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Application of Short-Term Load Forecasting for Optimizing the Storage Devices of a Base Station

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APPLICATIONOFSHORTTERMLOADFORECASTINGFOROPTIMIZINGTHESTORAGEDEVICESOFABASESTATION

Strictly as per the compliance and regulations of :

Application of Short-Term Load Forecasting for Optimizing the Storage Devices of a Base Station

Mishuk Mitra α, Metali Rani Datta σ, Chinmoy Mallick ρ & Atia Rahman Ѡ

Abstract- Energy is one of the important key factors to realize better socioeconomic development of a society and electrical energy is the most common form of energy for urban area both in commercials and residences. The instantaneous nature of electricity has made it different from other commodities as it has to be consumed just after the moment of generation. So, from generation parties to consumers at every stage of modern electricity grid it is every important to ensure the balance of consumption and production to achieve sustainability and reliability of the grid. Load forecasting is an important component for power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduces spinning reserve capacity and schedule device maintenance plan properly. It also reduces the generation cost and increases reliability of power systems. In this work, an artificial neural network for short term load forecasting is demonstrated. Based on the time and similar previous day load, artificial neural network model is built, which are eventually used for the short-term load forecasting. The aim of this work is to describe the development and evaluation of a forecasting model to schedule the onsite storage devices. The evaluated model is able to predict the day-ahead electricity demand of a traditional base unit in order to schedule the storage devices.

Keywords: artificial neural network (ANN), feed-forward neural network (FNN), renewable energy source (RES), photo voltaic (PV). base transceiver station (BTS), short term load forecasting (STLF), support vector machine (SVM), expert system (ES).

I. Introduction

The process of achieving this research is mainly divided into two main parts: assessing the forecasting model and scheduling of storage device [1]. The modelling and simulation is performed in MATLAB.

a) Data pre-processing & Data-analysis

The function of the data pre-processing is acquiring representative data, removing unusual consumption hike and other inconsistencies, defining proper format for time stamping (day, month, hour, minute) and splitting up the data in identification and validation sets [2]. The function of the data analysis is analysing the data to find underlining mechanisms, trend and variations in the data, use of clustering to get more insight in intraday correlation [3].

b) Forecasting of Consumption & Storage Device Scheduling

To schedule the storage devices, it is very crucial to have prior knowledge about electricity consumption on day-ahead. Therefore, short-term forecasting is an important step to ensure better scheduling of the storage devices [4]. Pre-processed data is used to evaluate the performance of the forecasting models. Initially two forecasting models, ANN is chosen to forecast the consumption profile. This model is evaluated with respect to some evaluation criterion. The use of load forecasting is widely accepted as operational aid for the control the electric power system as well as to enhance consumer participation in local energy market through providing financial benefits.

The forecasted consumption profile of a base station will be used to achieve optimum scheduling of storage devices [5]. The main idea is to utilize the surplus of PV generated energy after mitigating self-consumption. If a particular consumer can have an idea about the level of stored energy, it is possible to utilize the energy in various way like, load shifting, include some flexible loads to consume the extra energy, valley filling etc. However, for this research our target is to feed the extra stored energy in local market, so that the consumer can have some financial benefits from the trading.

II. Methodology

The research approaches are selection and description of the electricity consumption data and the different variables, processing and detection of missing values, methods are discussed to discover the cohesion and pattern in the selected data and then procedure of evaluation is appointed [6].

a) Data

Real data of electricity consumption is needed for estimation and validation purposes of the forecasted result. Moreover, to predict the amount of stored energy in the storage devices on day-ahead, the PV generated energy of the corresponding base stations are also needed. As the ultimate goal is to predict the base

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station forecasting, though additional Qualitative variables are introduced to recognize the precise pattern of the consumption behaviour of each consumer.

i. *Electricity Use Data*

Real energy consumption data of different BTS on a daily basis at 15 minutes of sampling is used. This data will be used to train the network and build the forecasted model. Then that forecasted model will be used to design the PV panel system and schedule the storage device [7]. All the data are taken in Wh and thus will be forecasted in the same unit.

a. *Normal Energy Consumption Data*

On average the yearly consumption of an identical base station in the Netherlands is 3500 kWh. So, daily electricity consumption on average is 9.5 kWh [37]. Consumption profile shown in the figure 2.1 is the electricity consumption pattern of a particular base station for the first week of March, 2013 with average consumption around 9 kWh per day.

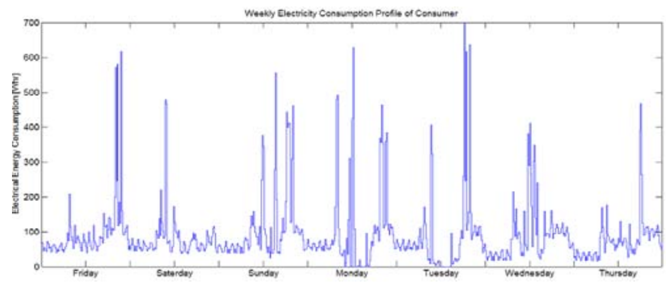

Figure 1: Weekly consumption pattern

However, the daily consumption patter in different depending on week days and weekend, even similar week days does not have similar consumption patterns shown in Figure 2.

