Short-Term Electricity Demand Forecasting Method for Smart Meters

K. S. K. Weranga*, D. P. Chandima*, S. R. Munasinghe+, S. P. Kumarawadu*, A. M. Harsha S. Abeykoon*
*Department of Electrical Engineering
University of Moratuwa, Katubedda 10400
Moratuwa, Sri lanka
kskasunweranga@gmail.com, dpchandima@ieee.org, sisilkuma@ieee.org , harsha@elect.mrt.ac.lk
+Department of Electronic and Telecommunication Engineering
University of Moratuwa, Katubedda 10400
Moratuwa, Sri lanka
rohan@ent.mrt.ac.lk

***Abstract*— The short-term electricity demand forecasting has become one of the major research area in power system engineering. By combining the smart metering to the short-term demand forecasting techniques, new features can be added to save on demand and electricity bill. This paper illustrates the methodology used to forecast electricity demand over short period of time which can be used with smart meters. Polynomial fitting with interpolation is used to forecast the demand by taking the apparent power sample points from smart meters. The outcome of this work will be beneficial to the residential or industrial electricity consumers to control the demand side loads. It will help the industrial consumers to save on maximum demand charge with the introduction of warning message or residential consumers to reduce their electricity bill by cutting down non-essential loads in peak hours.**

I. Nomenclature

GMS	Global System for Mobile Communications
LKR	Sri Lanka Rupees
SMS	Short Message Service
STDF	Short-Term Demand Forecasting

II. Introduction

DEMAND forecasting is an important component for any energy management system. Electricity demand forecasting can be divided into three categories that are short-term demand forecasting, medium-term demand forecasting and long-term demand forecasting [1-2]. STDF caters for prediction lead time of several minutes to few days ahead [3-4]. The model developed here is designed to forecast the demand for next 5 minutes and the time horizon is very small. Therefore it falls to the category of STDF.

STDF provides many advantages to the electricity suppliers and the consumers. In this research we focus on the STDF and how it contributes to the demand side load management. This methodology can be used with smart meters to forecast the demand, calculate the maximum demand and to control the demand side load. Furthermore the forecasted demand in next 5 minutes can be used to generate warning signals. However different utilities may have different sampling time period for their maximum demand calculation and the methodology can be modified accordingly. Ultimately the output of this research study will help to reduce the demand and save electricity bill for both residential and industrial consumers.

Industrial consumers are looking for better energy management practices to reduce cost of electricity. The electricity bill is prepared considering both active energy and maximum demand by some power utilities. Maximum demand is like a penalty for industrial consumers where they have poor power factor. They get extra reactive power from the system to drive their machinery apart from real power. This will cause additional current flow in the supply cables and increase the heat loss. With the improved power factor, the maximum demand can be reduced to some extent. It could be the installment of a capacitor bank at the consumer end. However this kind of mechanism provides only the reactive energy required. Although some industries have good power factors (above 0.9), they face problems due to the unexpected maximum demand which is higher than their average monthly demand. Due to simultaneous start of heavy electrical machinery, failure in already installed capacitor bank and run of non-essential loads at peak demand will lead to a higher maximum demand. By using a system to measure the abnormal change in demand with the STDF method, the maximum demand charge can be reduced under above conditions. It will be an additional benefit if the system can warn the consumer before the end of demand calculation time period where there is a potential of rise in demand.

When it comes to the residential electricity consumers, the STDF will be beneficial where they can save on electricity cost under real time price schemes. For an example activation of an alarm signal when there is a potential of rise in demand over the user defined demand and the tariff is over the specified level, will warn the consumer. This kind of mechanism will help switch off non-essential loads in peak hours thereby reduce their monthly bills. On the other hand STDF method contributes smart meters to take control actions when they have access to appliance and equipment controllers. It can be done by reducing loads to pre-set levels, switching off non-essential loads, cycling loads on and off according to pre-set timing schedules and sending waiting signals to loads at higher demands and higher tariff rates.

III. METHODOLOGY

Electricity demand forecasting models can be classified in one of the two broad categories: static models and dynamic models [5]. The load is considered as linear combination of explicit time functions, sinusoids, exponentials or polynomials in the static models. The coefficients of these functions are estimated trough linear regression or exponential smoothing techniques applied to a set of load data for recent past. Dynamic models incorporate in their predictions the cumulative effects of such factors as recent load behavior, weather and random effects [5].

