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Application of Short Term Load Forecasting for Optimal Selection and Sizing of DG in Distribution System

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Abstract: Optimal placement and size of the Distributed Generation (DG) units, based on the minimization of the power losses. Short Term Load Forecasting has been implemented with Artificial Neural Networks (ANN) and Auto Regressive Integrated Moving Average (ARIMA) models and a comparative study has been drawn based on Mean Absolute Percentage Error (MAPE). The load and price data have been taken from Australian Energy Market Operator (AEMO) on New South Wales (NSW) whereas the temperature data has been taken from Sydney Observatory from Bureau of Meteorology (BOM), over a 5 year period from 1st January 2006 to 31st December 2010. A price forecasting has also been carried out derived from the data. Because of the time-varying characteristics of demand and generation, the forecasted data has then been applied to find out the optimal placement and size of the Distributed Generation (DG) units, based on the minimization of the power losses. The proposed methodology has been applied to IEEE 69-bus test distribution system.

Keywords: Short-Term Load Forecasting, Artificial Neural Networks, Auto-Regressive Integrated Moving Average, Distributed Generation, optimal placement and sizing.

1. INTRODUCTION

In the current deregulated market scenario, it is of utmost importance that a balance is met between energy demand and supply. To substantiate this fact, the importance of electricalload forecasting is undeniable. Electrical load forecasting is utilized by the distribution designers and operators as a means for resource planning and generation dispatch. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development[1]. The types of electric load forecasting are divided broadly in three categories:

i) Short-Term Load Forecasting (STLF): between 1 hour to 1 week

ii) Medium-Term Load Forecasting (MTLF): between 1 week to 1 year

iii) Long-Term Load Forecasting (LTLF): longer than 1 year

The forecasts and the nature of forecasts for different time horizons are important and different for different operations within a utility company. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3% but impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations[2]. The different factors important for the implementation of load forecasting are:

- Short term load forecasting: time factors, weather data, previous load data
- Medium and long term load forecasting: historical load, weather data, economic and demographic data, appliance characteristics and sales data.

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Basically being a time series problem, there are a number of techniques that provide solution for load forecasting. They are neural networks[1-7], fuzzy expert systems [8-9], wavelet based networks [10-11], time series analysis [12-15] or combination of above [16-19].

In this paper, the further work has been inspired by proposition of the fact that the optimal placement and sizing of a renewable Distributed Generation (DG) is based on the demand present in the system[20].

The rest of the paper is structured as follows: Section 2 describes the ANN models for solution of load forecasting problem. Section 3 caters to the use of ARIMA models for the same. Section 4 portrays analytical expressions to determine the optimal sizing of the DG. Section 5 discusses the numerical and graphical results of the load forecasting using various models and the use of the obtained demand data on a 69-bus test distribution system to optimally place the DG. Finally, Section 6 summaries the contribution of the work.

2. ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network is based on biological neural system, in which the output of system depends on the control signals collected from different nodes through the links. By adjusting the weights of the links, the input mapped to the output and the error gets reduced. The weight values represent the strength of input and a neuron, Negative weights denotes the weakness of neuron system. The succive action forms the activity and the output of the neuron system is controlled by activation function

Mathematically, this process is described in the Figure 1.

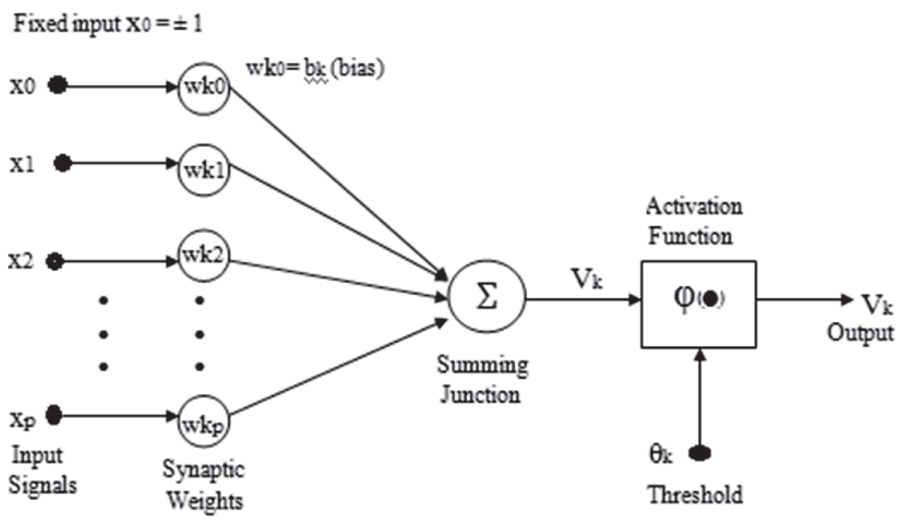

Figure 1: Mathematical Model of neuron

From this model the interval activity of the neuron can be shown to be:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \tag{1}$$

3. AUTO-REGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

Box and Jenkins (1976) first introduced ARIMA models, the term deriving from AR (Auto-Regressive), I (Integrated), MA (Moving Average). It is primarily based on the concept of “Stationarity”.

