2013 12th International Conference on Machine Learning and Applications

Very Short Term Load Forecasting using Cartesian Genetic Programming evolved Recurrent Neural Networks (CGPRNN)

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***Abstract*—Forecasting the electrical load requirements is an important research objective for maintaining a balance between the demand and generation of electricity. This paper utilizes a neuro-evolutionary technique known as Cartesian Genetic Programming evolved Recurrent Neural Network (CGPRNN) to develop a load forecasting model for very short term of half an hour. The network is trained using historical data of one month on half hourly basis to predict the next half hour load based on the 12 and 24 hours data history. The results demonstrate that CGPRNN is superior to other networks in very short term load forecasting in terms of its accuracy achieving 99.57 percent. The model was developed and evaluated on the data collected from the UK Grid station.**

***Keywords*—Cartesian Genetic Program (CGP), Cartesian Genetic Programming evolved Recurrent Neural Network (CGPRNN), Very Short Term Load forecast (VSTLF).**

I. Introduction

The price of Electrical Energy has increased over the last couple of decades. The price of the electrical energy as well as the electricity itself relies on using the Electrical power generation plant in an efficient and optimal manner that requires the establishment of a balance between the demand of electrical energy and its generation. The balance can be established by utilizing a forecasting system for the prediction of the demand of electricity. The forecasting system will equip us with the tools to predict the load demand at any particular instant of time which is necessary for the power system to operate efficiently. Forecasting the load requirement helps in better fuel scheduling and maintenance of the Power Generation System.

Over the years, various forecasting techniques have been developed for forecasting the electrical load. The use of Artificial Neural Networks for load forecasting is relatively a new concept. However it is cumbersome to come up with an optimum performing neural network that can efficiently handle the issue of predicting the load requirements. The utilization of evolutionary techniques will assist in automatically generating the optimum networks that has better accuracy in predicting the load requirements. The time horizon for load forecasting is divided into four different scales: long term load forecasting, medium - term load forecasting, short term load forecasting and very short term load forecasting. The scale of load forecasting will be termed as long term if forecasting extends for over a year. It will be termed as a medium term forecasting if considered for duration of a week. It will be termed as short term forecasting if its time horizon ranges between an hour and a week while it is called very short term forecasting if its time horizon is less than an hour. This paper utilizes an RNN based model that has been developed through the evolutionary technique called the Cartesian Genetic Programming for very short term load forecasting i.e. half an hour look ahead.

II. Load Forecasting

Load forecasting deals with efficiently planning the electricity supply from the grid stations as well as monitoring the future load escalations. The problems associated with Electrical Energy storage on large scale makes it important to come up with a load forecasting system that assists in establishing a balance between the demand and production levels. Over the years, various techniques have been used for efficient forecasting of the future load of a power system [1] [2]. The autoregressive model proposed in [3] takes the load as the combination of the earlier used loads for load forecasting. A non-linear regression algorithm, for load forecasting, is implemented in Autoregressive Moving Average (ARMA) model [4] and Autoregressive Moving Average with Exogenous variable (ARMAX) [5]. SVM is implemented in [6] for prediction of short-term load. A hybrid approach which utilizes both support vector regression and local prediction framework to forecast the load is proposed in [2]. Artificial Neural Networks is a popular approach in load forecasting [7] [8]. The neural network used in [9] for forecasting short term load, produces a simple correction value that is added to the data associated with a day exhibiting similar load conditions like the forecast day. The adaptive load forecasting model proposed in [10] automatically sets the parameters of the system when there is a change in the load condition. A self-supervised adaptive neural network for forecasting the short term load of a large power system that covers a huge service area with heavy loads is proposed in [11]. The self-supervised network is utilized for extracting the correlational features from load and temperature data. The proposed algorithm searches the historical data, trains the networks and performs the forecasting; that is why it provides a short term load forecast which is based on real time and has portability and adaptability. For Real Time Load Forecasting (RTLF) applications, a feed-forward neural network (FNN) is proposed in [12]. Four separate networks are

978-0-7695-5144-9/13 $31.00 © 2013 IEEE
DOI 10.1109/ICMLA.2013.181

utilized for predicting the next four hours load. [13] proposes ANN for short term load forecasting (ANNSTLF) that is based on Multilayer feed-forward network trained using back propagation algorithm. The neural network in [14] selects its input variables and parameters and converges to the least possible training error for specific set of input variables and network parameters. This network has the advantage of selecting the input variables, such as load time series and weather variables, based on the performance of the network. The experimental results show that the model is superior to the existing feed-forward neural networks. A novel approach that can be used for very short term load forecasting is proposed in [15]. The proposed approach utilizes artificial neural network for modeling the load dynamics and is much more robust in comparison to other traditional approaches. The forecasting results are more reliable especially when the weather conditions vary. In [16], three techniques : Fuzzy Logic, Neural Network, and Autoregressive model are proposed and compared for very short term load forecasting. The experimental results show that both fuzzy logic and neural networks are suitable for forecasting very short term load forecasting.