Some consumers typically follow the same load pattern for each week day. The load behaviors in weekend also have closer relationships. By considering the nature of the demand in consumers we can use a simple and accurate model using polynomial interpolation to forecast the demand for next 5 minutes which falls under the static models. Therefore this methodology can be applied to domestic or industrial consumers whose load patterns are highly time dependant for 15 minutes cycle.

Due to the small time horizon in STDF, the recent load behavior has a major effect on future demand. Hourly or half-hourly data are used in most short-term electricity forecasting studies [6]. In this research the forecasting time period has been narrowed down to 5 minutes. Therefore demand in last 10 minutes is taken to forecast the demand in next 5 minutes. Effective forecasting, however, is difficult in view of the complicated effects on load by a variety of factors [3-4]. Nevertheless this kind of static model can be easily implemented inside a smart meter to reduce the calculation time and narrow down the model parameters. When considering the smart meters, this system doesn’t require any kind of model parameters feed system to perform the calculation compared to other type of STDF methods. Proper analysis of historical demand data is mandatory before apply this method to a certain consumer. The accuracy should also be tested in long run after applying this method to a consumer.

The apparent power readings from the smart meter are collected in regular intervals and processed to build a mathematical model. The calculation time of demand is considered as 15 minutes which is commonly used in most countries. Ten sample points are taken to derive a 4th order polynomial considering the demand variation. Therefore within each 15 minute interval instantaneous apparent power is read in first 10 minutes. Thereafter the polynomial equation for the demand is derived and demand is forecasted for the next 5 minutes. If the forecasted demand exceeds the user defined demand level, the warning signal is generated.

4th order polynomial demand variation is selected in this study to illustrate the forecasting methodology. However this methodology can be modified for higher orders as well. It has been selected by pre study of several consumers whose demands are highly time dependant for 15 minutes cycle. By analyzing the historical data of a consumer for one week, we have found that fitting a 4th order polynomial gives a good accuracy compared to lower order polynomials. When the order is higher than the 4th order, the accuracy has small effects with the order. On the other hand when the order is high, more calculation time and more samples points are required. This will be a disadvantage when this methodology is implemented for microcontrollers in smart meters. Therefore 4th order polynomial fitting is selected considering above factors. However the polynomial order can be changed by analyzing the historical data for a given consumer. Higher orders might be more accurate for some consumers. Therefore this methodology can be modified accordingly in such occasions to increase the accuracy.

A. *Mathematical Model with Polynomial Interpolation*

In this research mathematical model is used to come up with the best possible forecast which the smart meter developers can accept with a reasonable confidence. Curve fitting is achieved using polynomial interpolation. Curve fitting is the process of constructing a curve that has the best fit to a series of data points involving interpolation. Interpolation provides more accuracy than extrapolation when the data have some noise. Otherwise extrapolation could be used to construct a 4th order polynomial by taking only five sample points within 15 minutes cycle.

In interpolation, it is assumed that the trend in the past will persist into the future [7]. It can be used where an exact fit to the data is required with statistical inference. It is focused on how much uncertainty is present in a curve that is fit to data observed with random errors. Even though the observed data are with random errors it provides an exact fit to the apparent power variation within 15 minutes interval. Therefore to develop a more accurate model, interpolation can be used with 10 sample points inside a 15 minutes cycle.

Now consider a particular consumer whose demand pattern is highly time dependant for 15 minutes cycle. If the historical data analysis shows a good accuracy for the 4th order polynomial fitting, the demand can be written as a function of time for 15 minutes as in (1).

$$f(t) = a_4 t^4 + a_3 t^3 + a_2 t^2 + a_1 t + a_0 \tag{1}$$

where;
$f(t)$ is the demand in kVA
t is the time in minutes
a_4 , a_3 , a_2, a_1, a_0 are coefficients of the polynomial and they will change in each 15 minutes cycle with time.

Now we can write 4 equations considering the average values for interpolation.

$$a_4\overline{t^4} + a_3\overline{t^3} + a_2\overline{t^2} + a_1\bar{t} + a_0 = \bar{f} \tag{2}$$
$$a_4\overline{t^5} + a_3\overline{t^4} + a_2\overline{t^3} + a_1\overline{t^2} + a_0\bar{t} = \overline{ft} \tag{3}$$
$$a_4\overline{t^6} + a_3\overline{t^5} + a_2\overline{t^4} + a_1\overline{t^3} + a_0\overline{t^2} = \overline{ft^2} \tag{4}$$
$$a_4\overline{t^7} + a_3\overline{t^6} + a_2\overline{t^5} + a_1\overline{t^4} + a_0\overline{t^3} = \overline{ft^3} \tag{5}$$
$$a_4\overline{t^8} + a_3\overline{t^7} + a_2\overline{t^6} + a_1\overline{t^5} + a_0\overline{t^4} = \overline{ft^4} \tag{6}$$