The model building steps of ARIMA are as under:

- Identification: Using graphs, statistics, Autocorrelation Functions (ACFs) and Partial Autocorrelation Function (PACFs), transformations, etc.

- Estimation: It finds the coefficients and its estimate using least squares and maximum likelihood methods,
- Diagnostics: verify the model Using graphs, statistics, ACFs and PACFs of residuals and check the decided model, otherwise repeat the above steps.
- Forecast: Using graphs, simple statistics and confidence intervals to determine the validity of the forecast and track model performance to detect out of control situation.

The following are the few processes that can be incorporated giving the values of '*p*', '*d*', '*q*' in the corresponding AR or I or MA processes respectively.

1. Autoregressive Process: ARIMA (p, 0, 0):

$$Y_t = \theta + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p} + e_t \tag{2}$$

2. Moving Average Process: ARIMA (0, 0, q)

$$Y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \tag{3}$$

3. Integrated Processes: ARIMA (0, 1, 0)

$$Y_t = Y_{t-1} + e_t \quad \rightarrow \quad \Delta Y_t = e_t \tag{4}$$

4. ARIMA (p, 0, q):

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \tag{5}$$

5. ARIMA (p, 1, q):

$$\Delta Y_t = \Phi_1 \Delta Y_{t-1} + \Phi_2 \Delta Y_{t-2} + \ldots + \Phi_p \Delta Y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \tag{6}$$

4. OPTIMAL PLACEMENT AND SIZING OF DG

Distributed Generation (DG) is defined as small generation units installed in distribution systems. DGs can significantly increase reliability, reduce losses and save energy while is cost effective, though it suffers from some disadvantages because of the isolated power quality functioning, and voltage control problems. DGs include diesel, combustion turbine, and combined cycle turbine, low-head hydro, fuel cells and renewable power generation methods such as wind and solar. In this paper, biomass is considered as DG source.

The reduction in power losses is currently the primary objective of any study. But many of the literature do not include the factors like time-varying characteristics of demand.

The total active power loss in a distribution system with N buses as a function of active and reactive power injections at all buses can be calculated as follows [20]:

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} [\alpha_{ij}(P_i P_j + Q_i Q_j) + \beta_{ij}(Q_i P_j - Q_j P_i)] \tag{7}$$

where, $\alpha_{ij} = \frac{r_{ij}}{v_i v_j} \cos(\delta_i - \delta_j)$; $\beta_{ij} = \frac{r_{ij}}{v_i v_j} \sin(\delta_i - \delta_j)$; $V_i\, \delta_i$ is the complex voltage at bus i; $r_{ij} + x_{ij} = z_{ij}$ is the ij^{th} element of Z_{bus} impedance matrix; P_i and P_j are active power injections at buses i and j, respectively; and Q_i and Q_j are reactive power injections at buses i and j, respectively.

Now, when the DG is installed, the real and reactive power injections at bus i are respectively given as:

$$P_i = P_{DGi} - P_{Di} \tag{8}$$

$$Q_i = Q_{DGi} - Q_{Di} \tag{9}$$

where, $Q_{DGi} = aP_{DGi}$, P_{DGi} and Q_{DGi} are respectively the active and reactive power injections from DG unit at bus *i,* a_i = (sign) $\tan(\cos^{-1}(pf_{DGi})$ [sign = +1: DG unit injecting reactive power, sign = −1: DG unit consuming reactive power]; P_{Di} and Q_{Di} are respectively the active and reactive power of load at bus i; pf_{DGi} is the operating power factor of DG unit at bus i. Substituting the values of Equation (8) and Equation (9) in Equation (7), we obtain the new power loss as:

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N}\left[\begin{array}{l}\alpha_{ij}((P_{DGi} - P_{Di})P_j + (a_i P_{DGi} - Q_{Di})Q_j) \\ + \beta_{ij}((a_i P_{DGi} - Q_{Di})P_j - (P_{DGi} - P_{Di})Q_j)\end{array}\right] \tag{10}$$

Now, this power loss will reach a minimum if the partial derivative of the P_{loss} with respect to P_{DGi} is zero.

