Short Term Energy Forecasting Techniques For Virtual Power Plants

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***Abstract*— The advent of smart meter technology has enabled periodic monitoring of consumer energy consumption. Hence, short term energy forecasting is gaining more importance than conventional load forecasting. An Accurate forecasting of energy consumption is indispensable for the proper functioning of a virtual power plant (VPP). This paper focuses on short term energy forecasting in a VPP. The factors that influence energy forecasting in a VPP are identified and an artificial neural network based energy forecasting model is built. The model is tested on Sydney/ New South Wales (NSW) electricity grid. It considers the historical weather data and holidays in Sydney/ NSW and forecasts the energy consumption pattern with sufficient accuracy.**

Key words—Distributed Energy Management System, Energy forecasting, Neural networks, Smart Power Grids, Virtual power plant;

I. Introduction

The current decade has witnessed momentous changes in the electric power sector. One of the notable changes is the supplanting of the conventional fossil fuels with renewable energy resources. The rapid growth in renewable energy resources such as wind energy and solar energy have resulted in the power system gradually shifting from a centralized structure to a distributed one. In addition, the recent advancements in technology and the advent of smart meters have paved way for the concept of 'virtual power plant' [1].

A virtual power plant (VPP) is a link-up of small, distributed power stations, like wind farms, photovoltaic systems, small hydropower plants, biogas units and loads that can be switched on and off. It effectively connects coordinates and monitors decentralized power-generating sites, storage facilities and controllable loads via a common intelligent control center. In doing so, it can act within various energy markets in a manner similar to a conventional power plant.

The virtual power plant offers a broad variety of services to power plant operators, industrial enterprises, public services, electricity suppliers, power brokers and grid operators. The commercial activities of VPP include whole sale market trading which involves aggregation of the distributed energy resource (DER) capacity and optimizing the revenue for the DERs. The technical activities include frequency, voltage and reserve regulation, black start, grid inertial response etc [2]. The effective functioning of the above mentioned services requires accurate forecasting of the consumer demand pattern.

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Short term load forecasting method for micro-grids is proposed in [3]. The load data is decomposed into different modes and trends using empirical mode decomposition (EMD). Extended kalman filter and machine learning algorithm are used to forecast the components with different characteristics.

With the advent of smart meters periodic monitoring of the energy consumption is possible. Hence, in recent years forecasting the consumer energy consumption is preferred to load forecasting which is well established in literature. Moreover, short term energy forecasting is an integral function of the VPP. As a VPP comprises DERs, storage as well as controllable loads it is required to take into account the storage requirements while forecasting the energy demand [4].

The commonly adopted energy forecasting techniques are based on time series regression methods, fuzzy logic, artificial neural network (ANN) and support vector machines [5-11]. Reference [6] investigates the influence of a one directional ANN structure (number of hidden layers and number of neurons in layers) on the midterm energy forecast quality. The over learning phenomena that occurs in an ANN is also discussed.

A fuzzy logic methodology proposed in [8] for midterm energy forecasting transforms the candidate input variables such as the gross national product, statistical indices of coal and oil into differences or relative differences. The final inputs are selected using correlation analysis. The primary advantage of the proposed fuzzy logic system is that the training set requires only few samples. Reference [8] also presents an adaptive ANN that employs correlation analysis to select the final input variables.

References [9] and [10] have proposed models for long term and midterm energy forecasting. Empirical mode decomposition method is used to disaggregate a time series into two sets of components, one describing the trend and the other the local oscillations in the energy consumption values. Support vector regression models [9] and ANN models [10] developed are then trained using these sets. An online forecasting method for solar power production is proposed in [11]. Solar power is normalized using a clear sky model based on quantile regression. Linear time series methods are then used to forecast the solar power. The inputs are numerical weather predictions and observations of solar power.

Short term energy forecasting plays a vital role in planning energy transactions, electricity market pricing and scheduling generation. However, there is a dearth of literature on short term energy forecasting. Hence, this paper deals with the development of a short term energy forecasting model for a virtual power plant. The additional inputs that are to be considered while developing an energy forecasting model suitable for a VPP are discussed. An adaptive neural network based short term energy forecasting model is employed to forecast the energy demand.