where;
$\bar{t} = \frac{1}{n}\sum t_i$, $\overline{t^2} = \frac{1}{n}\sum t_i^2$, $\overline{t^3} = \frac{1}{n}\sum t_i^3$, $\overline{t^4} = \frac{1}{n}\sum t_i^4$,
$\overline{t^5} = \frac{1}{n}\sum t_i^5$, $\overline{t^6} = \frac{1}{n}\sum t_i^6$, $\overline{t^7} = \frac{1}{n}\sum t_i^7$, $\overline{t^8} = \frac{1}{n}\sum t_i^8$
and
$\bar{f} = \frac{1}{n}\sum f_i$, $\overline{ft} = \frac{1}{n}\sum t_i f_i$, $\overline{t^2 f} = \frac{1}{n}\sum t_i^2 f_i$, $\overline{t^3 f} = \frac{1}{n}\sum t_i^3 f_i$, $\overline{t^4 f} = \frac{1}{n}\sum t_i^4 f_i$
n is referred to number of sample points

Converting the equations to matrix form

$$\begin{bmatrix} \overline{t^4} & \overline{t^3} & \overline{t^2} & \bar{t} & 1 \\ \overline{t^5} & \overline{t^4} & \overline{t^3} & \overline{t^2} & \bar{t} \\ \overline{t^6} & \overline{t^5} & \overline{t^4} & \overline{t^3} & \overline{t^2} \\ \overline{t^7} & \overline{t^6} & \overline{t^5} & \overline{t^4} & \overline{t^3} \\ \overline{t^8} & \overline{t^7} & \overline{t^6} & \overline{t^5} & \overline{t^4} \end{bmatrix} \begin{bmatrix} a_4 \\ a_3 \\ a_2 \\ a_1 \\ a_0 \end{bmatrix} = \begin{bmatrix} \bar{f} \\ \overline{tf} \\ \overline{t^2 f} \\ \overline{t^3 f} \\ \overline{t^4 f} \end{bmatrix}$$

Considering one particular 15 minutes cycle, 10 sample points can be taken from t=1 to t=10 minutes to fit the curve. Thereafter the demand and the area are forecasted for next 5 minutes. The sampling and forecasting method is illustrated in Fig.1.

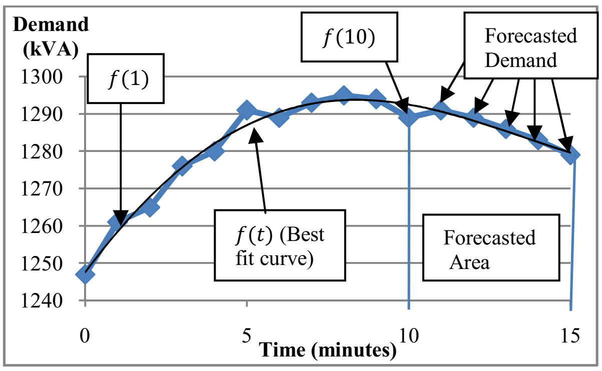

Fig. 1. Data sampling using demand pattern

Due to the 10 sample points, n=10. Therefore the matrix becomes

$$\begin{bmatrix} 2533.3 & 302.5 & 3.85 & 5.5 & 1 \\ 22082.5 & 2533.3 & 302.5 & 3.85 & 5.5 \\ 197840.5 & 22082.5 & 2533.3 & 302.5 & 3.85 \\ 1808042.5 & 197840.5 & 22082.5 & 2533.3 & 302.5 \\ 16773133 & 1808042.5 & 197840.5 & 22082.5 & 2533.3 \end{bmatrix} \begin{bmatrix} a_4 \\ a_3 \\ a_2 \\ a_1 \\ a_0 \end{bmatrix} = \begin{bmatrix} \bar{f} \\ \overline{tf} \\ \overline{t^2 f} \\ \overline{t^3 f} \\ \overline{t^4 f} \end{bmatrix}$$