$$\frac{\partial P_{loss}}{\partial P_{DGi}} = 2\sum_{j=1}^{N}[\alpha_{ij}(P_j + a_i Q_j) + \beta_{ij}(a_i P_j - Q_j)] = 0 \tag{11}$$

From this, the optimal size of the DG can be calculated as:

$$P_{DGi} = \frac{\alpha_{ii}(P_{Di} + a_i Q_{Di}) - X_i - a_i Y_i}{\alpha_{ii}(a_i^2 + 1)} \tag{12}$$

where, $X_i = \sum_{\substack{j=1 \\ j \neq i}}^{N}(\alpha_{ii}P_j - \beta_{ij}Q_j)$ and $Y_i = \sum_{\substack{j=1 \\ j \neq i}}^{N}(\alpha_{ij}Q_j - \beta_{ij}P_j)$.

5. RESULTS AND DISCUSSIONS

In this paper, the load and price data have been collected from Australian Energy Market Operator (AEMO) on New South Wales (NSW) whereas the temperature data has been taken from Sydney Observatory from Bureau of Meteorology (BOM), over a 5 year period from 1st January 2006 to 31st December 2010. In each day, a total reading of 48 is made which suggests that 2 readings are made per hour. This accounts for a total number of readings of 87648 in 5 years. The data gives us the temperature values viz. ‘Dry bulb’, which species air temperature free from moisture and radiation, ‘Dew Point’, which specifies temperature at which water vapor condenses the same rate it evaporates, ‘Wet bulb’, which means temperature felt by wet skin when exposed to moving air ‘humidity’, giving the moisture value in air, ‘Electricity Price’, on a half-hourly basis and ‘System load’, showing the dynamic load variation for every half an hour. The neural network was trained in MATLAB 7.11.0 (R2010b).

From the given data, a set of 8 predictors, that were required to forecast the data, were defined. They are: ‘Dry Bulb’, ‘Dew Point’, ‘Hour’, ‘Weekday’, ‘Is Working Day’, ‘Prev Week Same Hour Load’, ‘prev Day Same Hour Load’, ‘prev 24 Hr Ave Load’. Load forecasting being a regression model, the basic regression technique was first implemented followed by ANN and ARIMA. The results were compared based on Mean Absolute Percentage Error (MAPE), which is given by:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{y - y\text{Pred}}{y} \times 100 \tag{13}$$

where, y is the actual load and yPred is the predicted load in the paper.

The linear regression model shows the relationship between a response (dependent) variable and one or more (predictor) independent variables to the extent that information is contained in the data. It gave a MAPE of 3.7044% and the corresponding figure is shown in Figure 2.

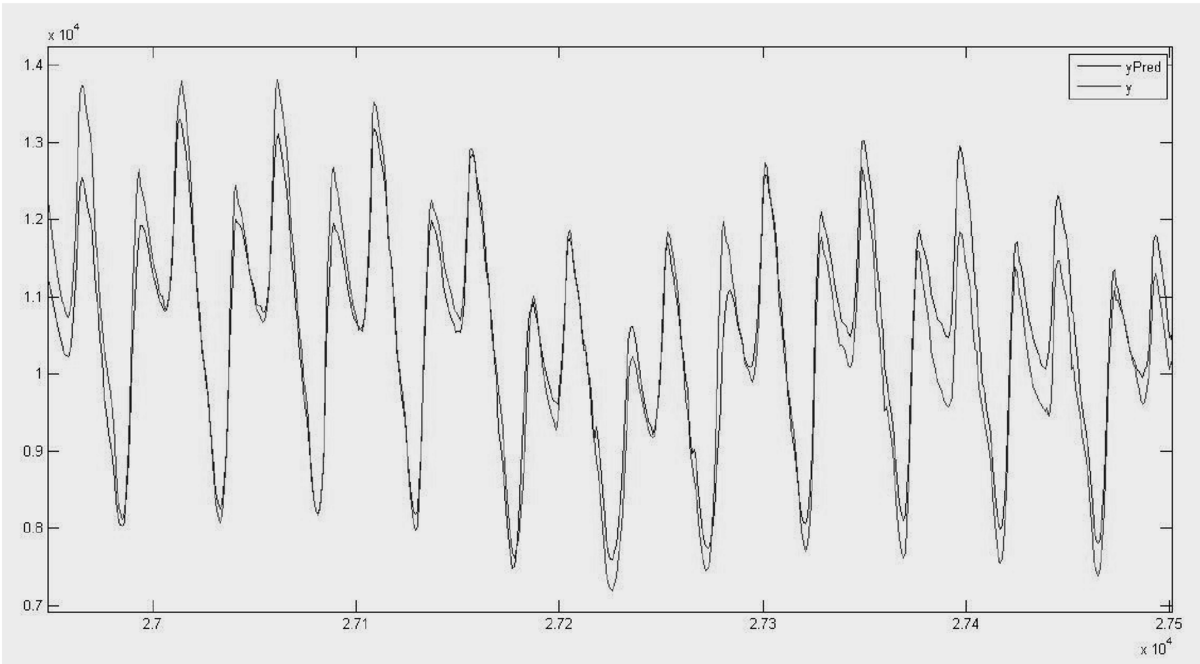

Figure 2: Actual load (*y*) and Forecasted load (*y*Pred) using linear regression

