

A New Approach for Optimal Sizing of DG based on statistical STLF

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Abstract:

The paper proposes a new approach for the optimal sizing of the distributed generator based on a statistical short-term load forecasting technique. The curve fitting method is used to perform the short-term load forecasting. Short term load forecasting in this paper is done by considering the sensibility of the network load to the temperature, humidity, day type parameters (THD) and previous load and also ensuring that forecasting the load with these parameters can be best done by the curve fitting method. The analysis of the load data recognizes that the load pattern is not only dependent on temperature but also is dependent on humidity and day type. A unique norm with a, b, c and d constants based on the history data has been proposed for the STLF using the concept of curve fitting technique. The optimal sizing of the DG is obtained based on the results of the STLF done. The technique is implemented on a real time dataset. The algorithms implementing this forecasting and optimal DG Sizing techniques have been programmed using MATLAB. The simulation results show the robustness and suitability of the proposed norm for the STLF as the forecasting accuracies are less than 3% for almost all the day types and all the seasons. The reduction in the overall system losses proves the suitability of the developed technique for the optimal sizing of the distributed generator.

Keywords — Short term load forecasting, THD (Temperature, Humidity, Day Type), CFM (Curve Fitting Method), Distributed Generator, Optimal Sizing

1. Introduction

Load forecasting is an important component for power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. Besides playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. The system operators use the load forecasting results as a basis of off-line network analysis to determine if the system might be vulnerable. If so, corrective actions should be prepared, such as load shedding, power purchases and bringing peaking units online.

With the recent trend of deregulation of the electricity markets, STLF has gained more importance and is facing greater challenges. In the market environment, precise forecasting is the basis of electrical energy trade and spot price establishment for the system to gain the minimum electricity purchasing cost. In the real-time dispatch operation, forecasting error causes more purchasing electricity cost or breaking-contract penalty cost to keep the electricity supply and consumption balance. There are also some modifications of STLF models due to this implementation of the electricity market. Weather is defined as the atmospheric condition existing over a short period in a particular location. It is often difficult to predict and it can vary significantly even over a short period. Climate

also varies with time: seasonally, annually and on a decade's basis [1]. The relationship between demand and temperature is non-linear with the demand increasing for both low and high temperature [2]. The range of the possible approaches to the forecast is to take a microscopic view of the problem and try to model the future load as a reflection of previous [3]. In the case of large variation in the temperature compared to that of the previous year, the load also changes accordingly. In such cases there would be the shortage of similar days' data and the task of the forecasting load is very difficult [4]. For making the distribution grid smarter it is required to deploy communications and leverage advanced controls that are common place in substation automation, remedial actions schemes, power management systems, and industrial closed-loop power automation [5]-[7]. Inclusion of Distributed Generators will improve the grid utility and also help in the reduction of overall system power loss. Cost is one major constraint in the inclusion of DG's in the power system. But with the advent of renewable energy, the cost issue can be addressed efficiently.

II. Data Analysis

A. Load Curves

For the analysis and implementation of load forecasting and optimal DG sizing, data is taken from EUNITE network that was provided to participants for a competition many years ago (see acknowledgement). In the data analysis part, we are going to analyse load variation with respect to day type, weather condition such as seasonal variation of load with temperature and humidity. Analysing the monthly and yearly load curves given in Fig.1 and Fig.2 and also load variation with respect to temperature and humidity given in Fig.3 and Fig.4 the following observations are made:

- The load curve patterns of two consecutive years is similar
- The load curves of similar months of two consecutive years is also similar

- The load curves are having different pattern in weekdays and weekend days in the month
- The load curves on the weekends are similar
- Taking in consideration the above observations the days of the week are classified based on the following categories:

- Normal week days (Tuesday - Friday)
- Monday
- Sunday
- Saturday

Monday is accounted to be different to weekdays so as to take care for the difference in the load because of the previous day to be weekend.

