Distribution System Short-TermLoad & Frequency Forecasting (STLFF)for OptimalUI Charges: ANeural-Wavelet based Approach

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Abstract

A classical back-propagation neural network is designed for the short term load forecasting along with the expected average frequency of the system in a given unit time-block is tested on the energy consumption of the Southern Power Distribution company Limited, Andhra Pradesh. The short-term prediction of load (three days in-advance) and scheduling of the load with a time blocks of 15/30 minutes are to be prepared and submit to the AP Transco. Ltd by all the Distribution Companies of Andhra Pradesh. The scheduling is a major influencing factor to run the Distribution Companies economically profitable. A multilayer network with fourteen inputs and one output with five hidden layers are proposed. This network is tested over a three years of load data with one minute resolution. The wavelet approach in transforming the predicted data onto a resolution of 15/30 min time-block resolution.

Keywords:UI charges, wavelet, prediction, back-propagation, electricity regulatory commission, wavelet, short-term load &frequency forecast (STLFF)

1.INTRODUCTION

In the globalization scenario, with the induction of the liberalization polices and the trend in automation demands the estimation or forecasting of the event. The load forecasting is an essential tool for the intensification of transmission planning and for the future power generation. For smoother operation of the Electrical power system in the deregulated scenario, the coordination is vital between electrical power generating companies, transmission companies, distribution companies and the independent system operator. The economic viable operation and maintenance of Distribution Company is focused in the present work through short term load forecasting which play a vital role in increasing the profits of the Distribution Company. Profitable operation of the Distribution Company depends on the load schedules that are generally submitted by various Distribution Companies well in advance to the independent system operator.

The Peng et.al [1], described using Adaline for ahead a week prediction of load based. The spectral method used for finding the periodicity of loads and categorized the load into high loads and low-loads. The methods described in [1], is not suitable for base-load estimation. Also, the Harmonic nature of load variations presented doesn't occur in practical cases. This is major limitation the work suffers from. It is observed that the weather effect is not properly modeled into the simulation. The approach discussed in [1] is not suitable for the Distribution system short-term load forecasting, because in the deregulated scenario, the time block resolution is fifteen minutes.

Jian-chang Lu et.al [2] work emphasis on the forecasting in real-time using system identification approach on a real-time data with fifteen minutes interval is considered. But, the effect of weather is not focused. Also, the noise characteristic in the data is not clearly defined. The energy consumption variations occur due to load variations and cannot be treated as noise.

Shu Fan, et.al [3] investigated the weather diversity effect over an area on load diversity using support vector machine (SVM). Weather information access in developed countries is easy. However, such facilities in the developing and under developing countries are meek or unobtainable. This approach fails when the weather information is not available. In [3], the weather effect on loads like residential, industrial, agriculture, commercial, etc., are not addressed. The weather influence differs from the one type of load to another.

The energy cost that is purchased by the Distribution companies depends on various factors. However, the influence of power drawl frequency is a major concern in the open-market scenario. The methods described in [1], [2] and [3] has not dealt with the influence of grid frequency. In the present work the effect of frequency on the load-patterns is discussed.The work rendered by Takeshi Haida and Shoichi Muto [4] describes a transformation technique in conjunction with the effect of season transition using a transformation technique that converts the temperature data into a function. However, the approach is empirical which doesn't show direct influence or instantaneous influence of the temperature on the electrical energy utilization. Also, the transform approach makes the series stationary and isolate the temporal components of interest [5].

M.Y.Cho, et.al [6] made an attempt, to establish a relationship between ARIMA model and transfer function model in load prediction, using the relationship between the load utilized and the geographical temperature for customers like residential loads, commercial loads, industrial loads, etc., ahead of a week. The derivation of ARIMA model is cumbersome and tedious process to obtain. Also, choosing the optimum correlation order play vital role in the estimation which is a statistical approach. Too many statistical approaches in the model yields more error and requires expertise support.Huifen Niu, et.al, [7] explained an approach in predicting the water content present in the crude oil. Jianhua Zhang, et.al [8] explained the forecasting of electricity load price with MLP neural network approach through considering the non-Gaussian data series. Yanmei Li [9] explained short term load forecasting using Bayes algorithm and Rough Set (RS) reduction approach that implements MLE algorithm. The objective of the work is based on the non-Gaussian data analysis. It is true that the load patterns are always non-Gaussian because the mean of the power consumption is never zero, hence the data is to be considered as the non-Gaussian only.

In all of the [1], [2], [3], [4], [5], [6], [7] [8] and [9] the authors unable to establish the effect of the UI (unscheduled Interchange) charges that is a function of the system frequency at which the electrical load is drawn for the utilization by the various distribution companies that are connected to the system.The frequency of the system is dependent on the load drawn and the power injected by the generation companies.