The result of the linear regression is not satisfactory enough and so we test the system with ANN.

$$F(x_0, ..., x_{N-1}) = \sum_{i=0}^{N-1} f_i^2(x_0, ..., x_{N-1}) \tag{14}$$

The neural network was trained with 70% of the data, tested for 15% of the data and validated with the rest 15%.There were 8 inputs provided, as in terms of the predictors and a single output, as system load is taken. Three forms of neural networks, based on the hidden layer, were tested that are discussed as under:

i) Single layer with 20 neurons: This system gave a MAPE of 1.9583% in 124 iterations and is shown in Figure 3.

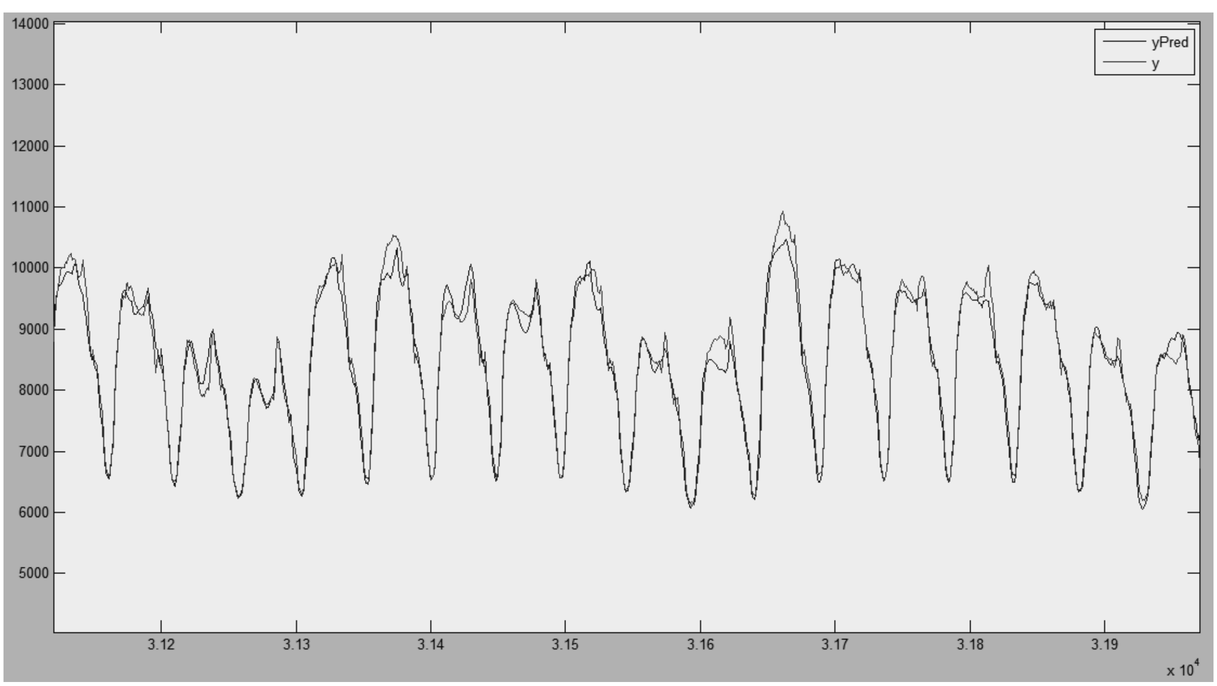

Figure 3: Actual load (*y*) and Forecasted load (*y*Pred) using single layer 20 neurons

ii) Single layer with 40 neurons: This system gave a MAPE of 1.7770% in 177 iterations and is shown in Figure 4.