The paper is organized as follows section II explains the basic structure of a VPP, section III discusses the factors that influence short term energy forecasting in a VPP, section IV describes the ANN based energy forecasting model, section V describes the energy consumption patterns in Sydney, Australia, section VI presents the case studies where the forecasting model is used to predict the energy demand in Sydney/ New South Wales (NSW) and section VII the conclusion.

II. STRUCTURE OF A VIRTUAL POWER PLANT

The basic structure of a virtual power plant is shown in Fig. 1.

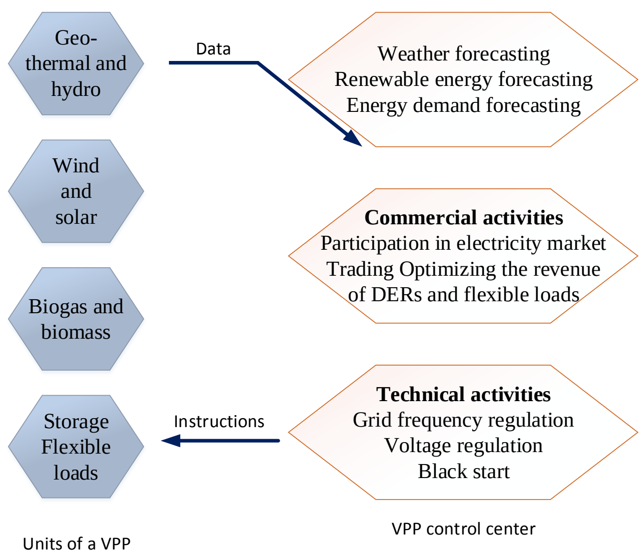

Fig. 1Basic structure of a virtual power plant

The DEMS forecasts the weather, renewable generation and energy demand. Based on these forecasts it carries out generation management, load management and scheduling. The DEMS while performing generation management has to consider the technical constraints of the DERs, the actual state of the DERs and its real and reactive power set points and while performing load management, the number of controllable loads available with a given consumer, the control strategy adopted, building area characteristics etc.

III. FACTORS INFLUENCING ENERGY FORECASTING IN VPP

Energy consumption is a non-stationary process influenced by a wide range of factors. For accurate prediction of energy demand, the forecasting model should take into account the variables that influence the consumption of energy. In addition to the traditional factors, energy demand in a VPP is influenced by several other factors. The main factors that influence energy forecasting in a VPP are discussed in this section.

A. *Traditional factors*

The following are the traditional factors that affect short term energy forecasting

Calendar variables: The day of the week whether it is a weekday or holiday and hour of the day influence energy forecasting significantly.

Seasonality

Weather variables: Climatic conditions considered may include temperature, humidity, wind chill index, illumination, rainfall, precipitation, cloud cover and some special events like typhoon or sleet occurrences.

Holiday effects: Local events, including holidays and festivities, also affect the energy demand. These events may lead to either an increase or decrease in demand. Influences of these events are usually local and highly depend on the customs of the area. The energy demand also depends on what holiday it is and whether it occurs on a weekday or a weekend.

Random events and disturbances such as abnormal consumption behavior, idiosyncratic and social habits of the individuals.

B. *Additional factors to be considered for a VPP*

The additional variables that are to be considered while forecasting energy consumption in a VPP are:

Storage requirements in a VPP: The storage requirements in a VPP vary according to the services provided by the VPP. For example in order to regulate grid frequency a VPP requires batteries with high power, fast response and long partial life cycle [10]. Hence, energy forecasting depends upon the cost of energy storage, number of storage units available and reliability of the storage units.

Flexible loads in a VPP: The number of controllable devices each customer has, the type of control strategy adopted, the start and end time of each load control cycle and the length of each time step influence energy forecasting in a VPP.

Smart grid factors: Smart grid factors such as electricity prices, demand response, distributed energy resources and electric vehicles also affect energy forecasting

Lack of historical data: Almost all of the short term forecasting tools rely on historical data for the development of a forecasting model. Typically several years of reliable historical data is needed for this purpose. The impediments for obtaining reliable historical data are the rapid increase in electricity demand over the past few years. This has resulted in dramatic changes in the energy consumption pattern. The regulated era historical load data is being employed to predict the demand pattern in a deregulated, price sensitive environment. Some holidays are observed based on the lunar calendar. Hence, the day-type and the time factor of those holidays change every year. Therefore, there is a dearth in historical data available to forecast the energy consumption pattern for these holidays.