Taking the inverse matrix

$$\begin{bmatrix} a_4 \\ a_3 \\ a_2 \\ a_1 \\ a_0 \end{bmatrix} = \begin{bmatrix} 2533.3 & 302.5 & 3.85 & 5.5 & 1 \\ 22082.5 & 2533.3 & 302.5 & 3.85 & 5.5 \\ 197840.5 & 22082.5 & 2533.3 & 302.5 & 3.85 \\ 1808042.5 & 197840.5 & 22082.5 & 2533.3 & 302.5 \\ 16773133 & 1808042.5 & 197840.5 & 22082.5 & 2533.3 \end{bmatrix}^{-1} \begin{bmatrix} \bar{f} \\ \overline{tf} \\ \overline{t^2 f} \\ \overline{t^3 f} \\ \overline{t^4 f} \end{bmatrix}$$

where;

$$\bar{f} = \frac{1}{10}\begin{bmatrix} f(1) + f(2) + f(3) + f(4) + f(5) \\ + f(6) + f(7) + f(8) + f(9) + f(10) \end{bmatrix}$$

$$\overline{ft} = \frac{1}{10}\begin{bmatrix} f(1) + 2f(2) + 3f(3) + 4f(4) + 5f(5) \\ + 6f(6) + 7f(7) + 8f(8) + 9f(9) + 10f(10) \end{bmatrix}$$

$$\overline{ft^2} = \frac{1}{10}\begin{bmatrix} f(1) + 2^2 f(2) + 3^2 f(3) + 4^2 f(4) + 5^2 f(5) \\ + 6^2 f(6) + 7^2 f(7) + 8^2 f(8) + 9^2 f(9) + 10^2 f(10) \end{bmatrix}$$

$$\overline{ft^3} = \frac{1}{10}\begin{bmatrix} f(1) + 2^3 f(2) + 3^3 f(3) + 4^3 f(4) + 5^3 f(5) \\ + 6^3 f(6) + 7^3 f(7) + 8^3 f(8) + 9^3 f(9) + 10^3 f(10) \end{bmatrix}$$

$$\overline{ft^4} = \frac{1}{10}\begin{bmatrix} f(1) + 2^4 f(2) + 3^4 f(3) + 4^4 f(4) + 5^4 f(5) \\ + 6^4 f(6) + 7^4 f(7) + 8^4 f(8) + 9^4 f(9) + 10^4 f(10) \end{bmatrix}$$

Now the coefficients become

$$\begin{aligned} a_4 = {} & 0.003f(1) - 0.003f(2) - 0.002f(3) + 0.000f(4) \\ & + 0.003f(5) + 0.003f(6) + 0.000f(7) - 0.002f(8) \\ & - 0.003f(9) + 0.003f(10) \end{aligned} \tag{7}$$

$$\begin{aligned} a_3 = {} & -0.006f(1) + 0.073f(2) + 0.061f(3) - 0.004f(4) \\ & - 0.005f(5) - 0.060f(6) - 0.016f(7) + 0.048f(8) \\ & + 0.068f(9) - 0.049f(10) \end{aligned} \tag{8}$$

$$\begin{aligned} a_2 = {} & 0.579f(1) - 0.553f(2) - 0.525f(3) - 0.040f(4) \\ & + 0.369f(5) + 0.446f(6) + 0.158f(7) - 0.290f(8) \\ & - 0.464f(9) + 0.310f(10) \end{aligned} \tag{9}$$

$$a_1 = -2.079f(1) + 1.491f(2) + 1.619f(3) + 0.373f(4) - 0.816f(5) - 1.159f(6) - 0.507f(7) + 0.644f(8) + 1.162f(9) - 0.728f(10) \quad (10)$$

$$a_0 = 2.499f(1) - 0.833f(2) - 1.249f(3) - 0.417f(4) + 0.499f(5) + 0.833f(6) + 0.417f(7) - 0.417f(8) - 0.833f(9) + 0.499f(10) \quad (11)$$

Equation of the polynomial can be found if the values are known from $f(1)$ to $f(10)$. However to generate a warning signal regarding the maximum demand, the average apparent energy within 15 minutes should be calculated. Therefore it is necessary to forecast the apparent energy during *t*= 10 minutes to *t*=15 minutes. To find the apparent energy for next 5 minutes, the polynomial should be integrated form *t*=10 to *t*=15 minutes.

If the forecasted apparent energy in next 5 minutes is A_1

$$A_1 = a_4 \int_{10}^{15} t^4 dt + a_3 \int_{10}^{15} t^3 dt + a_2 \int_{10}^{15} t^2 dt + a_1 \int_{10}^{15} t^1 dt + a_0 \int_{10}^{15} t^0 dt$$

By replacing coefficients

$$A_1 = 18.382f(1) - 27.908f(2) - 16.755f(3) + 10.406f(4) + 26.872f(5) + 20.672f(6) - 5.435f(7) - 33.956f(8) - 32.667f(9) + 45.387f(10) \quad (12)$$

The units of A_1 is kVAmin

Digital meters have different sampling rates and discrete time equations to calculate the apparent energy and the accuracy may differ meter to meter. Therefore (13) is used for better accuracy considering continuous signal.

$$A_0 = \int_{t=0}^{t=10} F(t)dt \quad (13)$$

A_0 *is* referred to apparent energy over 10 minutes in kVAmin and $F(t)$ is referred to apparent power signal.