It is very important to identify the non-linearity of the consumption pattern, because forecasting model selection is depend in the degree of non-linearity of the input data.

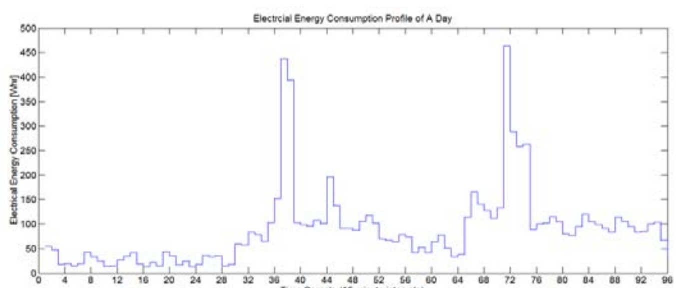

Figure 2: Daily load consumption

b. *Electrical Energy Consumption Compromised with PV*

After careful analysis, some data are found in the data set which follows a particular pattern but the average electricity consumption is less than the standard one. Figure 2.3 shows a consumption profile of a day which goes close to zero at mid-day [8]. Moreover, this particular base station has installed PV as local generation source. So, it is very much understandable this consumption profile is the net amount of energy consumed from grid after mitigating some load with PV. Thus, the electricity energy consumption data of this type of base stations cannot be used to identify the proper forecasting model.

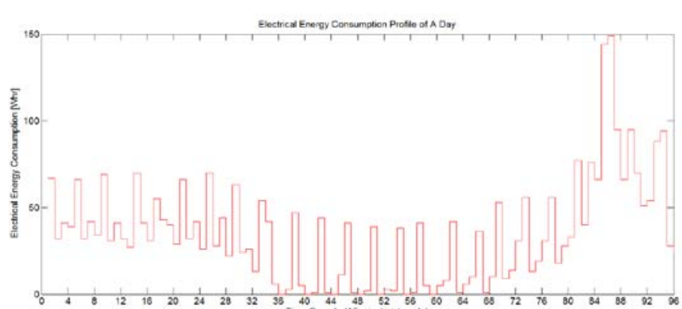

Figure 3: PV Compromised Electricity Consumption

Moreover, there are some consumption profile data sets with very low average daily consumption. A consumption profile of total 3.62 kWh is shown in Figure 4. At Figure4

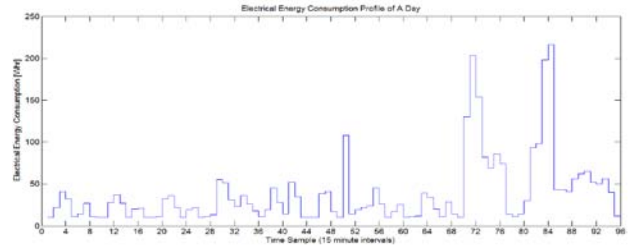

Figure 4: Electricity consumption of some particular equipment

Consumption is very low but at night it goes high. So most probably it is the consumption profile of cooling system. Though this consumption profile cannot give the proper idea about the consumer load behaviour.

ii. *Qualitative Variables*

Beside input variables (electrical energy consumption), also the qualitative variables are important for forecasting. Qualitative variables are better known as dummy variables; do not have a natural ordering. These variables contain descriptive values, like the day of the week. Moreover, all the data are 15 minute sampled so hour information is also a qualitative input variable. Depending on the time electrical consumption varies like at working days from 9.00AM to 6.00AM consumption should be low and at night when everybody is at home consumption goes high at base station. However, this hour based consumption pattern also depends on season. Thus, seasonal effect can be an input variable for forecasting. But this research is focused on STLF and to capture the consumer behaviour, electricity consumption data of two or three months is used as training data. So most of the case seasonal identification remains same for all training data. Finally, day identification along with our identification is considered as qualitative input variables for the forecasting model.

b) *Data Pre-processing*

Real life data contains huge amount of noise and often has quality issues. Such volatility must be removed before simulation can be performed. If the input values to a forecasting model are poor, it will be hard to produce a good forecast, irrelevant of the quality of the forecast model. All the steps has to be taken into consideration before simulation as pre-processing is given below

- Duplicate data check
- Missing data check
- Filtering unusual and noise from PV generation data set

Duplicate and Missing Data check:

The electricity consumption data of different base station of a year is given as Wh/15 min. Smart meters are used as measuring device, thus it has high possibility of missing data and duplicate data. Initially the full data set is passed through some checking algorithm to identify duplicate data and missing data as Pre-processing step. However, data with same time stamp is treated as duplicate data. For missing data on weekdays, average value of the immediate 7 weekday's consumption data on the same time sample is taken. However missing data for weekend days, average consumption of the previous 4 same days on the same time sample is calculated.

As an example, to find a missing data on weekdays at y_t it should take the average of previous seven weekdays on the same time t shows in Figure 5.

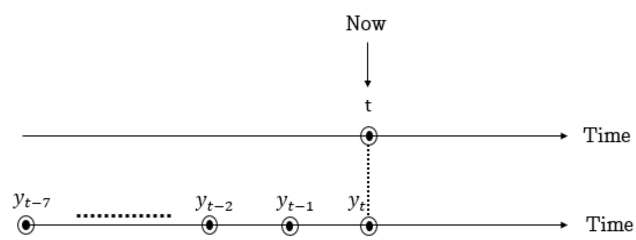

Figure 5: Average value for missing data on weekdays

Moreover, to find a missing data on weekend (as an example Saturday) it has to take the average of previous 4 Saturday of the same time sample shown in Figure 2.6.

