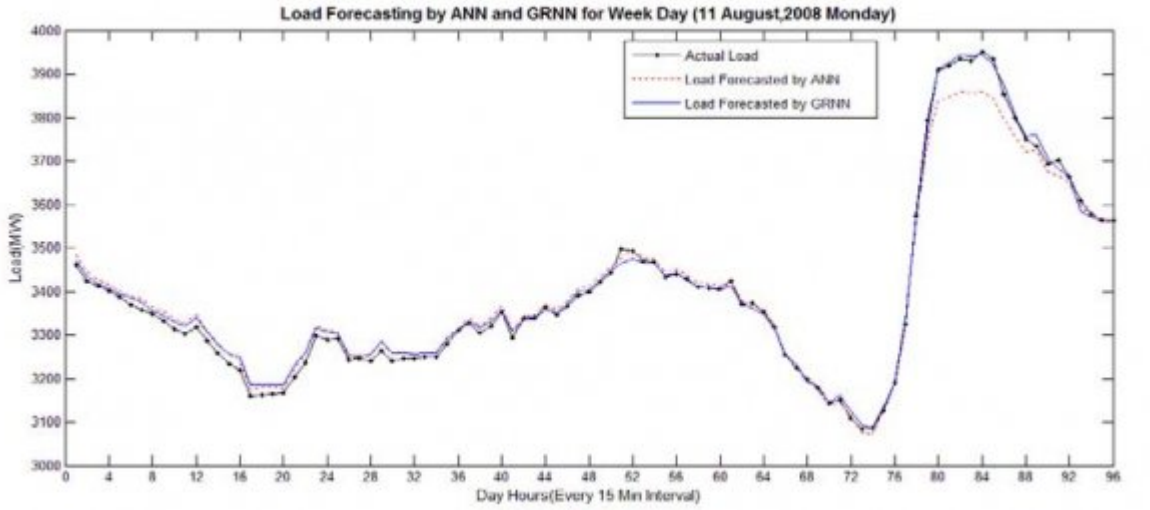
Figure 5: Fig. 4 :



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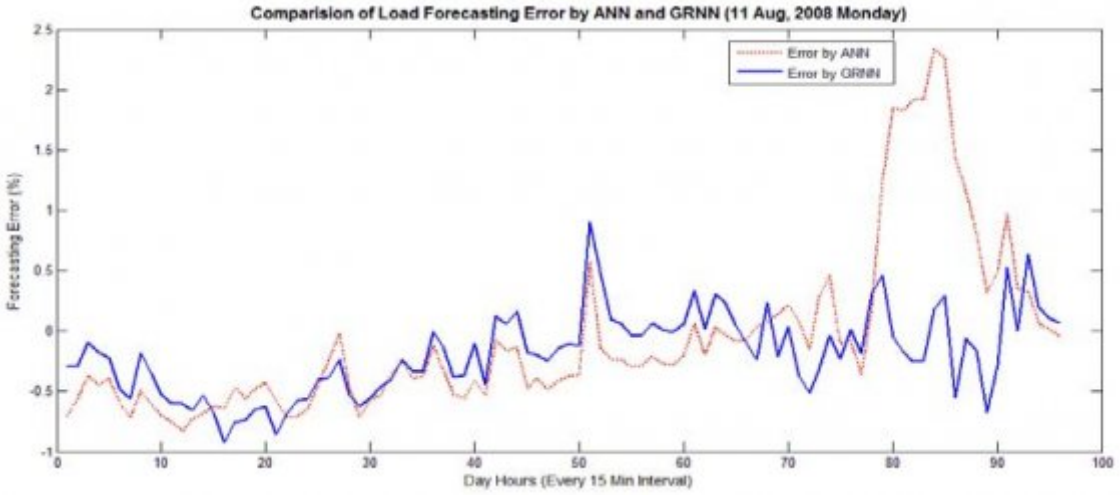