Now the forecasted average demand (D_f) can be written as

$$D_f = (A_0 + A_1)/15 \quad (14)$$

Ultimately (7), (8), (9), (10) and (11) can be used to derive the forecasted demand equation. For the maximum demand warning signal, (14) can be used.

B. Algorithm of STDF for Smart Meters

Smart meter is the combination of all energy metering and intelligence which provides good solutions to overcome from the problems that we face with the old grid system. Smart meters can read real-time energy consumption information including values of voltage, current, active power, reactive power, apparent power, phase angle, frequency and securely communicate that data [8]. They have many advantages including energy savings for residential customers, promoting energy efficiency and more reliability of supply. They are still evolving and many governments, organizations and companies are trying to establish different standards and policies [9].

Our study focuses on development of an algorithm that can be easily implemented on smart meter software/hardware. The input parameter for the system is electricity demand. The developers can use either smart meter hardware or data obtained via communication link like RS 232. Therefore with smart meters we can easily get the apparent power samples in regular time intervals to construct the forecasted demand equation.

GSM network can be used to transfer the warning signal to the consumer via SMS. However there are certain questionable issues regarding GSM network such as its scalability, reliability and security, especially under high load [10].

Smart meters record energy consumption and power quality at a preset interval, usually an hour or less. The characterization of patterns useful for consumption analysis and demand forecasting is instantiated by the collection of such meter readings [11]. We can use the this kind of data to read values from $f(1)$ to $f(10)$. If we consider one hour period, there are four 15 minutes intervals each starts at *t*=0, *t*=15, *t*=30 and *t*=45 minutes. Real time clock source may be used to generate interrupts in minute's basis. At the beginning of each 15 minute cycle, the calculation should be started. Therefore $f(1)$ is read at 1 or 16 or 31 or 46 minutes. $f(2)$ is read at 2 or 17 or 32 or 47 minutes. Same pattern can be followed to read values from $f(3)$ to $f(10)$. Ultimately when the readings are taken they can be used to fit the polynomial.

When *t*=10, 25, 40 or 55 minutes, the A_0 and A_1 can be found. D_{u1} is the user defined demand level. If $D_{u1} < D_f$ condition is satisfied the maximum demand warning signal is generated. The next condition is to check whether the demand and current tariff exceed the user defined level. As we know some power suppliers use time of use tariff schemes. The tariff may vary hourly basis or minute basis. However the suggest system checks the tariff in each 15 minutes interval. This is because smart meters are normally fed with hourly tariff or daily tariff. If the tariff ($C(t)$) and the demand ($f(t)$) are going to exceed the user defined demand value (D_{u2}) and user defined tariff level (C_u), the smart meter can warn the consumer or control demand side loads to save the electricity cost. Otherwise it follows the next instructions of the program. The next instructions may be the other part of the smart meter main software. This algorithm can be used with an interrupt routine when using a microcontroller. The algorithm is shown in Fig. 2.