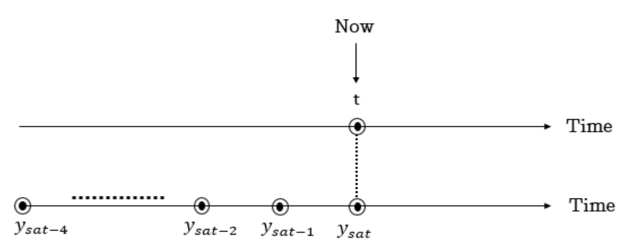

Figure 6: Average value for missing data on weekend

Filtering unusual and noise from PV generation data set:

The PV generated data is also measured in 15-minute interval but it is very important to identify the noise or unusual production. Normally electronics based measurement devices are used to capture the data from controller [38]. So, to have unusual production peak or noise (like production level 1 or 2Wh) is very common.

Moreover, synchronize PV production and consumption data for the same consumer is also important for scheduling of stage device.

c) Data Analysis

i. Day identification Number as Input of ANN

It is very important to make some difference among the different days of the week so that the models can identify the target data set according to the train data set. Initially these identification variables are coded into integer value. The days of the week is represented by 1,2,3,4,5,6,7 respectively for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday.

Correlation or patterns within the electricity use can aid the forecast if well defined. To discover patterns in the electricity use, self-organizing map (SOM) is used [9]. The motivation behind SOM analysis is to find the pattern of consumption of each day of a week. SOM clustering of seven days of a week is shown in Figure 2.7.

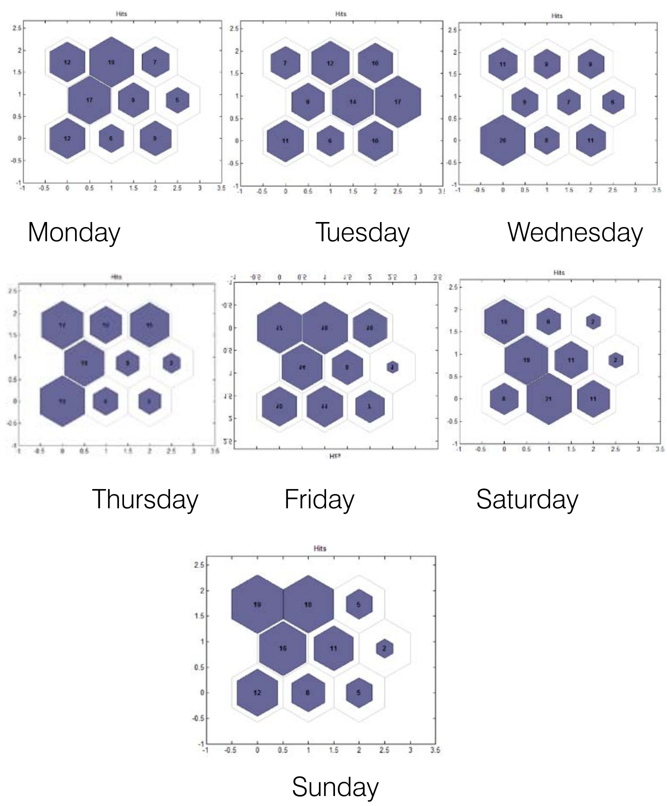

Figure 7: SOM clustering of electricity use per day

Figure 2.7 illustrates different electricity consumption pattern of each day. So, as an input of ANN day identification number will be different for each day.

d) Evaluation Method

An evaluation method is necessary for three aspects;

- Model identification
- Performance comparison between models
- Insight in model performance for practical use

In order to evaluate a forecast made with a specific model, forecast-error metrics or so called performance indicators are defined. Three types of performance indicators are discussed. The first used performance indicators are the scale dependent metrics. These indicators are on the same scale as the data. One of the most used scaled performance indicator is the mean are extremely large when the actual values reaches zero [10]. When considering data which contain zeros, the metric is undefined. An example of percentage based metric is the MAPE, which is one of the most used squire error (MSE). The other category is percentage based performance indicators, which can be used to compare different data sets as they are scale independent. To overcome division by zero, a scale free error is proposed by Hyndman and Koehler in 2006 [40]. The above-mentioned performance indicators are given below.

In each of the forthcoming definitions y_t is actual value, f_t is the forecasted value, $e_t = y_t - f_t$ is the forecast error and n is the size of the test set. Also, $\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t$ is the test mean and $\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n}(y_t - \bar{y})^2$ is the test variance.

i. *The Mean Squire Error (MAE)*

The mean absolute error is defined as [41] [42]

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}(\, e_t)^2 \qquad \text{(a)}$$

Its properties are –

- It measures the average absolute deviation of forecasted values from original ones.
- It shows the magnitude of overall error, occurred due to forecasting.
- In MSE, the effects of positive and negative errors are canceled out.
- For a good forecast, the obtained MSE should be as small as possible.
- Extreme forecast errors are not panelized by MSE.

ii. *The Mean Absolute Percentage Error (MAPE)*

This measure is given by [41] [43]

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100\,\% \qquad \text{(b)}$$

Its important features are:

- This measure represents the percentage of average absolute error occurred.
- It is independent of the scale of measurement, but affected by data transformation.
- It does not show the direction of error.
- MAPE does not panelize extreme deviations.
- In this measure, opposite signed errors do not offset each other.