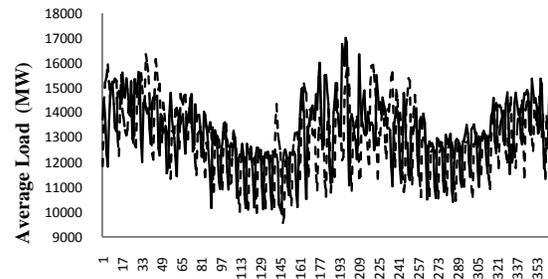


Figure 1. Yearly load curves of 1996 and 1997.

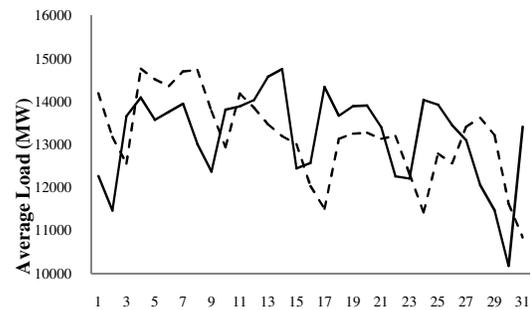


Figure 2. Monthly load curves of Mar'96 and Mar'97.

B. Variation of load with temperature

The variation of the temperature variable results in a significant variation in the load. Fig 3 shows a plot between the maximum temperatures versus average demand. In Fig. 3 the dots represent the actual values and the solid line is the best fitted curve. The graph shows a positive correlation between the load and temperature i.e. demands increases as the temperature increases [7-8].

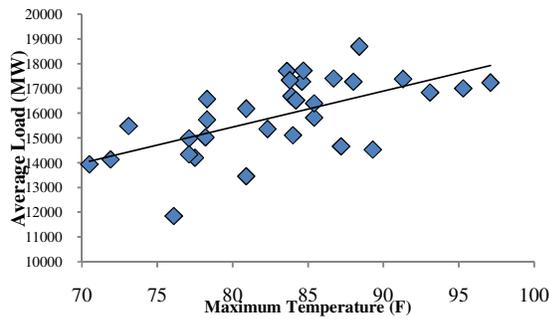


Figure 3. Monthly load variation with temperature

C. Variation of load with humidity

Fig. 4 shows the plot between the average humidity versus average demand. From the graph it can be seen that there exists a positive correlation between load and humidity i.e. demand increases as the humidity increases.

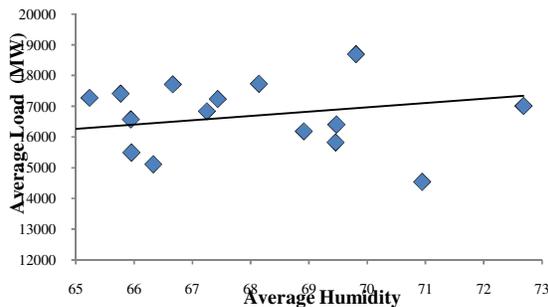


Figure 4. Monthly load variation with humidity

D. Autocorrelation of load

It is seen from the plots that the load pattern of the present year is similar to the load pattern of previous year and also the load curve of a given month is similar to the load curve of the previous years' same month. Hence it can be considered that the load of similar month of previous year can greatly help in load forecasting along with the THD parameters.

III. Short Term Load Forecasting using Curve Fitting

The relation between load and the THD parameters is are to be understood as they have direct impact on the load as seen in the earlier section. As it is clear from the data analysis that the load is totally dependent on the temperature,

humidity and day type parameters, hence curve fitting is used to obtain the relationship between load and these parameters. The method is basically divided into three parts as follows:

- Load variation with respect to temperature
- Load variation with respect to temperature and humidity
- Load variation with respect to temperature, humidity and day type

The methodology that is developed for the short-term load forecasting of load using the curve fitting method would mainly focus on the variation of power with these three main parameters we have already mentioned i.e. Temperature, Humidity and the particular Day Type [9 - 13].