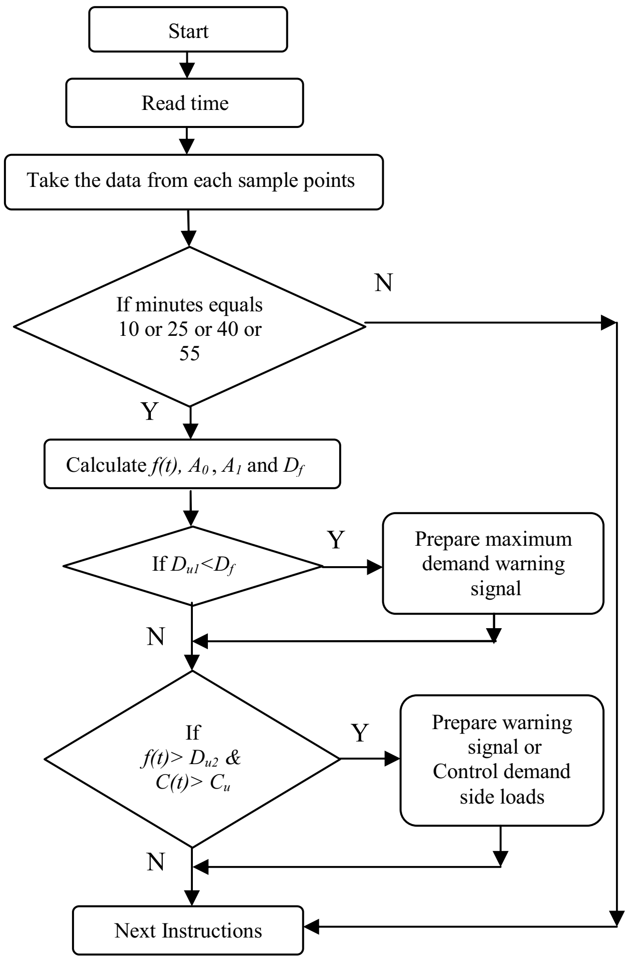

Fig. 2. Demand forecasting algorithm

IV. Results and Discussions

Medium voltage (33kV) porcelain industry was selected for the data measurement. The major electricity consuming units are the 'Biscuit kiln' and the 'Decoration kiln'. Other dominant loads are nine units of ball mills and filter units including preparation machines. According to the consumption data for 2009 - 2011, the average monthly electricity consumption was around 588 MWh and the average monthly maximum demand was 1514 kVA. Remote metering records were taken to analyze the demand profile for 6 different days starting form 19.04.2011. These remote energy measurements were taken at the 33 kV side of the transformers, and consumption and demand data were available in one minute intervals. Fig. 3 shows the load profile of the factory with the time of use tariff scheme.

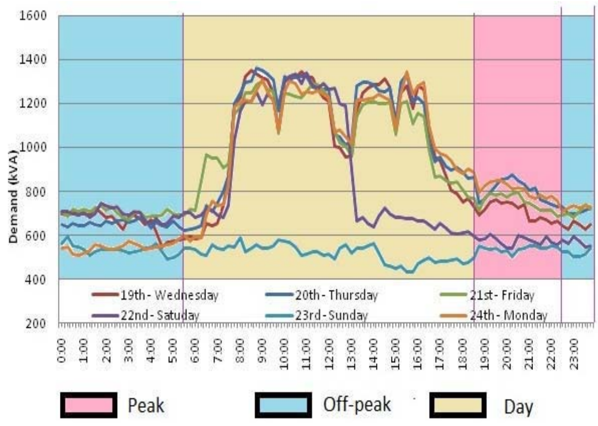

Fig. 3. The load profile of the factory with time of use tariff scheme

We can clearly see that the demand pattern of this industry is same for week days. By analyzing the demand within 15 minutes of each day, polynomial demand variation was observed. Data in Fig. 3 were tested by applying the methodology which has been described previously. There were 576 of 15 minutes cycles for 6 days. D_f was calculated for each case not only for 4^{th} order but also for few other orders. The actual demand and the calculated demand were compared. Percentage values of accuracy were found for each case considering the order of the polynomial. Then the probability of getting 95% of accuracy was calculated against the order of polynomial. Table I shows the results obtained.

TABLE I
TEST RESULTS

Order of the polynomial	Probability of 95% accuracy
1	0.4128
2	0.8173
3	0.8934
4	0.9563
5	0.9564
6	0.9564

It can be seen that when the order is high the accuracy is also high. However after 4^{th} order, the accuracy has less effect with the order of the polynomial. Therefore 4^{th} order polynomial demand variation can be applied for this consumer with reasonable confidence considering the historical data for 6 days.

For the calculation we have used only the demand variation from 7.30 a.m to 9.30 a.m where the first peak demand occurs. The average values are taken for the above time interval except Sunday. The average demand variation and the best fit curve are shown in Fig. 4.

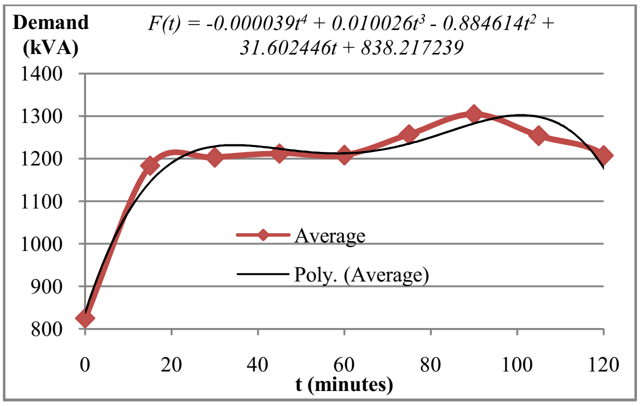

Fig. 4. The variation of average demand with time

The time interval from 7.30 a.m to 9.30a.m can be divided in to 8 sub intervals of 15 minutes. Here the first sub interval (7.30 a.m to 7.45) is selected to find $f(t)$ and D_f. Sample points are taken from t=1 to t=10.