III. Model Building

a) ANN based Forecasting Model

Artificial neural networks (ANNs) constitute a class of flexible nonlinear models designed to mimic biological neural systems of brain. Typically, a biological neural system consists of several layers, each with a large number of neural units (neurons) that can process the information in a parallel manner as illustrated in Figure 3.1. Like biological neuron, ANN has also multi-layer structure such that the middle layer is built upon many simple nonlinear functions and able to receive multiple input signals from other neurons. The procedure of selecting optimal network architectures and their learning approaches are described for forecasting the wind speed in two different time horizon [11][13].

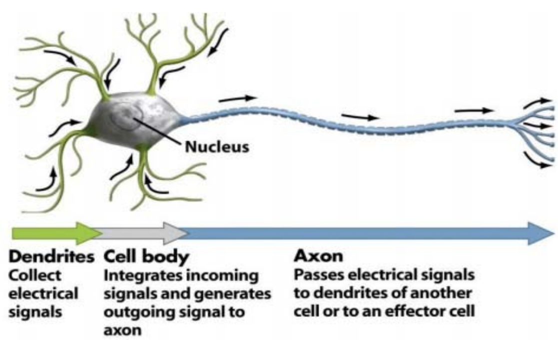

Figure 8: Flow of information in biological neuron.

b) Working Principle of Forecasting Model

ANNs are networks typically composed of several layers with interconnected elements called neurons. The first or lowest layer is the input layer which gathers external information. The middle or hidden layers process this information in a fairly elementary way to produce signals for the connected neurons at output layer. The neurons or nodes at the adjacent layers are usually fully connected by acyclic arcs from a lower layer (input) to a higher layer (output).

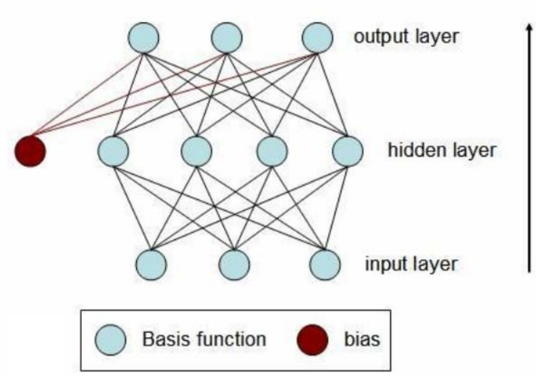

Figure 9: A general ANN structure with one hidden layer

Input values are processed by this network to form output values as depicted in a simple non-linear model, the inputs are independent variables. The functionality estimated by the ANN can be written as:

y1, y2,…… ,yn=f (x1,x2,……,xn)

Where, x1,x2,……,xn are independent input variables and y1,y2,…… ,yn are dependent output variables.

Weights are the key factors of network performance. These weights are continuously updated during the training period to carry out complex non-linear mapping [12]. In this research the developed forecasting model is trained in supervised way. Once the network is trained with appropriate training data set, it is ready to perform desire task.

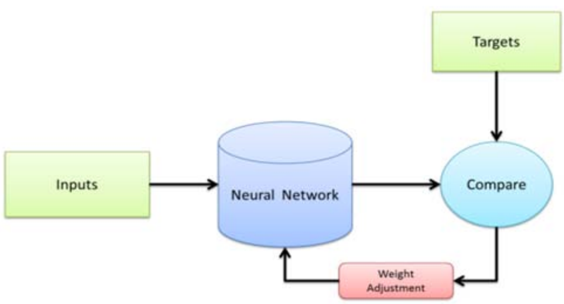

Figure 10: Illustration of network weights in supervised learning process

c) Network Architecture

Complicacy of ANN mainly arises for the hidden layers which are used to build the connection between inputs and outputs. Thus, it creates an indirect relationship between inputs and outputs. Information received from the input layer is first processed in the hidden layer, and then transmitted to the output layer. So, the learning capability due to nonlinearity of the input data is mostly depend on number of hidden layers. A multilayer forecasting model with one hidden layer can perform an arbitrary convex approximation to any continuous non-linear mapping. According to the universal approximation theorem for neural networks [49], the standard multilayer feed forward network with a single hidden layer and finite number of hidden neurons is sufficient for any complex simulate nonlinear function with any desired accuracy. It concludes with the view that number of hidden layers has an influence according to the complicacy of the problem otherwise system will be more complicated, even single hidden layer requires large number of nodes. So, it is always a tradeoff of number of hidden layers depending on complicacy of the problem.

d) Selection of the Network

Depending on the structure of the network ANN can be classified in several models. Figure 3.4 shows different types of neural networks used for forecasting applications.