III. CARTESIAN GENETIC PROGRAMMING EVOLVED RECURRENT NEURAL NETWORK (CGPRNN)

Recurrent networks are of great significance when dealing with a wide domain of non-linear and dynamic systems. CGPRNN is a NE algorithm that utilizes the superior capability of CGP for generating recurrent artificial neural architectures [18]. Where as Neuro-evolution (NE) is the process of evolving different neural network attributes such as connection weights, node function, connection type and the topology of the network, and Cartesian Genetic Programming (CGP) provide the efficient genetic programming framework for evolution of neural networks [17].It utilizes a direct encoding method in which the weights, topology and activation functions are all directly encoded in the form of a genotype. The genotype is then evolved to obtain the best set of weights, functions and topology that is augmented to perform a specific task. The offspring is generated using the 1+λ (λ=9) evolutionary strategy.

CGPRNN is based on TWEANN and is both constructive and destructive algorithm. Some of the topological features in the CGPRNN are added while others are removed during the process of evolution. The functions, weights, inputs, connection types and outputs are modified to obtain the offspring using mutation. The connections that are disabled during the mutation process are not removed; indeed they continue to exist since there is a probability of them being used again in later generations. The architecture of CGPRNN when compared to the traditional RNNs is different because the neurons in a CGPRNN network are not all connected in the final network. This assists CGPRNN in producing topologies with less implementation cost and efficient processing time [18].

The CGPRNN genotype consists of nodes representing the neurons of RNN. There are certain inputs supplied to the nodes along with connections, weights and functions. The inputs either come from the program inputs, or the previous node or the feedback input. There are two states for a node i.e. if its output is used in the final path of phenotype from input to out then it is an active node otherwise it is a junk node. The weights values are randomly generated between -1 and +1. A non-linear function is applied to the sum of the product of all the inputs and weights of connected inputs. This non-linear function can be either log sigmoid, tangent hyperbolic or step function that is used to produce the output at each and every node. The output is then utilized as either the input to the other node or the output of the system. If the recurrent input is used, then feedback to the nodes is supplied by the output of the network. The CGPRNN is evolved using mutation for a number of generations in order to attain the desired level of fitness. The transformation of resulting genotype results in the artificial neural architecture producing the desired results [18].

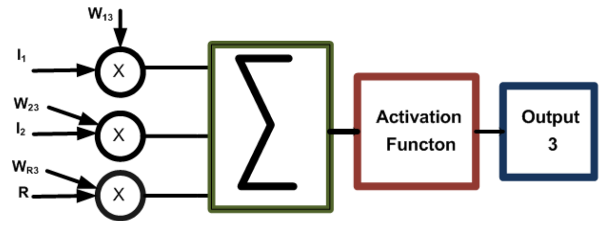

Fig. 1. A typical CGPRNN Node

Figure 1 shows a typical CGPRNN node. The weights are multiplied with the inputs which are then summed up. The sum is then passed through an activation function which in this case is a sigmoid function producing the output. The input R is the recurrent input i.e. the feedback from the output.

IV. CGPRNN FOR VERY SHORT TERM ELECTRICITY LOAD FORECASTING

The forecasting of time series is a tedious job specifically due to the high amount of fluctuations involved. Electric load also constitutes a time series that has tremendous amount of variation. The forecasting of electric load for a very short time increases the difficulty even more since the load is highly fluctuating in short durations. CGPRNN model due to its highly efficient architecture and evolving strategy provided by CGP is capable of producing a recurrent neural network architecture that can deal efficiently with a time series data with high fluctuations such as electricity load, foreign currency, electricity tariff etc. That is why this research utilizes CGPRNN for efficiently forecasting the load for very short interval of time. The following subsection explains the experimental setup under which the proposed CGPRNN model was trained and tested.