The demand variation in Fig. 4 can be written as

$$F(t) = -0.000039t^4 + 0.010026t^3 - 0.884614t^2 + 31.602446t + 838.2172 \quad (15)$$

Using (7), (8), (9), (10) and (11) we can calculate the coefficients.

$a_4 = -0.000040$, $a_3 = 0.010057$, $a_2 = -0.878208$,

$a_1 = 31.507987$, $a_0 = 838.114272$

Using (1), the forecasted demand equation can be written.

$$f(t) = -0.000040t^4 + 0.010057t^3 - 0.878208t^2 + 31.507987t + 838.114272$$

Using (12), the forecasted area can be calculated.

A_1=5562.4890 kVAmin

Using (13) and (15), the apparent energy within 10 minutes can be found.

$$A_0 = \int_0^{10} F(t)dt = 9691.70796 \text{ kVAmin}$$

Using (14), the forecasted demand can be found.

D_f= 1016.9464 kVA

If the user defined maximum demand is below 1016.9464 kVA, the demand warning signal is generated at t=10 minutes. Same procedure can be used to calculate the $f(t)$ and D_f for other 15 minutes intervals form 7.45 a.m to 9.30 a.m.

Simulated results were obtained using Matlab software for demand data available form 7.30 a.m to 9.30 a.m. Using the demand variation on Monday 24th April 2011 from 7.30 a.m to 9.30 a.m, the Matlab program was written to generate the forecasted demand and to generate warning signals. When the demand is going to exceed the user defined demand (D_{u1}), the warning signal is displayed on the figure at the forecasted time. In black dots the actual demand variation is shown. Sample points are taken in every minute and shown in green dots. The cross marks are the forecasted demand values for next 5 minutes. The results are shown in Fig. 5. For the illustration of warning, we have defined D_{u1}=1000 kVA which is always below than the actual demand within the selected time period. However in actual scenario D_{u1} should greater than or equal to the average maximum demand of the year.

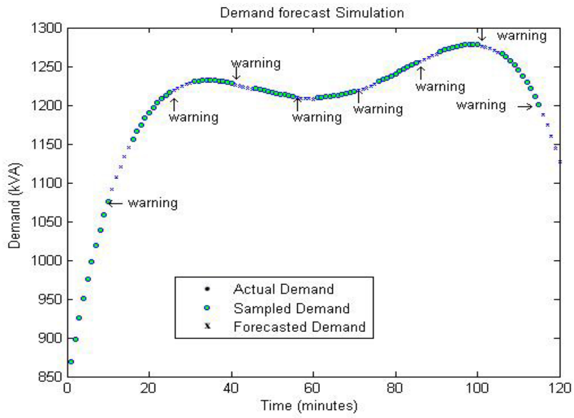

Fig. 5. Output figure when D_{u1}=1000 kVA

The forecasted and actual demand values can be obtained when the program executes on Matlab. Table II shows the data obtained using the Matlab program.

TABLE II
SIMULATED RESULTS

Time(minutes)	Actual average demand (kVA)	Forecasted average demand = D_f (kVA)	Accuracy (%)
0-15	1048.932	1016.9526	96.95
15-30	1144.314	1199.4992	95.18
30-45	1227.454	1229.2780	99.85
45-60	1235.679	1214.5453	98.29
60-75	1281.353	1216.1727	94.91
75-90	1321.802	1247.6467	94.39
90-105	1273.934	1275.0688	99.91
105-120	1247.920	1217.1555	97.53

Simulation results indicate the accuracy of prediction results was up to 99.91%. In the same time it shows an inaccuracy of 5.09% for the given data set. However this system should be tested for more historical and more future data to get a reasonable number for the accuracy. The accuracy range obtained here is sufficient for an application like warning signal generation.

In the next step of simulation, time of day tariff scheme and user defined demand level is used to generate the warning signal. Data pattern in Fig. 5 has been used for this simulation. However now there are two parameters to generate the warring signal which are D_{u2} and C_u .

The time of use tariff scheme is shown in Table III.