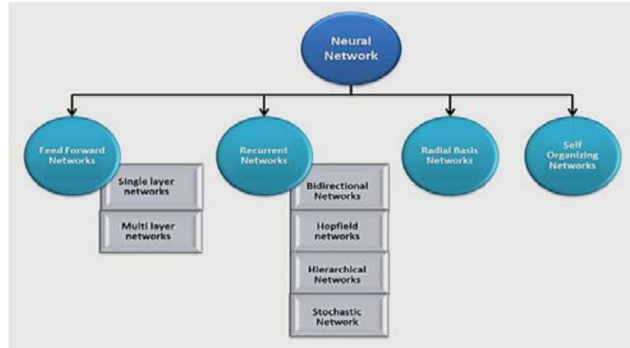

Figure 11: The taxonomy of ANN architecture

Feed-forward neural network (FNN) is fast and simplest ANN because in the case of Multilayer layer network it transmits information form input layer to output layer using some simple structured hidden layer [13]. Normally it maps the static relationship between input and outputs

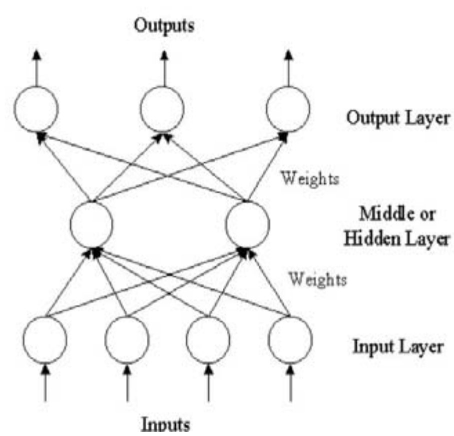

Figure 12: Structure of FNN

through a unidirectional information flow (only form input towards output). The inputs are fed directly to the outputs via a series of weights. Each connection may have different weights. Due to lack of any feedback, FNN must use a large number of input neurons for learning the historical data and consequently achieving good results. Despite of being simple, feed-forward networks are more efficient in complex nonlinear forecasting problem with bigger number of input variables [15].

e) Mathematical Model

In a mathematical model, has been developed referring to the Figure 3.5

$$\boldsymbol{y_t = a_0 + \sum_{j=1}^{q} a_j\, g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t\,, \forall\, t}$$

Here $\boldsymbol{y_{t-i}}$ $(\boldsymbol{i = 1, 2, 3, \ldots\ldots p})$are the input and $\boldsymbol{y_t}$ is the output. The integers $\boldsymbol{p}$ ***and*** $\boldsymbol{q}$ are the number of input and hidden nodes respectively. $\boldsymbol{a_j\,(j =}$

$\mathbf{1, 2, 3, \ldots \ldots q}$) and $\boldsymbol{\beta_{ij}} = (\boldsymbol{i} = \mathbf{1, 2, 3, \ldots\ldots p}; \boldsymbol{j} = \mathbf{1, 2, 3, \ldots \ldots q})$ are the connection weights and $\boldsymbol{\varepsilon_t}$ is the random variable, $\boldsymbol{a_0}$, $\boldsymbol{\beta_0}$ are the bias term. Usually, the logistic sigmoid function $\boldsymbol{g(x)} = \frac{\mathbf{1}}{\mathbf{1+e^{-x}}}$ is applied as the nonlinear activation function. Other activation functions, such as linear, hyperbolic tangent, Gaussian, etc. can also be used depending upon the use case.

The feed forward ANN model in Equation 1 in fact performs a non-linear functional mapping from the past observations of the time series to the future value, i.ey_t=f (y_(t-1),y_(t-2) 〖,y〗 _(t-3),……y_(t-p) ,W)+ ε_t where Wa vector of all parameters is and f is a function determined by the network structure and connection weights [15]

To estimate the connection weights, non-linear least square procedures are used, which are based on the minimization of the error function

$$\boldsymbol{F(\varphi)} = \sum_{t} \boldsymbol{e_t^2} = \sum_{t} (\boldsymbol{y_t} - \boldsymbol{\hat{y}_t})^2$$

Here $\boldsymbol{\varphi}$ is the space of all connection weights. The optimization techniques used for minimizing the error function Equation 2 are referred as Learning Rules. The best-known learning rule in literature is the back propagation or Generalized Delta Rule.

IV. Simulation Results and Analysis

The optimal structure of ANN is used to forecast the BTS electricity consumption on day-ahead. In this case 31st of October, 2012 is considered for the demonstration of the model. The imbalance power is calculated by the power deviation between day-ahead forecaster and 15 minutes ahead forecaster. The flexible entities are activated in way to reduce this imbalance power. A simple MATLAB-based GUI has been implemented to demonstrate how this tool can be user-friendly for a customer.

a) Assumptions

The historical data are in Wh and the time interval is 15 minutes. As input, total 92 days of previous data is taken for pre-processing [14][15].The time range is March 1st, 2013 to May 31st 2013. The forecasted data represents the consumption for the next day, June 1st 2013.

b) Electricity Consumption Forecasting

i. *Model of Feed-Forward ANN*

Designing a three-layer FNN model for STLF involves several major steps:

1) Determine the number of outputs: An FNN model may have only one output, which can be corresponding to the electrical load of a consumer, or several outputs, which can represent a 24-hour load profile of several BTSs. Some drawbacks of the multiple outputs FNN were discussed in [26].
2) Determine the number of inputs: previous consumption data of a particular consumer along with day identification number is used as target and input of FNN.
3) Determine the number of hidden neurons: It is followed a trial and error method to select an optimal hidden layer structure for used data set at FNN. The number of hidden neuron layer mostly depends on: MAPE, Elapsed Time & Epoch.