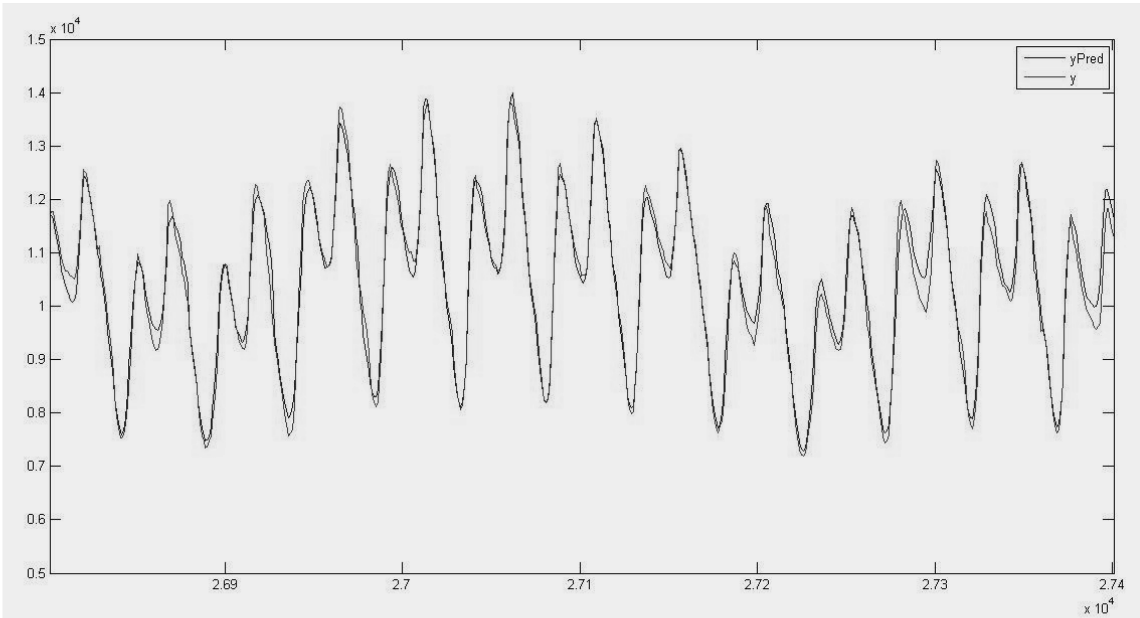

Figure 4: Actual load (*y*) and Forecasted load (*y*Pred) using single layer 40 neurons

iii) 2 layer with 20 neurons in each level: This system gave a MAPE of 1.6149% and is shown in Figure 5.

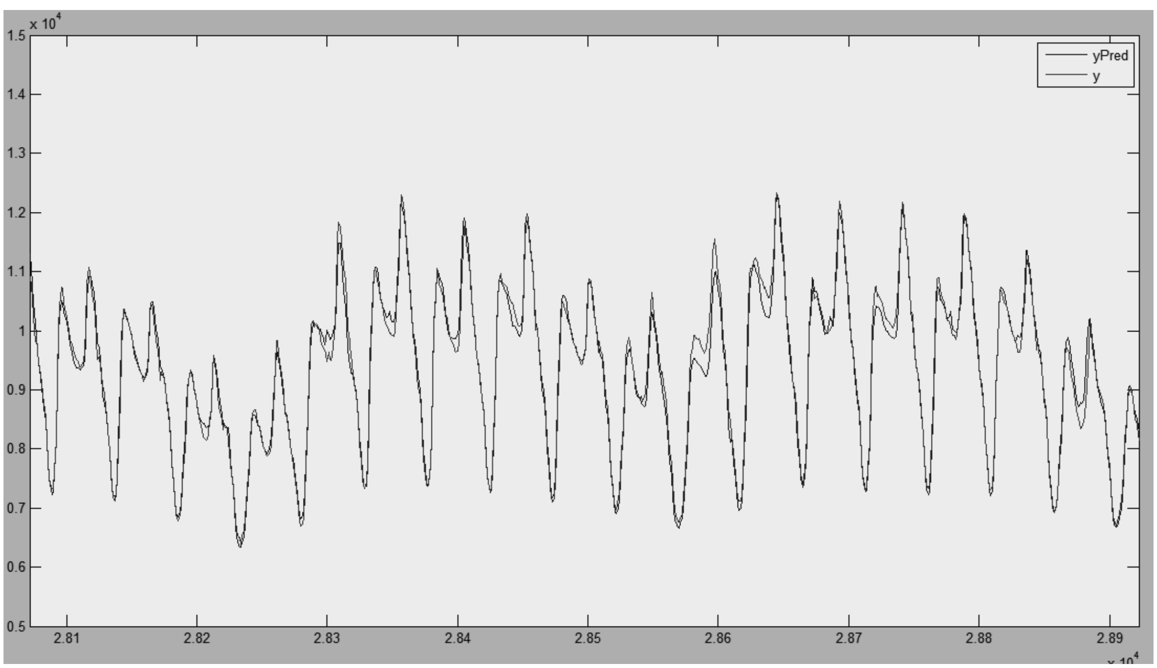

Figure 5: Actual load (*y*) and Forecasted load (*y*Pred) using 2 layer 20 neurons in each level

Thus, it can be easily concluded that the usage of multiple layer neurons, we obtain a better forecasting result than what we obtained from the single layer neurons.