The first two parameters, quite evidently come under the weather changing phenomenon, but considering the time dependent variation of the load, the data that is available could not only be classified into a particular day type but it also follows a similar month pattern which implies that, for example, if we take the data of January of one particular year, there are steep chances that it is almost identical to the one we had in the same month of its previous year under a similar working environment. We use all three factors for the forecasting the load. It is explained in the curve fitting algorithm.

A. Curve Fitting Algorithm

Step 1: Write the equations between power and its parameters using curve fitting

$$\begin{aligned}
 P &= a + b.T + c.H + d.D \\
 \sum P &= a.N + b.\sum T + c.\sum H + d.\sum D \\
 \sum PT &= a.\sum T + b.\sum T^2 + c.\sum HT + d.\sum DT \\
 \sum PTH &= a.\sum TH + b.\sum T^2H + c.\sum H^2T + d.\sum DTH \\
 \sum PTHD &= a.\sum THD + b.\sum T^2HD + c.\sum H^2TD + d.\sum D^2TH
 \end{aligned}$$

Step 2: Using previous year data of similar month calculate coefficient of a, b, c and d

$$\begin{bmatrix} \sum P \\ \sum PT \\ \sum PTH \\ \sum PTHD \end{bmatrix} = \begin{bmatrix} N & \sum T & \sum H & \sum D \\ \sum T & \sum T^2 & \sum HT & \sum DT \\ \sum TH & \sum T^2H & \sum H^2T & \sum DTH \\ \sum THD & \sum T^2HD & \sum H^2TD & \sum D^2TH \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} N & \Sigma T & \Sigma H & \Sigma D \\ \Sigma T & \Sigma T^2 & \Sigma HT & \Sigma DT \\ \Sigma TH & \Sigma T^2 H & \Sigma H^2 T & \Sigma DTH \\ \Sigma THD & \Sigma T^2 HD & \Sigma H^2 TD & \Sigma D^2 TH \end{bmatrix}^{-1} \begin{bmatrix} \Sigma P \\ \Sigma PT \\ \Sigma PTH \\ \Sigma PTHD \end{bmatrix}$$

Assuming the coefficients

$$\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix}$$

Step3: Coefficient substitution in the Step 1

$$P_{forecast} = a_1 + a_2.T_{forecast} + a_3.H_{forecast} + a_4.D_{forecast}$$

Step4: Calculating the forecasting power of each day in present month

Step5: Calculating MAPE (Mean Absolute Percentage Error) of power

$$MAPE = \sum_{i=1}^N \frac{|P_A^i - P_F^i|}{P_A^i} * 100$$

Step6: For next month forecasting of power repeat Step2 to Step 5

Step7: Result analysis

Step8: End

Using the above algorithm the Short Term Load Forecasting using the parameters can be easily obtained.

IV. STLF based Optimal DG Sizing

The STLF results are obtained for different zones of the ISO New England transmission network using the curve fitting technique. Based on the load forecasts values the optimal size of the distributed generator is fixed using the Particle Swarm Optimization technique.

The load flows of the real time system considered is performed without distributed generator and with distributed generator. The system's total power loss shows a fall with the inclusion of the DG. To further minimize the loss, the DG size is optimized for different time zones of the day. Each day is

divided into four-time zones based on the load variations:

Time Zone 1: 6AM – 9AM

Time Zone 2: 9AM – 5PM

Time Zone 3: 5PM – 10PM

Time Zone 4: 10PM – 6AM

A. Algorithm

This algorithm depicts the procedure for the optimal placement of DG in transmission system with the following steps:

1. Data used to carry out load flow is taken from the EUNITE data available
2. Base case load flow is performed without DG to obtain the voltage profile and total system power loss
3. DG is placed at that bus with lowest voltage profile
4. The optimal size of DG is obtained by using the PSO technique, considering the power loss as the objective function

V. Results and Analysis

The result analysis of the simulation performed on the load variation with respect to its corresponding parameters clearly suggests the dependency of the load on the three factors of Temperature, Humidity and Day Type considered in the present work.

The various parameter values obtained for one test case are given in Table I.