The lowest MAPE, lowest time and highest Epoch is found for the chosen number of layer. Observing these parameters, the best output is obtained from 25 hidden layer amongst different options.

ii. *Consumption forecasting on mid-summer (June 01, 2013)*

Practical consumption data from 30 BTS will be used to evaluate the forecasting performance of the models. In this context, at first it is tried to forecast the consumption profile of each consumer on the same day with training data set of previous 3 months (92 days).

Table 1: FNN Evaluation

Consumer	ANN		
	R	MSE	MAPE (%)
1	0.94285	3.63E+03	33.9695
2	0.89787	1.26E+04	39.39
3	0.78771	8.70E+03	28.5366
4	0.91719	1.49E+03	52.8844
5	0.83974	572.452	15.9883
6	0.41161	440.1884	103.0053
7	0.97297	1.27E+03	47.334
8	0.91181	343.6435	25.3231
9	0.9641	1.23E+03	26.5852
10	0.9468	537.9639	27.9004

11	0.8576	4.71E+03	52.6619
12	0.85425	3.95E+03	79.4627
13	0.85881	281.4154	227.0793
14	0.90321	805.5652	40.9806
15	0.9535	1.71E+03	42.787
16	0.90626	1.01E+04	43.5497
17	0.93196	2.39E+03	19.4287
18	0.82326	6.87E+03	20.21
19	0.9188	2.71E+03	46.3432
20	0.94752	9.59E+03	18.249
21	0.94696	914.3805	53.9584
22	0.91646	1.04E+04	20.6975
23	0.93604	2.93E+03	40.1062
24	0.95008	1.97E+03	114.3078
25	0.85898	5.49E+03	72.9944
26	0.91428	1.92E+03	68.4901
27	0.87358	5.23E+03	28.0127
28	0.93541	2.10E+03	20.6213
29	0.84505	519.5149	626.8921
30	0.88409	1.45E+03	19.0804

a. Forecasting with FNN

Form Table 1, it can be mentioned that FNN performed well. Some out of range data is found in MAPE which happened because those consumers had no usage of electricity in their consumer profile at some hours of the day. Considering the case of MAPE, site 5 has the best output as 15.9883%. Consumer 5 has a moderate level of error (MSE = 572.452) and a very noticeable regression mismatch as it is far away from 1 (R=0.83974)

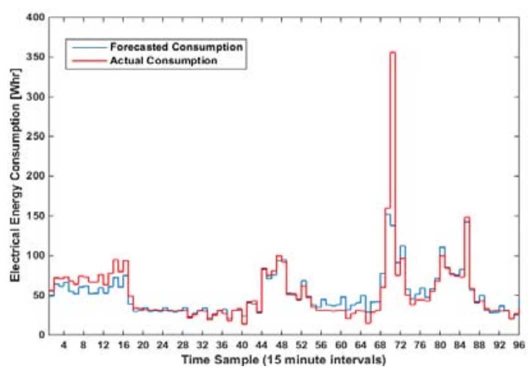

Figure 13: Forecasting performance of FNN for site 5

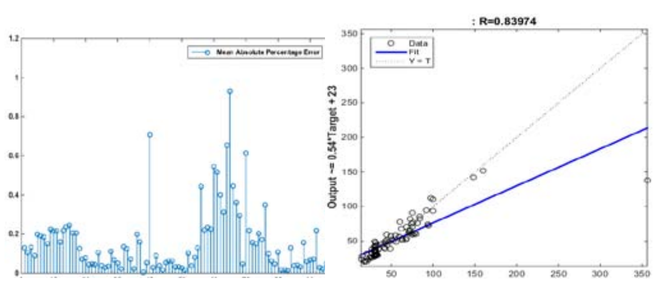

Figure 14: MAPE and R of forecasted output of site 5 by FNN

In Figure 4.2, the regression function and MAPE for the consumer is shown. The dotted line in the regression represents the exact result and the solid line represents the best fit regression line between the input and the output. The main reason for this deflection is for changing the behavior of the consumer at that particular time.

Lest MSE belongs to consumer 8 (MSE=343.6435). But the percentage error is as high as MAPE=25.3231%. In Figure 6-3 it is clearly visible that the output profile almost followed the trend. And most of the points are well predicted, though many of them are lower than the actual data