A. Experimental Setup

The proposed very short term load forecasting method is based on the historical load data which is the only input variable used for the network. A number of factors can be taken into account for predicting the load however this paper only uses the load historical data of one month for training the proposed model. The model predicts the load for next half an hour based on the historical data of 12 and 24 hours. Using the sliding window mechanism, the proposed model predicts the load for one month. Initially, a random population of ten CGPRNN networks is generated. Sigmoid function is used as the activation function. The mutation rate (μ_r) is set at

10% [18]. The number of CGPRNN rows is only one which means that the number of nodes is the same as the number of columns. The inputs supplied to the network are 48 with two different feedback scenarios of 24 and 48 feedback paths. The input is supplied to the initial population of genotype and the MAPE value of all the networks is used to determine the fittest network. The network with the optimum MAPE value is then used as the parent genotype and promoted to the next generation for producing offspring. This network produces further offspring by mutating the parent genotype. The process continues until either the maximum generations are attained or the MAPE value becomes zero. During the training phase, all the experiments run for one million generations [16]. The evolutionary strategy of 1+λ is used, with one parent and λ offspring. λ is set at nine (9) for all these experiments.

The performance of the proposed model is evaluated using the data from the United Kingdom National grid in form of the half hourly load consumption. The network is trained using the complete month data from January, 1997, while the data from the year 1998 is used for evaluating the performance of the evolved networks. MAPE is used as the performance criterion. A range of experiments are performed with the number of nodes in the network altered between 50,100,150, 200, 250, 300, 350, 400, 450 and 500; while the feedback paths are either 24 or 48. It must be noted that the final phenotype does not necessarily use the entire network of nodes and only about 5-10% of the nodes actively participate in producing the final phenotype [18]. The training and testing results are tabulated in terms of the Mean Absolute Percentage Error (MAPE).

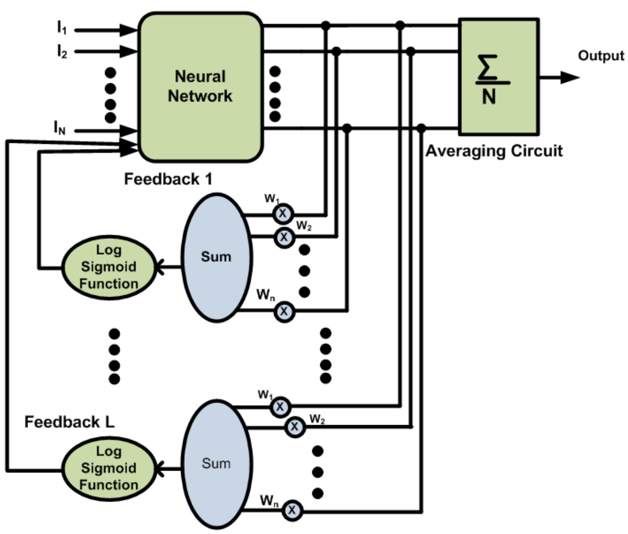

Fig. 2. A CGPRNN network with L feedback paths

Figure 3 shows the network with L feedback path scenario. The inputs to the system are both system inputs and the feedback from output. The feedback inputs are the weighted sum of the output passed through the activation function.

B. Results and Analysis

Table I presents the training results in terms of MAPE values for 24 and 48 feedback path scenarios with 50, 100, 150, 200, 250, 300, 350, 400, 450 and 500 nodes. The model

Nodes	24 Feedback Paths	48 Feedback Paths
50	**4.585623917**	4.843892309
100	4.717034019	4.615231448
150	4.599076102	4.862156838
200	4.733913542	4.804855899
250	4.598047037	4.640542843
300	4.810179744	**4.590327819**
350	4.641895445	4.598063231
400	4.620114693	4.622486704
450	4.617272019	4.612687697
500	4.596943734	4.596904766

TABLE I. THE TRAINING RESULTS FOR CGPRNN MODEL WITH 24 AND 48 FEEDBACK PATHS.

Day	24 Feedbacks	48 Feedbacks
Saturday	1.159	0.6902774
Sunday	0.8912	0.8937765
Monday	1.04794	0.7248641
Tuesday	0.59613	0.7910092
Wednesday	0.78741	1.327143
Thursday	0.75816	1.8188059
Friday	**0.43261**	**0.546351**

TABLE III. THE MAPE VALUES OF THE CGPRNN WITH 50 NODES AND 24 FEEDBACK PATH SCENARIO, AND 500 NODES WITH 48 FEEDBACK PATH SCENARIO IN VSTLF FOR THE FIRST WEEK OF APRIL 1998.

with 50 nodes and 24 feedback scenarios produce the optimum MAPE values. Table II presents the testing results for all months of the year in terms of MAPE, utilizing CGPRNN for predicting the next half hour on the basis of the data of the past 24 hours for 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 nodes with 24 feedback scenarios. It is evident that the best result is produced by 350 nodes network scenario for the month of July. Table III shows the MAPE values for the proposed model with 50 nodes and 24 feedback path scenario. The optimum result in terms of the MAPE is on Friday with MAPE value of 0.432. Table III also shows the MAPE values for the proposed model with 500 nodes and 48 feedback path scenario. The best result in terms of the MAPE is on Friday with MAPE value of 0.546351.