TABLE I

PARAMETERS OF CFM ALGORITHM

PARAMETERS	VALUES
P _{AVERAGE}	13053.34
R	0.0014
T _{AVERAGE}	48.6190
H _{AVERAGE}	38.2240
D _{AVERAGE}	3.1448
a	11279.72
b	3.71783
c	-29.0868
d	760.9079

TABLE II

WEEKLY LOAD FORECASTING RESULTS

Date	Day Type	Load in MW		
		Actual Load	Forecasted Load	MAPE %
2/11/97	1	11021.91667	10929.62926	0.837308176
3/11/97	3	12754.66667	12495.5655	2.031422499
4/11/97	4	13030.375	13190.33612	1.227601821
5/11/97	4	13077.625	13355.7966	2.127080421
6/11/97	4	13264.5	13402.55266	1.040767906
7/11/97	4	13129.41667	13343.56988	1.63109466
8/11/97	2	12054.45833	12057.19216	0.022678997

From the above analysis it is clear that the curve fitting method is quite suitable for the short-term load forecasting and the STLF results of the same are having forecasting accuracies with MAPE values of less than 3%. The curve fitting method is simple and it yields good results for days of all types as the weekly result values clearly indicate.

The results of the STLF based optimal sizing of the DG for the eight load zones of the ISO-NE operator are discussed below. Table III and Fig. 5 to Fig. 8 clearly indicate an improvement in the voltage profiles with the inclusion of Distributed Generator in the power system.

TABLE III

VOLTAGE PROFILES OF 8 LOAD ZONES OF ISO-NE

Voltage Profile 10PM-6AM		Voltage Profile 6AM-9AM		Voltage Profile 5PM-10PM		Voltage Profile 9AM-5PM	
Without DG	With PSO-DG	Without DG	With PSO-DG	Without DG	With PSO-DG	Without DG	With PSO-DG
0.7740	0.8587	0.7885	0.8801	0.8057	0.8865	0.8155	0.8947
0.7757	0.8598	0.7898	0.8808	0.8068	0.8872	0.8165	0.8954
0.7589	0.8504	0.7752	0.8743	0.7941	0.8816	0.8043	0.8902
0.7723	0.8581	0.7869	0.8798	0.8043	0.8864	0.8142	0.8946
0.7613	0.8573	0.7805	0.8834	0.8006	0.8913	0.8106	0.8997
0.7339	0.8575	0.7661	0.8954	0.7934	0.9070	0.8036	0.9156
0.7225	0.8585	0.7604	0.9017	0.7910	0.9148	0.8012	0.9235
0.7179	0.8565	0.7539	0.9006	0.7846	0.9139	0.7953	0.9227