Further, using the data provided, a rough forecasting of the price was also made in which the number of predictors was increased up to 12 viz.'Dry Bulb', 'Dew Point', 'Hour', 'Weekday', 'Is Working Day', 'Current Load', 'Prev Week Same Hour Load', 'prev Day Same Hour Load', 'prev 24 Hr Ave Load', 'Prev Week Same Hour Price', 'prev Day Same Hour Price', 'prev 24 Hr Ave Price'. A single layer 20 neuron layer was used with 70% training, 15% testing and 15% validating data. The MAPE of the system was obtained to be 1.07% and is shown in the Figure 6.

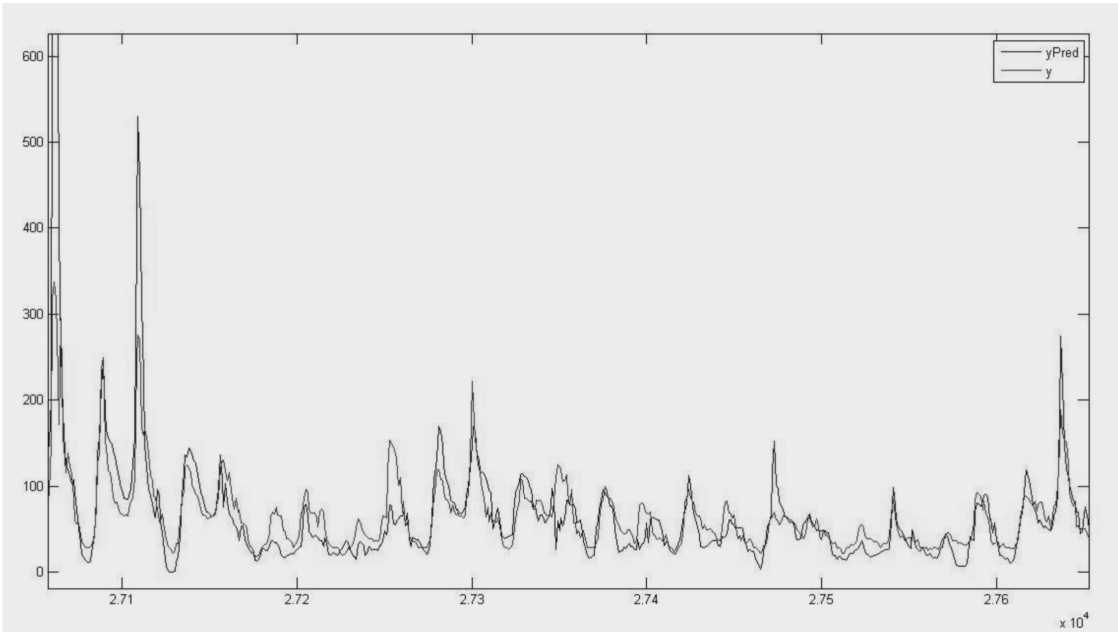

Figure 6: Actual Price (*y*) and Forecasted Price (*y*Pred) using 1 layer 20 neurons

The next phase of work in the paper was carried out on the ARIMA model forecasting of the system. ARIMA being a major tool in the forecasting and analysis of complex economics graphs was deduced to provide a proper forecasting of the system. The quantum of calculations in ARIMA tends to be very high. So a system was designed to reduce the data set in the system. To cater to this need, the 'month peak load' was calculated over a period of 5 years pertaining to 60 data on which the ARIMA was implemented. The best ARIMA model found for the system using ACFs and PACFs was (1, 0, 2) thus converting it into an ARMA model. The results were not satisfactory as the output obtained had a MAPE of 7.2834% and the corresponding graph shown in Figure 7.