Table VI presents a comparison of various other networks and systems that have been used for very short term load forecasting to date and CGPRNN. The results showed that CGPRNN performed superior to contemporary networks in very short term load forecasting. The MAPE value of 0.43 for Friday in the first week of April, 1998 is the best result when compared to other models. The results were also generally more accurate for the months of March, April and June. This is because of the better weather conditions during these months in UK.

V. CONCLUSION

This paper proposed a novel neuro-evolutionary technique known as Cartesian Genetic Programming evolved Recurrent Neural Network for very short term load forecasting. Historical data of 12 and 24 hours was used to train the network in predicting half hourly load for a period of one month. The experimental results showed that CGPRNN is superior to all other contemporary networks in predicting the load for the

Nodes	50	100	150	200	250	300	350	400	450	500
Jan	2.89114	3.11754	**2.89094**	3.04947	2.89457	3.16273	2.92327	2.91444	2.90443	2.89501
Feb	3.01459	3.14006	**3.0088**	3.13304	3.02321	3.15717	3.0295	3.0445	3.03083	3.01872
Mar	2.83396	2.88076	**2.82391**	2.90116	2.84151	2.92537	2.84752	2.85593	2.84667	2.83468
Apr	2.97881	3.17149	2.9484	3.58972	2.94483	3.23474	2.9271	**2.92358**	3.07447	2.95658
May	3.03797	3.3448	2.9591	4.09896	2.96913	3.45091	**2.91004**	2.93692	3.19264	2.98529
Jun	2.72974	3.12295	2.63424	4.1937	2.64655	3.24273	**2.56195**	2.62036	2.9527	2.6619
Jul	2.62415	3.03988	2.5281	4.06043	2.5482	3.11847	**2.46515**	2.52572	2.83537	2.55448
Aug	2.73961	3.20097	2.6331	4.37858	2.65979	3.33311	**2.57056**	2.66024	2.97469	2.66388
Sep	2.81284	3.22861	2.715	4.04645	2.74365	3.31108	**2.67476**	2.68627	3.00337	2.7528
Oct	2.79457	3.11212	**2.7203**	3.21973	2.77255	3.07359	2.74553	2.67258	2.85367	2.74906
Nov	2.73494	3.003	2.72625	2.88161	2.72842	3.03304	2.74108	2.75793	2.74505	**2.72482**
Dec	2.71112	3.0327	2.74114	2.9608	**2.70691**	3.037	2.74513	2.70593	2.7343	2.70959

TABLE II. THE TESTING RESULTS IN TERMS OF MAPE OF CGPRNN EVOLVED NETWORKS PREDICTING THE NEXT HALF HOUR ON THE BASIS OF A SINGLE DAY DATA HISTORY WITH 24 FEEDBACK SCENARIO FOR A PERIOD OF ONE MONTH.

S.N	Model	MAPE
1	Self-Supervised Adaptive ANN [4]	0.91%
2	FNN for RTLF[5]	0.88%
3	ANNSTLF[13]	2%
4	RBF forecaster	1.3393%
5	Model in [14]	0.66%
6	Multiplicative Decomposition Model[15]	0.7601%
7	Seasonal ARIMA model [15]	1.6108%
8	Model 1 [16]	1.792%
9	Model 2 [16]	1.813%
10	**CGPRNN (proposed model)**	**0.43%**

TABLE IV. COMPARISON OF CGPRNN WITH OTHER METHODS IN TERMS OF MAPE

next half hour. The model is highly accurate for forecasting the load for very short term using 24 feedback paths scenario. Increasing the feedback did not provide us with more accurate results and it was noted that with increase in feedback paths; the number of nodes required to provide us with accurate results also increased. The proposed model did not take into account the weather conditions and other variables. In future, there is a need to study the effect of other parameters such as weather conditions on load forecasting for providing us with even better very short term load forecasting model. The model can be further explored in other areas of time series prediction thus a possible future direction for this research.

ACKNOWLEDGMENT

The authors would like to express their gratitude for the generous funding and resources provided by the National ICT R & D Fund Pakistan.

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