Comfort index of the user Building characteristics (construction materials and dimensions)

IV. Neural Network Based Energy Forecasting Model

An artificial neural network based energy forecast model is used to predict the energy consumption.

A. *Artificial neural network (ANN)*

An ANN is a highly connected array of elementary processors called neurons. A multi-layered feed-forward neural network is shown in Fig. 2.

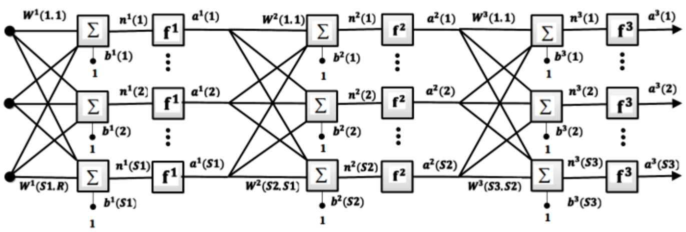

Fig. 2 A three layered feed-forward neural network

It consists of one input layer, one or more hidden layers and one output layer. Each layer employs several neurons and each neuron in a layer is connected to the neurons in the adjacent layer with different weights (W_{ij}). Signals flow into the input layer, pass through the hidden layers, and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by the interconnect values between neurons. The neuron then produces its output signal by passing the summed signal through a sigmoid function.

A total of P sets of training data are assumed to be available. The factors that influence energy forecasting are the inputs to the ANN and they are imposed on the top layer. The ANN is trained to respond to the corresponding target vectors, on the bottom layer. The training continues until a certain stop-criterion is satisfied. Typically, training is halted when the average error between the desired and actual outputs of the neural network over the P training data sets is less than a predetermined threshold. The training time required is dictated by various elements including the complexity of the problem, the number of data, the structure of network, and the training parameters used [12,13].

B. *Training of the neural network*

In a neural network signals can only be propagated from the input layer to the hidden layers and from the hidden layers to the output node. Signal propagation between nodes within the same layer or from the input layer directly to the output layer is not permitted.

For each neuron in the input layer, the neuron output is the same as the neuron input. For each neuron i in the hidden layer $k+1$, the net input is given by

$$n^{k+1}(i) = \sum_{j=1}^{Sk} w^{k+1}(i,j)a^k + b^{k+1}(i) \quad (1)$$

where, j is a neuron in the preceding layer.

The neuron output is given by

$$a^{k+1}(i) = f^{k+1}(n^{k+1}(i)) \quad (2)$$

This paper uses Levenburg-Marquardt algorithm [12]to derive the connection weights of the feedforward network from the P input output patterns. Levenburg-Marquardt algorithm is an approximation of the Newton's method and is explained in this section.

For a M layered network the system equations in matrix form are given as

$$\underline{a}^0 = \underline{p}$$

$$\underline{a}^{k+1} = \underline{f}^{k+1}(W^{k+1}\underline{a}^k + \underline{b}^{k+1})$$

$$k = 0,1,\ldots,M-1 \quad (3)$$

The network has to learn the association between specific input and output pairs $\{(p_1,t_1), (p_2,t_2),\ldots (p_p,t_p)\}$

The performance index of the network is the sum of squares function

$$V(\underline{W}) = \sum_{j=1}^{P} e_i^2(\underline{W}) \quad (4)$$

Levenburg-Marquardt algorithm is used to solve(4) which is to be minimized with respect to the connection weights

$$\Delta\underline{W} = [J^T(\underline{W})J(\underline{W}) + \mu I]^{-1}J^T(\underline{W})\underline{e}(\underline{W}) \quad (5)$$

where, $J(\underline{W})$ is the Jacobian matrix

$$J(\underline{W}) = \begin{bmatrix} \frac{\partial e_1(\underline{W})}{\partial W_1} & \cdots & \frac{\partial e_1(\underline{W})}{\partial W_p} \\ \vdots & \ddots & \vdots \\ \frac{\partial e_p(\underline{W})}{\partial W_1} & \cdots & \frac{\partial e_p(\underline{W})}{\partial W_p} \end{bmatrix}$$

C. *Energy forecasting model based on ANN*

The development of an energy forecasting model based on ANN is described in this section. The flowchart describing the design of energy forecasting model is shown in Fig. 3.