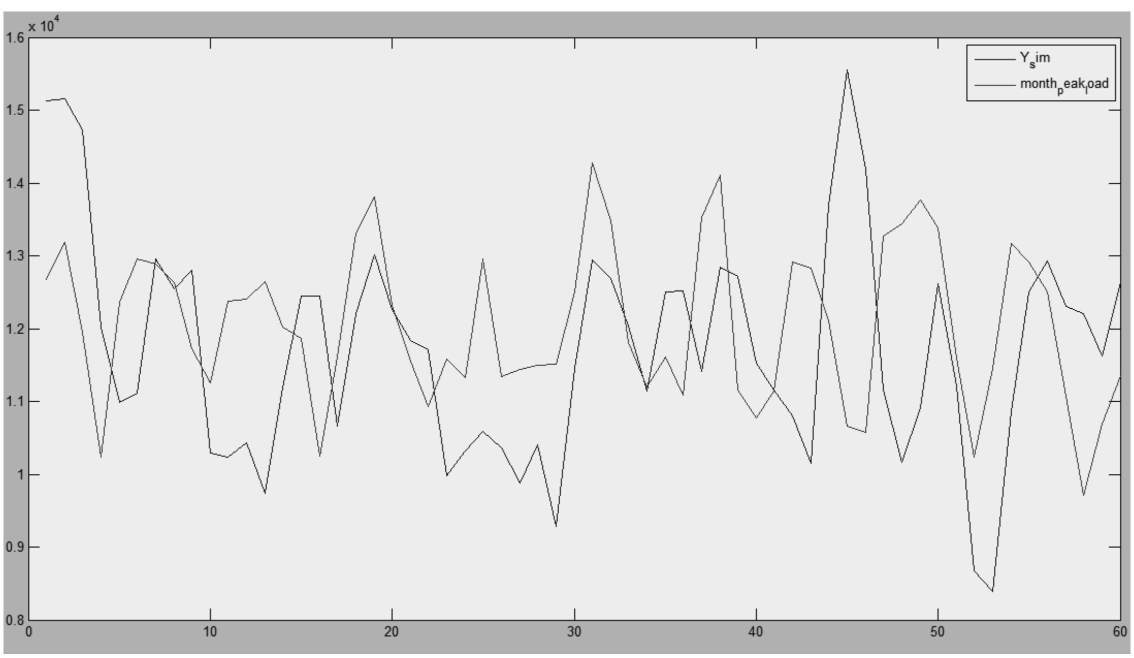

Figure 7: Actual Peak Month load and Predicted ARMA model

Simultaneously when ANN was applied to the same system, it provided a MAPE of 3.9123% which was fair enough owing to the fact of limited values. Further, to check how the system behaves when both ARMA and ANN are included in the first and second step respectively, it was seen that the overall result of ARIMA reduced to 6.1844%. Thus, ANN improves the system performance,and it was found out that ARMA modeling is not best suited for the forecasting problem in the paper and that ANN outperforms ARMA. The corresponding ANN and ARMA-ANN results are shown in Figure 8 and Figure 9 respectively.