TABLE III
TIME OF USE TARIFF

Day (0530 to 1830 hrs)	Peak (1830 to 2230 hrs)	Off- Peak (2230 to 0530 hrs)
10.25 LKR	13.40 LKR	7.15 LKR

For the simulation we defined D_{u2}= 1200 kVA and C_u = 10.00 LKR. The simulated results obtained under above conditions are shown in Fig. 6.

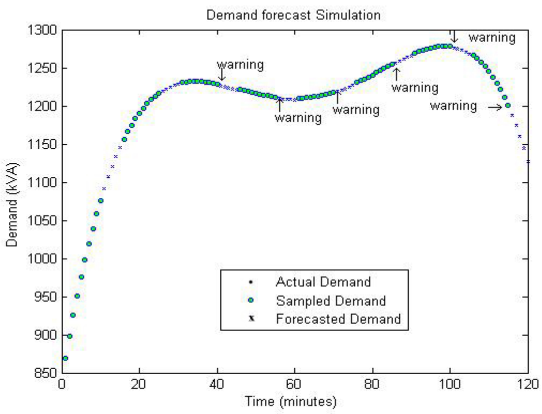

Fig. 6. Output figure when D_{u2} =1200 kVA and C_u= 10.00 LKR

V. Conclusion

A new approach for 5 minutes electricity demand forecasting is presented using polynomial interpolation. This research study will be helpful to industries where they really suffering from higher maximum demand charges and to residential consumers who are interested in energy saving. Due to the simplicity of the methodology and reduced calculation time, it can be easily developed using smart meter software/hardware. By adding this as a feature to smart metering, warning signals can be sent to the industrial consumers via SMS or other communication link. Residential consumers benefit from the alarm signals on higher demands during peak hours. When the smart meters have access to the consumer's loads, control actions can be taken to reduce the demand. Ultimately the suggested system will help demand side load management and electricity bill reduction. The results were obtained only by simulation. This system should be implemented and tested for long run to verify the accuracy.

References

[1] I. A. B. W. A. Rasak, Md. S. B. Majid, H. Abd. Rahman, and M. Y. Hassan, "Short term load forecasting using data mining technique," in *Proc.* 2008 *IEEE Power and Energy Conf.*, pp. 139-142.

[2] A. Setiawan, I. Koprinska, and V. G. Agelidis, "very short-term electricity load demand forecasting using support vector regression," in *Proc.* 2009 *IJCNN Neural Networks Conf.*, pp. 2888-2894.

[3] Y. Chen, P. B. Luh, C. Guan, Y. Zhao, L. D. Michel, M. A. Coolbeth, P. B. Friedland, and S. J. Rourke, "Short-term Load Forecasting: SimilarDay-based Wavelet Neural Networks," *IEEE Trans. Power Systems*, vol. 25, pp. 322-330 , Feb 2010.

[4] Y. Zhao, P. B. Luh, C. Bomgardner, and G. H. Beerel, "Short-term LoadForecasting: Multi-level Wavelet Neural Networks with Holiday Corrections," in *Proc. 2009 IEEE Power and Energy Society General Meeting*, pp. 1-7.

[5] A. D. Papalexopoulos, and T. C. Hesterberg, "A regression-based approach to short-term system load forecasting," *IEEE Trans. Power System*, vol. 5, pp. 1535-1547 , Nov. 1990.

[6] J. W. Taylor, and A. Espasa, "Special issue on energy forecasting," *Forecasting. Int .J.* vol 24, pp. 561-565, 2008.

[7] S. Towill, "Estimation of maximum demand on a British electricity-board system (forecast periods of 1-3 years)," i*n Proc. of Institute of Electrical Engineers,* vol. 121, pp. 609 – 615, July. 1974.

[8] S. S. S. R. Depuru, L. Wang, V. Devabhaktuni, and N. Gudi, "Smart meters for power grid – challenges, issues, advantages and status," in *Proc. 2011 IEEE Power Systems Conference and Exposition.*, pp. 1-7.

[9] L. Zhou, F. Y. Xu, and Y. N. Ma , " Impact of smart metering on energy efficiency," *in Proc.* 2010 *Machine Learning and Cybernetic Conf.,* pp. 3213-3218.

[10] S. S. Sheikh, and S. Sharma, "Design and implementation of wireless automatic meter reading system," *Engineering Science and Technology. Int. J.* vol.3, no. 3, pp. 2329-2334, Mar. 2011.

[11] D. De Silva, Y. Xinghuo, D. Alahakoon, and G. Holmes, "Semi-supervised classification of characterized patterns for demand forecasting using smart electricity meters," in *Proc. Int. Conf. Electrical Machines and Systems*, Beijing, 2011, pp.1-6.