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Figure 7: Fig. 5 :F

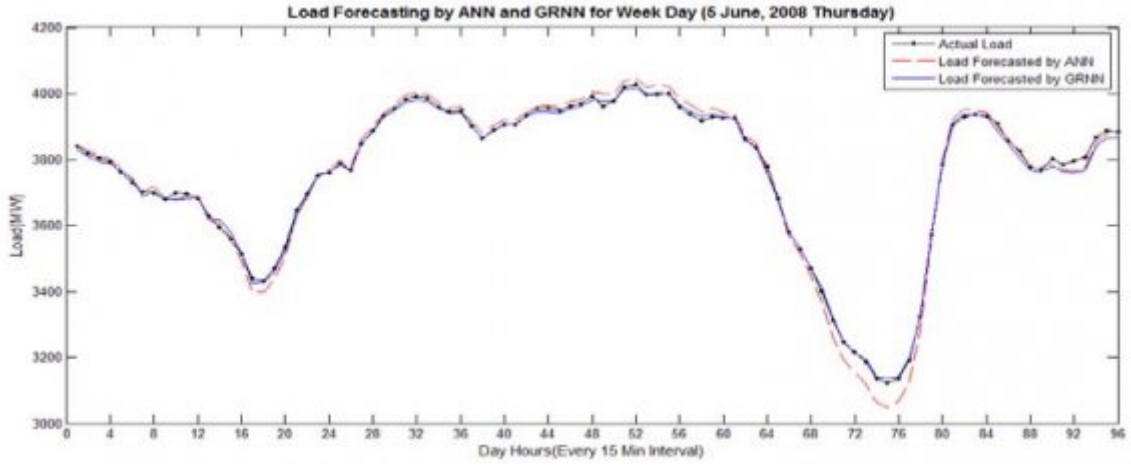

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Figure 8: Fig. 6 :

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Figure 9: Fig. 7 :

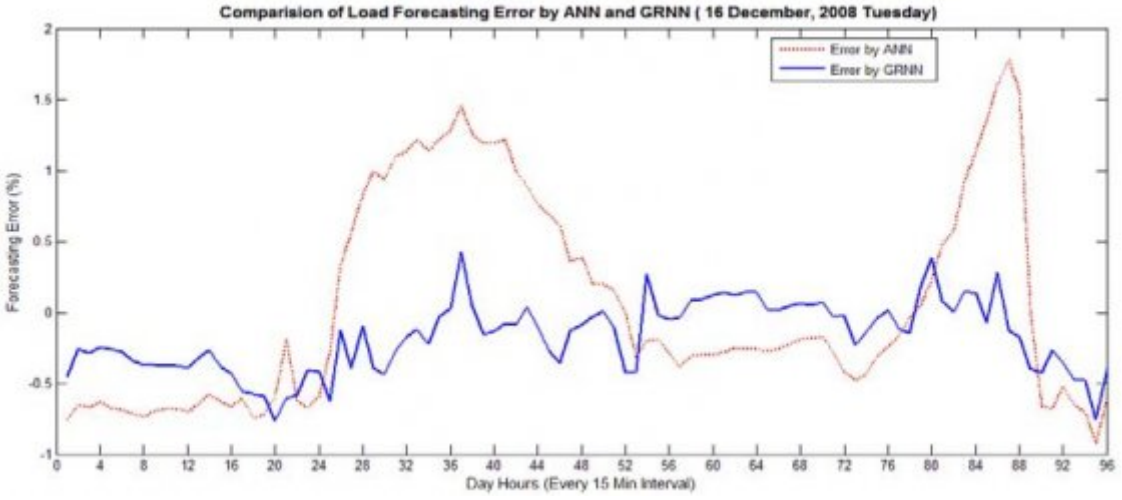

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Figure 10: Fig. 8 :

1

During result evaluation phase following points were noticed:
?

Figure 11: Table 1 :

Season	Model	Max. % Error	MAE	MAPE
	ANN	0.0035	2.3852	23.003
Summer				
	GRNN	0.0021	1.0237	8.8046
	ANN	0.0073	2.3468	12.137
Monsoon				
	GRNN	0.0047	0.9272	10.712
	ANN	0.0009	1.7770	31.306
Winter				
	GRNN	0.0029	0.7645	11.316

Figure 12:

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