The reforms in electrical power sector are aimed for the accountability of losses, increased responsibility of system running and maintenance for quality service through maintain good voltage profile and frequency of supply. It is known fact that the power drawl frequency has its significant impact on the electrical energy consumption. As the load on the system increases, the frequency on the system (grid) drops and vice-versa. Therefore the system frequency is strategic parameter in the load prediction approaches particularly in the short term load forecasting.Therefore, in the present work an attempt is made to form the relationship between frequency and the load using the artificial neural network assuming that the energy consumption patterns are non-Gaussian.

Also, most of the STLF techniques deal with the hourly data, rather minute by minute data. The present work also includes the prediction of minute by minute analysis because as the data points are more, the error is less. The present approach is quite useful for unit commitment in handling the unscheduled Interchange (UI) charges, as the UI charges are functional dependent of the frequency as well as the energy drawn from the grid.

2. SHORT – TERM LOAD FORECASTING: NEURAL NETWORK APPROACH

The process of estimation of future conditions through a systematic basis is referred as forecasting. In general, the forecasting targets at reducing the uncertainty which influences the decision making by the management with respect to costs, profit, sales, production, distribution, and so forth. One should keep in mind that the prediction is accuracy depend on the assumptions considered for the estimation. Therefore, there must be some error allowable in the forecasting. Any forecasting systems follows the following steps:

1. Observation of past changes.
2. When those changes occurred.
3. Reasons for changes.

Various forecasting techniques/methods are available in literature [10]. However, the extrapolation, regression analysis, time series forecasting are useful methods in the electrical load forecasting. Also, none of the approaches dealt with the estimation of the systems frequency at which the transactions take place.

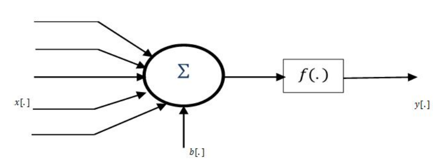

Fig. 1: A single artificial neuron model

The Neural Networks implement recursive algorithms through which the solution is derived from the previous solution as a refined-tuning. Basically, a neural network is a collection of various artificial neurons. The fig. 1 depicts such an artificial neuron. The neural network model provides stronger parallel processing of the data than the existing data processing tools. Moreover, it mimics the human learning process, recognition, estimation, adaption, etc. However, it suffers from sluggish convergent, larger time to train, etc.

The load forecasting is of three types, namely Short-term (a week ahead to less than a month), Medium-term (one month to one year) and long-term (beyond a year). The short-term load forecasting/prediction is quite useful tool to ensure efficient power system operation and control in the modern era which play a crucial for power planning and allocation, etc.The artificial neural network is a good mathematical tool for complex problems such as data analysis, data feature extraction, prediction/estimation, recognition etc. The artificial neural network simply neural network mimics the neuron functionality of the brain. The fig.2 depicts a typical designed BPNN, consisting of two types of inputs, each type takes seven inputs. This network is properly configured with the user data (i.e., the daily energy consumption data of the company and the grid frequency are the two types of the inputs considered in the present NN model).

This BPNN model configuration as described: The neural network consist of five hidden layers which connects the input and output. In contrast the designed BPNN consist of 14 (fourteen) inputs nodes and one output node as shown in the fig. 2. This network is typically a multi-layer perceptron model. Each layer having seven nodes that have the linear activation function expect the fifth hidden layer has only one output which is connected to the output layer. All the nodes are connected through 280 weight elements, with five biases that are connected to each of the summing node.The supervised learning or training algorithm is used, in which a set of input & output/target data are presented to the designed network. The designed network consist of two input data sets and one output/target data set. (i.e.$x[n]; d[n]$) where each input consists of 7 data points and the target with one sampled point. The output simulated is represented by $\boldsymbol{y}[\boldsymbol{n}]$for each of the input. Thus the error generated from the desired output and simulated output is given by$\boldsymbol{e}[n]$. This error is given mathematically as:

$$\mathbf{e}_k[n] = \mathbf{d}_k[n] - \mathbf{y}_k[n] \qquad (1)$$

where*k*is the iteration index

The network weights are adjusted in such a way that the error given by eq. (1) is minimized in some sense such as least square, absolute, mean, least mean square, etc. Once, the network is trained it can be put in use for the intended applications such as recognition, prediction, classification, etc.

The selection of the activation function play the key role in simulating the desired output. Many activation functions are available in the literature that may be used a single activation function or combinational functions. However, a single activation function i.e. positive line is used in the current model. The power and/or energy are linear functions of frequency in another words as the frequency increases the energy generated is increased. If the frequency (f) is dropped the power (P) utilized increased and vice-versa. But for a grid connected system the frequency rise or drop is a function of the net power. i.e., difference of the actual power generated and actual power consumed. However, the power is a function of frequency and it is related directly proportional to the system frequency. Therefore,

$$P \propto f \qquad (2)$$

where N is the speed of the rotor, in-turn the frequency is the dependent parameter of the speed of the machine.