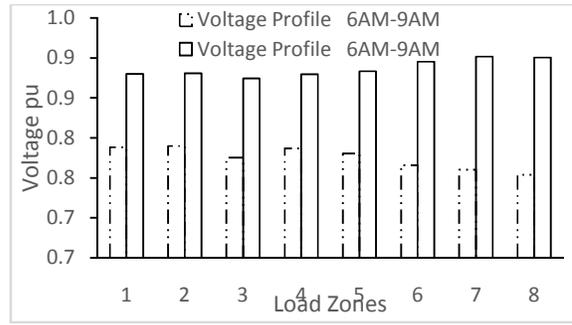


Figure 5. Voltage Profile without and with PSO-DG – 6AM TO 9AM

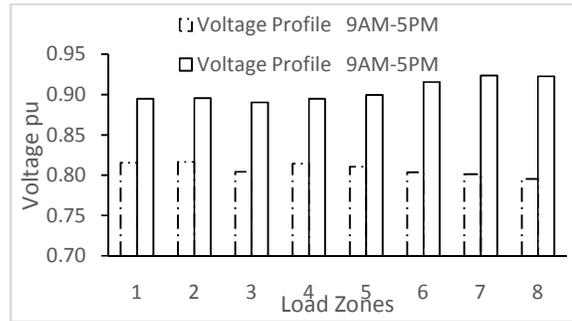


Figure 6. Voltage Profile without and with PSO-DG – 9AM TO 5PM

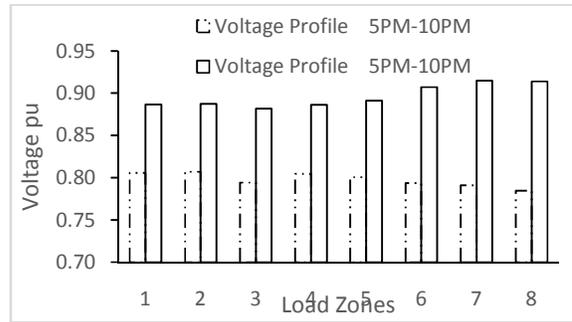


Figure 7. Voltage Profile without and with PSO-DG – 5PM TO 10PM

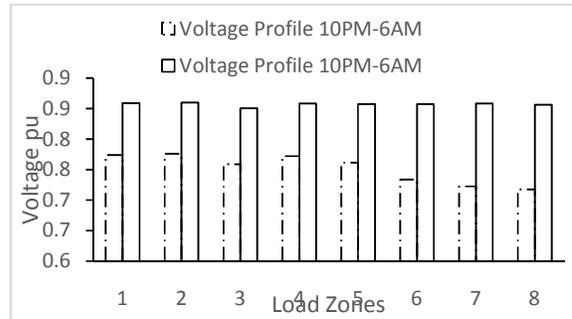


Figure 8. Voltage Profile without and with PSO-DG – 10PM TO 6AM

Table IV and Fig. 9 show the decrease in the power loss obtained after the placement and optimization of the distributed generator. The optimized DG size to obtain minimum power loss are also given.

ISO-NE	Power Loss without DG	Power Loss with PSO-DG	DG Size (MW)
Time Zone 1	4874.5377	4152.3548	4311.8290
Time Zone 2	6906.2304	6194.4044	4647.9244
Time Zone 3	7617.6253	6891.5563	4266.6698
Time Zone 4	7262.5197	6391.8543	4303.1754

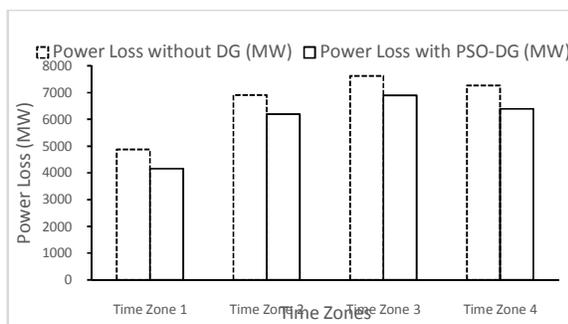


Figure 9. Comparative System Power Loss without and with PSO-DG

VI. Conclusions

As the state-of-the-art Smart Grid design needs innovation in a number of dimensions: distributed and dynamic network with two-way information and energy transmission, seamless integration of renewable energy sources, management of intermittent power supplies, real time demand response etc. Accurate load forecasting and optimal DG Sizing is very important for electric utilities in a competitive environment created by the electric industry deregulation. In this paper, we have presented the curve fitting method for short term load forecasting and PSO optimized DG sizing for minimum power losses. The following are the conclusions derived from the proposed methods:

- In this paper the curve fitting method have strongly proved the impact of THD parameters in the STLF

using the relation between input and output variable through the systematic rule.

- The simulation results indicate that the efficiency of the curve fitting method is due to the consideration of the previous years' similar month as the training dataset for the calculation of the constants. The data analysis part of Section II indicates the strong impact of the previous year similar month load on the present month.
- The PSO optimized DG sizing has been proven as a very efficient and simple technique for reducing the overall power losses and improving the voltage profile
- The method has been successfully implemented on a real time data set and is very suitable for all day types and all seasons

VII. Acknowledgment

The authors gratefully acknowledge Mr. R. Venkatendra for providing the EUNITE Network load forecasting data, which has been used for simulation study in this paper. Author's information about the source of data is based on the information provided by Mr. R. Venkatendra.

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