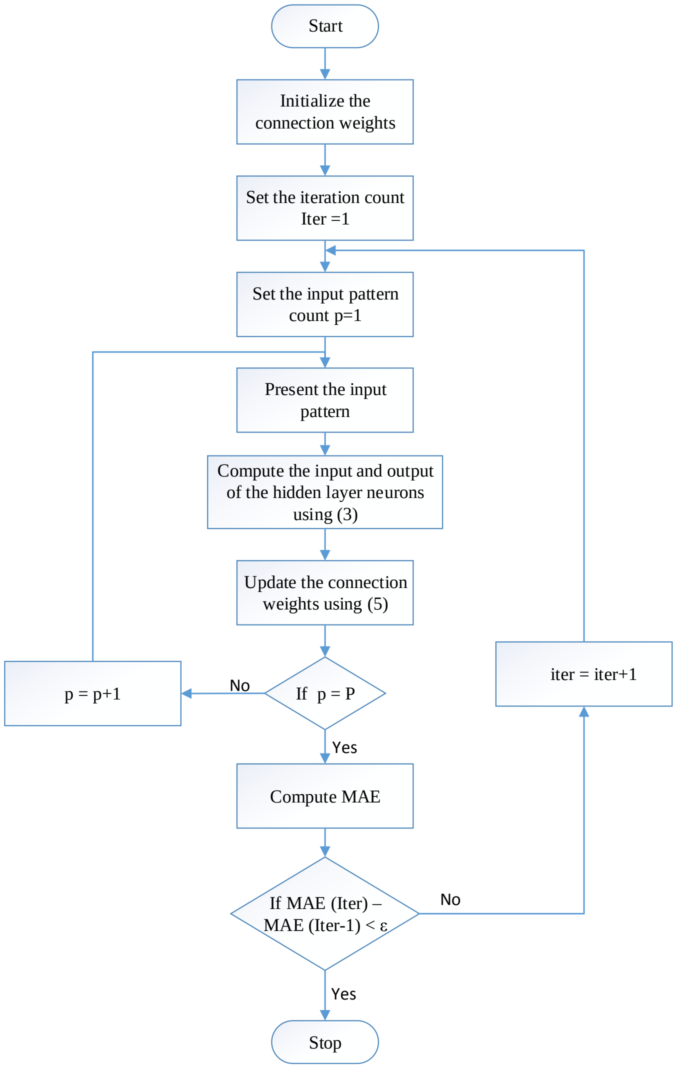

Fig. 3 Flow chart for Energy Forecasting Model

The training set comprises historical hourly energy consumption data and weather data. The input signals for a particular training pattern include the daily temperatures, humidity, holidays, average loads for the preceding week and the calendar variables.

The multilayer feed forward neural network is then trained using Levenburg-Marquardt algorithm. The performance index to be minimized is the standard demand prediction metric, mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{P}\sum_{t=1}^{P}\frac{|\hat{E}_t - E_t|}{|E_t|} \quad (6)$$

where, P is the number of energy values, $\hat{E}_t$ is the forecasted energy values.

The output layer contains only one unit which provides the output which is the system peak load.

V. Energy Consumption Pattern

The energy consumption pattern in Sydney/ New South Wales (NSW) is discussed in this section. The hourly energy data for Sydney/ NSW during the time period of 2006-2009 is obtained from Australian energy market operator (AEMO).

The hourly energy consumption during weekdays and weekends is shown in Fig. 4. The hourly energy consumption is identical during weekdays but during weekends the amount of energy consumed is less. The maximum energy consumption occurs around 11:00 AM during weekdays and 3:30 during weekends. The maximum energy consumed during a weekday is 9874.72MWh while during weekends is 8745.81 MWh implying a 13% increase in energy consumption during weekends.