As discussed in [3] and [5], the weather influences the energy consumption to some extent and may not be the same manner by the each of the consumer. However, the reflection on the power consumption can be sensed on the grid frequency in view of equation (2). Therefore, preprocessing of the data may be eliminated so as to make robust analysis.

3. NEURAL-WAVELET BASED STLFF FOR OPTIMAL UNSCHEDULED INTERFACE CHARGES

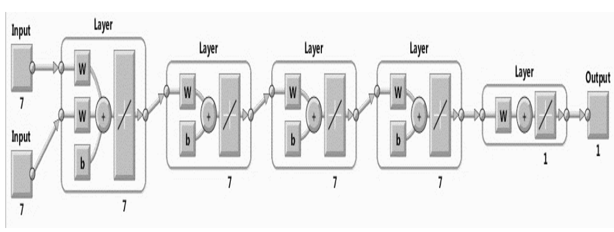

Fig. 2: Custom designed Back Propagation Neural Network (BPNN) model for STLP for SPDCL of A.P.

The back-propagation algorithm is very popular approach for training the designed neural networks particularly useful in estimation/prediction algorithms. The objective of the training approach is to minimize the error ref. eq. (1) in some

TABLE 1: UNSCHEDULED INTERFACE CHARGES OF THE AP DISCOM FOR VARIOUS FREQUENCY RANGES
(U/S Schedule A, clause (1) of Regulation 5)

Below (Upper Limit)	Not Below (Lower Limit)	UI Charges (Paisa per KWh)
---------	50.20	0.00
50.20	50.18	16.50
50.18	50.16	33.00

50.16	50.14	49.50
50.14	50.12	66.00
50.12	50.10	82.50
50.10	50.08	99.00
50.08	50.06	115.50
50.06	50.04	132.00
50.04	50.02	148.50
50.02	50.00	165.00
50.00	49.98	193.00
49.98	49.96	222.00
49.96	49.94	250.50
49.94	49.92	279.00
49.92	49.90	307.50
49.90	49.88	336.00
49.88	49.86	364.50
49.86	49.84	393.00
49.84	49.82	421.50
49.82	49.80	450.00
49.80	49.78	478.13
49.78	49.76	506.25
49.76	49.74	534.38
49.74	49.72	562.50
49.72	49.70	590.63
49.70	49.68	618.75
49.68	49.66	646.88
49.66	49.64	675.00
49.64	49.62	703.13
49.62	49.60	731.25
49.60	49.58	759.38
49.58	49.56	787.50
49.56	49.54	815.63
49.54	49.52	843.75
49.52	49.50	871.88
49.50	---------	900.00

sense such as mean absolute, mean square, etc. There are plenty of training algorithms are available algorithms such as Levenberg-Marquadt, Bayesian regularization, BFGS Quasi-Newton back propagation, Resilient back propagation, scaled conjugate gradient search, Powell/Beale conjugate gradient, Fletcher-Powell conjugate gradient, Polak-RibiéreConjugate Gradient, one-step secant, etc., algorithms that finds usefulness in optimize the given criterion. The

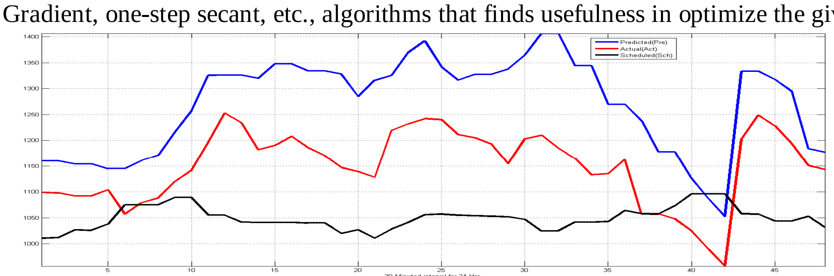

Fig. 3: Comparison of power.

designed custom neural network is basically a back propagation neural network (BPNN) algorithm, whose performance is measured through mean square error (normalized) during learning/training process. The designed training process is stopped/ceased based on one of the criterions such as the minimum error gradient, maximum learning rate ( ) or maximum number of epochs/iterations. The Levenberg-Marquadt algorithm is the faster supervise algorithm among many training approaches which is used as the present training algorithm. The Bayesian Regularization algorithm is found useful for the training and estimating the frequency of the systems. The on-duty LMC staff of the Distribution Company prepares & submits the power requirement through their schedules three days ahead based on the available data of the previous day, same day of the previous week, same day of the previous month and the same day of the previous year. According to the quota/based on availability of the power the indented load is allocated for the Distribution Company's on the scheduled days for each time-block (each time-block is equal to15 min). When the utility of the Distribution Company less than or equal to the scheduled the Distribution Company is power tariff is charged as per the agreement. If the utility ofDistribution Company exceeds than the scheduled load then the DISOM is