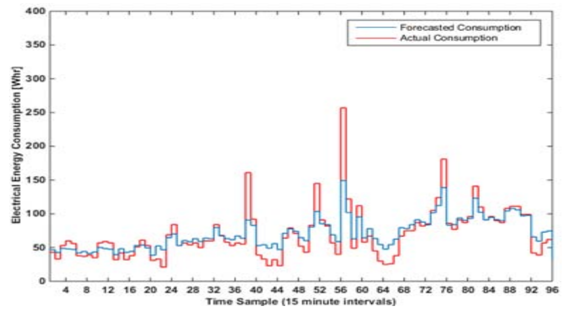

Figure 15: Forecasting performance of FNN for site 8

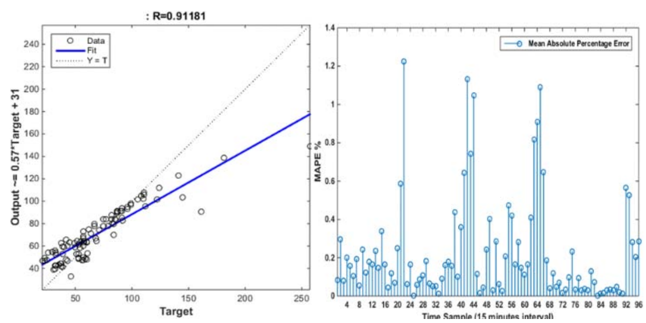

Figure 16: MAPE and R of forecasted output of site 8 by FNN

Figure 6-4, obtained regression function is comparatively good. The mismatched area lies in between 50 to 100Wh and the MAPE shows a scattered pattern of error. Moreover it is clear that the errors largely occurred at the peaks.

Finally, another consideration is done for other consumer for optimized evaluation. In this case the overall performance has been considered. The selected one is being consumer 2. For the selected consumer, R=0.8978; MSE=1260; MAPE=39.39. Though the R is obtained parameters are at moderate level as slightly mismatched from the ideal value, MAPE has been obtained in an acceptable range. But the MSE is so large that can affect the overall performance of the forecasting model.

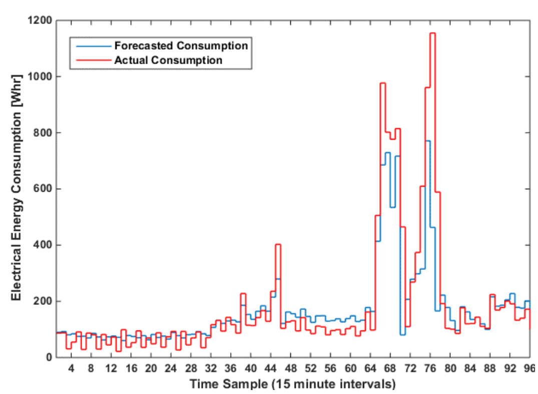

Figure 17: Forecasting performance of FNN for site 2

From the Figure 4.5, the forecasted data is matched in almost every point with the actual consumption profile. The major mismatch is found at the higher peaks. Though the forecasted model has followed and detected the positions of the peaks well, but the values estimated are lower than the actual consumption. This mainly happens for the change in the consuming behaviour of the consumer.

The regression function plotting is lineated based on the best points to be found. The most mismatching is found around 100 to 300Whr. Noticeable percentage errors are found at the peaks from the scattered plotting.

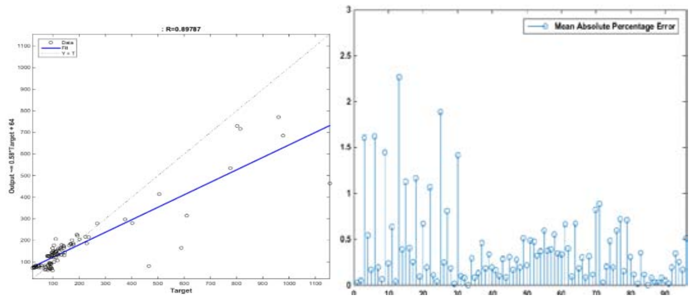

Figure 18: MAPE and R of forecasted output of site 2 by FNN

c) Scheduling

Based on the forecasted model, scheduling of the BTS storage device is designed and operated. For this research two ideal profiles are chosen. For the betterment of the demonstration, the available energy is compared with both actual consumption profile and the forecasted consumption profile.

For the demonstration consumer 2 is chosen. Figure 4.7 shows the scheduling of a storage device with the actual consumption profile. From the figure, available energy and stored energy is utilized in a balanced way. During the mid-hour of the day, amount of the available and stored energy is adequate. And the individual BTS has used the stored energy to meet its requirements.

The PV rating, in this case, is 7.5KW. So, the figure below clears out that, the consumer is using around 400W. That means, he can schedule the storing of the device a day ahead to save the rest 7.1KW of energy [16].