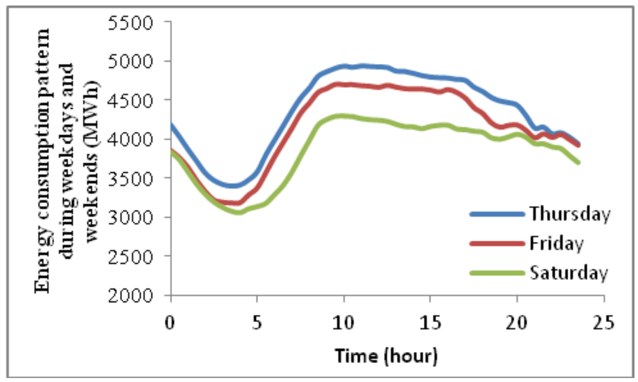

Fig. 4 Energy consumption pattern during weekdays and weekends

The energy consumption pattern during 2006-2009new years is shown in Fig. 5

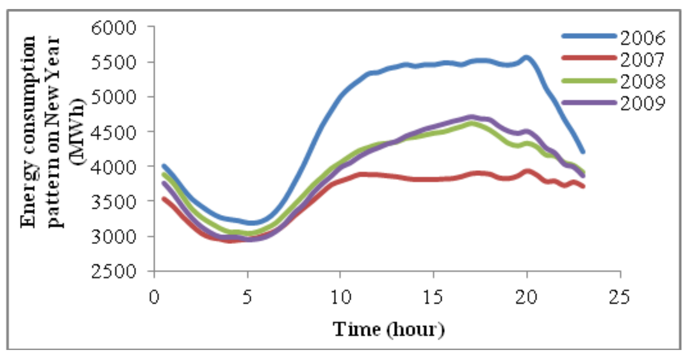

Fig. 5 Energy consumption pattern during New Years

It can be seen from Fig. 5 that energy consumption during New Year exhibits an identical pattern during the years 2006-2009. However, the energy consumed during the year 2006 is significantly higher (11,112.76 MWh) than the other years and in years 2008 and 2009 the energy consumption is almost similar. Hence as discussed in section III it is imperative that a forecasting model considers weekdays, weekends and holidays while forecasting energy.

VI. Simulation Studies

The ANN based energy forecasting model described in section IV is used to predict the energy consumption pattern in Sydney / NSW during the year 2010.

A. *Data used*

The historical hourly load pattern and temperatures obtained from AEMO for Sydney/ NSW during the years 2006 – 2009 are used to train the ANN based energy forecasting model.

The forecasting model also considers the type of day (weekdays or weekends or holidays such as Christmas and New Year) while predicting the energy consumption pattern. Table I gives the list of holidays during the time period considered.

TABLE I
LIST OF HOLIDAYS IN SYDNEY/NSW (2006-2009)

Date	Holiday
1/1/2006, 1/1/2007, 1/1/2008, 1/1/2009	New Year's Day
1/26/2006, 1/26/2007, 1/26/2008, 1/26/2009	Australia Day
4/14/2006	Good Friday
4/17/2006	Easter Monday
4/25/2006, 4/25/2007, 4/25/2008, 4/25/2009	Anzac Day
6/12/2006, 6/12/2007, 6/12/2008, 6/12/2009	Queens Birthday
10/2/2006, 10/2/2007, 10/2/2008, 10/2/2009	Labour Day
12/25/2006, 12/25/2007, 12/25/2008, 12/25/2009	Christmas
12/26/2006, 12/26/2007, 12/26/2008, 12/26/2009	Boxing Day
4/6/2007	Good Friday
4/9/2007	Easter Monday
3/21/2008	Good Friday
3/24/2008	Easter Monday
4/10/2009	Good Friday
4/13/2009	Easter Monday

The other input variables considered while training the neural network are the

- Dry bulb temperature
- Wet bulb temperature
- Humidity
- Dew point temperature
- Hour of day
- Day of the week
- Previous 24-hr average load
- 24-hr lagged load
- 168-hr (previous week) lagged load

B. *Simulation studies*

The forecasting model described in section IV is trained using the energy consumption data obtained during the period of January 2006 to December 2009. The total size of training data 14610 and it comprises the weather and energy consumption data. The model is developed using MATLAB toolbox [13]. An adaptive neural network with two hidden layers and twenty neurons in each layer is created. The number of connecting weights is 281.

The model is then tested by forecasting the energy consumption during the year 2010 and comparing it with the actual energy demand in 2010.The half hourly pattern of energy forecasted during 2010 is compared with the actual energy pattern in Fig. 6. From Fig. 6 it can be seen that the energy forecasting model is capable of forecasting energy consumption with sufficient accuracy. The mean average percentage error is 2.03 % and the mean absolute error is 89.57 MWh which is within acceptable limits. The daily peak MAPE is 2.13 %.