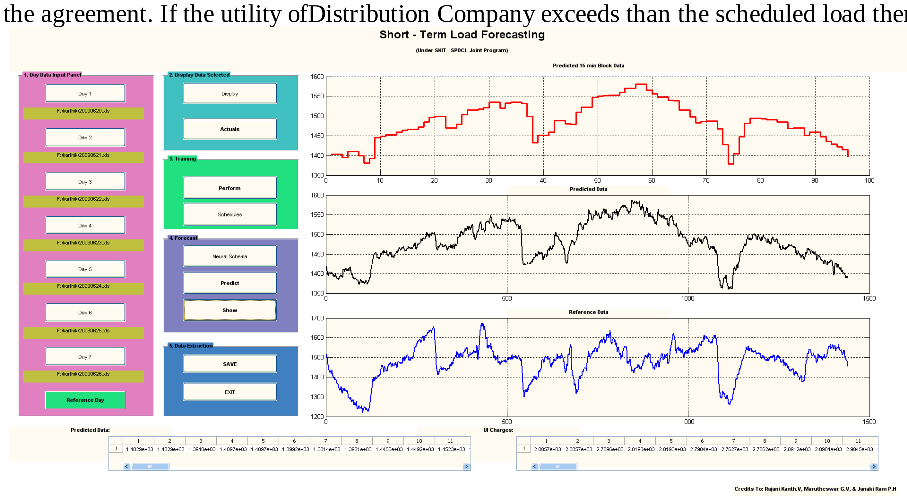

Fig. 4: Application panel (modifiable) developed of Short-Term Load Forecasting.

penalized. This penalty is called the Un-Scheduled Interface (UI) charges. According to the APERC (Andhra Pradesh Electricity Regulatory Commission), the UI charges are shown in the table – I for various frequency ranges that lie in the interval 50.20 – 49.50 Hz. It may be observed that when the Distribution Company is drawing the energy beyond the 50.20 Hz, for the excess drawl the UI charges is zero. In other words the Distribution Company need not pay for the additional drawl as per the schedule. However, the UI charges Therefore the LMC on-duty staff are to be careful during the preparation of their schedules so as to minimize/avoid the UI charges and make the Distribution Company profitable. The system frequency forecasting is not considered in the earlier literature. Also, the on-duty staff of the distribution company are not considering the frequency effect in the computation of the unscheduled interchange charges. An attempt is also made is estimating the average system frequency so as to minimize the UI charges. An attempt is made through designing a forecasting neural network that uses the wavelet based technique as in [11] for preparing the time-block data. The fig.3 emphasis the predicted power drawl (blue solid line), scheduled power (red solid line) & actual power drawn (black solid line). It is observed that the scheduled power is less than the actual power drawn from the grid and thus deviating from their schedules. This causes to impose UI charges/penalty on the Distribution Company. The schedules is shown on 30 min resolution for better understanding through the illustration fig.3. The time block resolution is presently is 30 min, but the policy makers planned to fix the resolution to 15 min instead 30 min. The designed forecasting neural schema is also used for not only the energy forecasting, but also for the predicting the average frequency with a time resolution of one minute. The signal processing tool wavelet is used as in [11] for computing the require time unit-time block resolution so as to compute the unscheduled interchange (UI) charges. The predicted load estimation is coupled with the predicted frequency for computing average UI charges. Thus, while preparing the schedules by the on-duty LMC staff finds usefulness of the proposed approach for optimal (minimizing) UI charges. The results are validated with the data available in the Distribution Company.

The UI charges are soon going to impose on all the Distribution Companies of Andhra Pradesh. Accordingly, the Distribution Companyhave to pay not only for the additional energy drawn but also for the scheduled energy whether the Distribution Companyis utilized the allocated energy or not in the given unit time block. In simple term all transaction/unit committed violation in the energy utilization is penalized based on the energy drawn in view of the system frequency ref. to Table 1. It is observed that the LMC staff of the Distribution Companyare preparing the schedules in excess to their requirement irrespective of the allotted unit block quota. The present neural schema discussed is quite useful utensil in minimizing/optimizing the unscheduled interchange charges so as to minimize the effect of unscheduled energy management.The panel of the application product developed for SPDCL shown in fig.4 that aids the performance of the on-duty staff in preparing the schedules optimally.

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