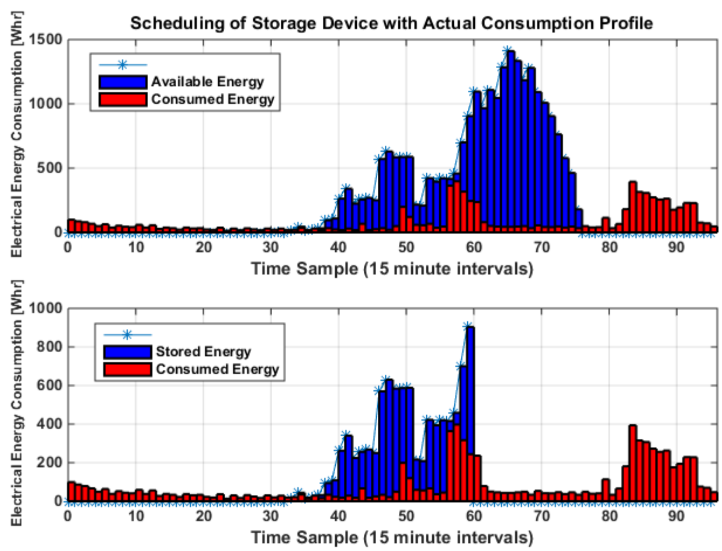

Figure 19: PV production and available energy for site 2

Forecasted consumption profile demonstrates the typical scheduling for the device. This is to determine the charging time of the storage device at the day ahead and to be aware of the amount of the energy to be used. From the figure 4.8, the needed energy for the next day can be estimated. It will be used to determine the time to store the energy and the dissipating time of the power. And based on the forecasted model, stored energy can be used to make the BTS grid free user. Thus a BTS can be grid independent and produce, store and consume its own energy.

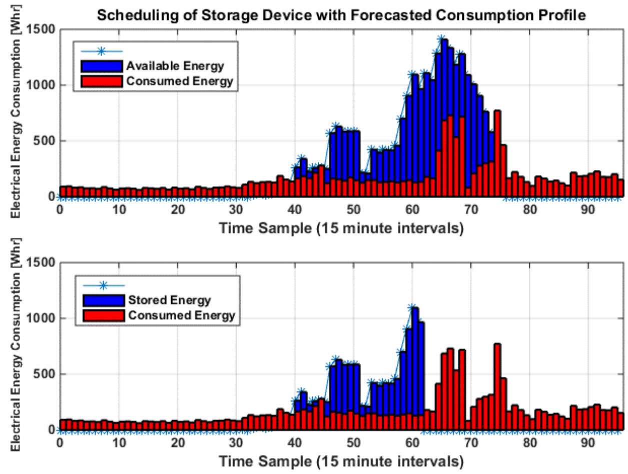

Figure 20: Storage device scheduling using FNN forecasted consumption profile

For further evaluation, consumption model of another consumer is illustrated in Figure 4.9, 4.10 that demonstrates the same scenario for consumer 17. That means, this profile will help the consumer to schedule, store and use the energy for its own.

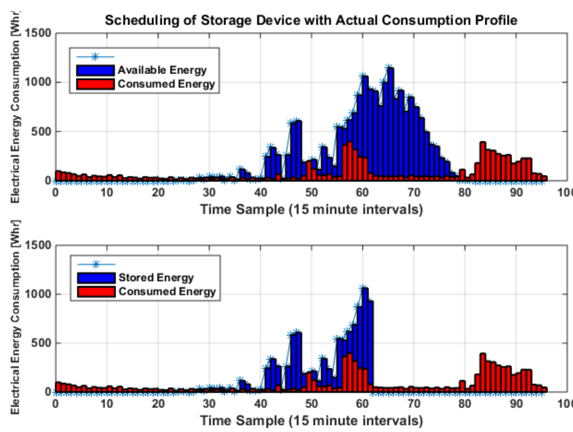

Figure 21: PV production and available energy for site 17

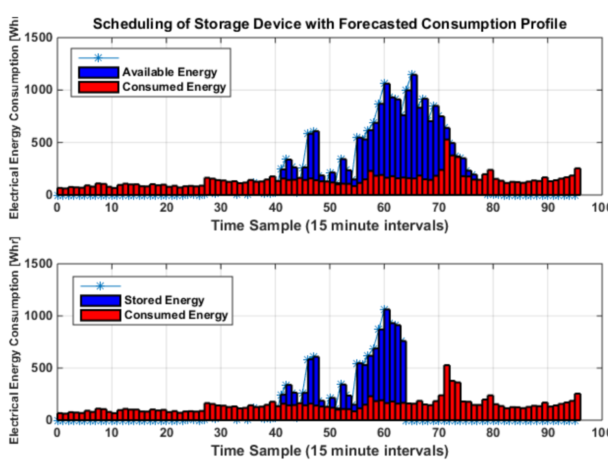

Figure 22: Storage device scheduling using FNN forecasted consumption profile

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V. Conclusion & Future Work

The main focus of this research work was to identify and justify a optimized forecasting model to forecast the electricity consumption at BTS and comparing the results on the basis of the major error measurement parameters and establishing a reliable and most accurate FNN forecasting model. The forecasted data can be used for designing the scheduling and designing the independent power source for the BTS. This will help the consumer to use its own power to meet its requirement. Thus, it can become grid free consumer.

However, the following recommendations are suggested for improving the forecaster.

Instead of using Levenberg-Marquardt algorithm; which is computationally heavy; another learning method called Scaled Conjugate Gradient (SCG) for bigger ANN approximation and prediction. Larger iteration number of hidden neurons is preferable for finding optimum solution. In STLF, ARIMA is proved as a poor forecaster because of having a significant level of non-linearity in historical data. However, a hybrid model combined with ANN and ARIMA is needed to be investigated. The input variables for the forecasting model should be selected based on partial mutual information (PMI) algorithm instead of the last known research experience only. This method will detect non-linear dependencies between the input and output as well as prevent the selection of inputs with redundant information. It will reduce the dimension of the input layer. Aside of using Neural Network Toolbox™ of MATLAB, better flexibility would be expected. Thus, the user will have more control on every step of the program.

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