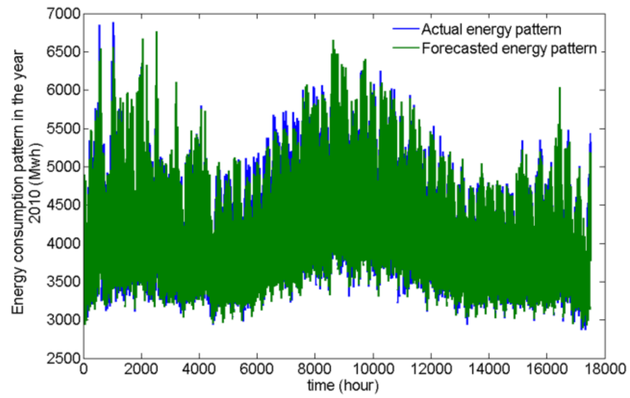

Fig. 6 Comparison of actual and forecasted energy consumption during 2010

Fig. 7 shows the error in forecasting. From Fig. 7 it can be seen that the maximum error is 944.318MWh further substantiating the accuracy of the ANN model.

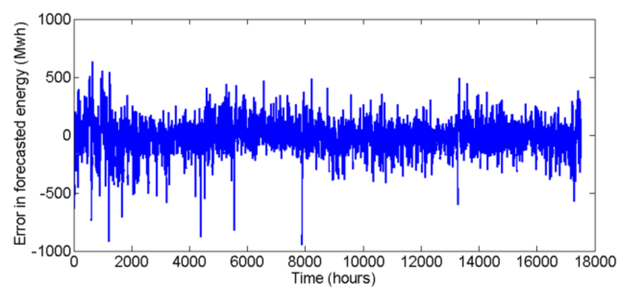

Fig. 7 Error in energy consumption forecasting

The histogram of error distribution is shown in Fig. 8. From Fig. 8 it can be seen that the error distribution is symmetric and the mean is at the centre which is around -10 MWh. The percentage absolute error exhibits a distribution that is skewed right and the maximum frequency of occurrence is around 0 to 0.26%.

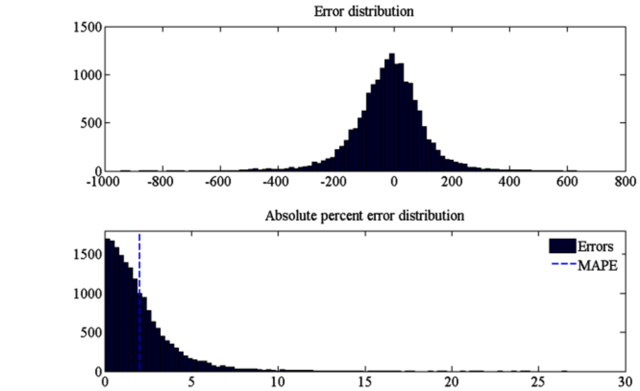

Fig. 8 Histogram of error distribution and MAPE distribution

The half hourly consumption pattern for a week between 01/01/2010 to 07/01/2010 is also shown in Fig. 9. The MAPE for the specified duration is only 1.6586%. Therefore, from the simulation results it can be concluded that the forecasting model provides an adequate prediction of the energy consumption pattern.

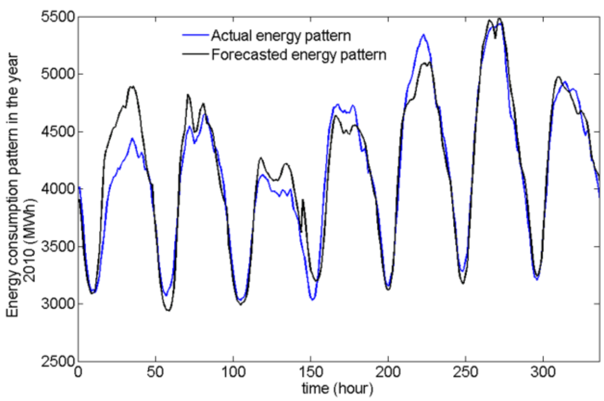

Fig. 9 Weekly energy consumption pattern

VII. Conclusions

This paper deals with the forecasting of short term energy consumption in a virtual power plant. The major factors that influence short term energy forecasting in a VPP are discussed. An ANN based short term energy forecasting model is built. The developed model is then tested on the Sydney/NSW system. The ANN based forecasting model predicts the energy consumption with sufficient accuracy. The MAPE and MAE indices are within permissible limits. Future challenges involve developing a forecasting model that considers the storage requirements in a VPP while forecasting energy.

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