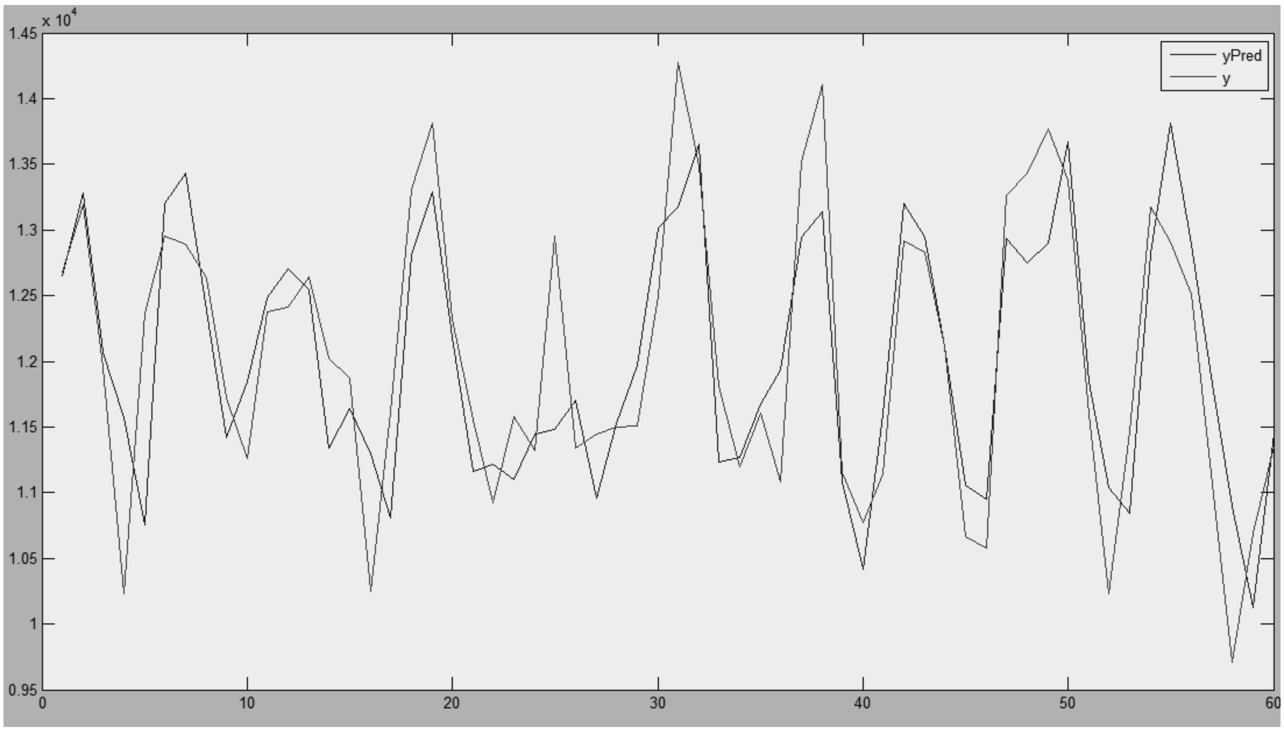

Figure 8: Actual Peak Month load (*y*) and Predicted ANN model (*y*Pred)

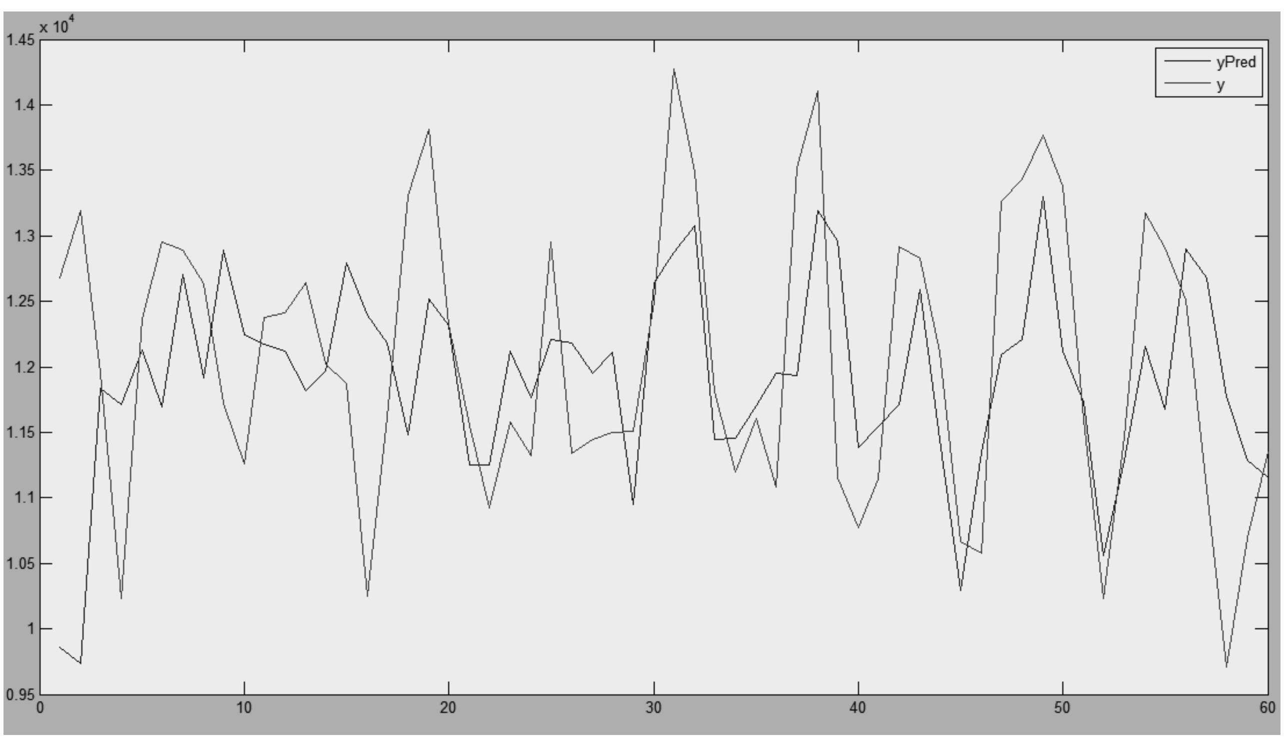

Figure 9: Actual Peak Month load (*y*) and Predicted ARMA-ANN model (*y*Pred)

For finding out the optimal DG placement and size, we derive an hourly load curve from the total data. The hourly load curve of a day represents each season viz. winter, spring, summer and fall. The load curve of four 24-h days (24 × 4 = 96 h) subsequently represents the four seasons in a year and is depicted in Figure 10.

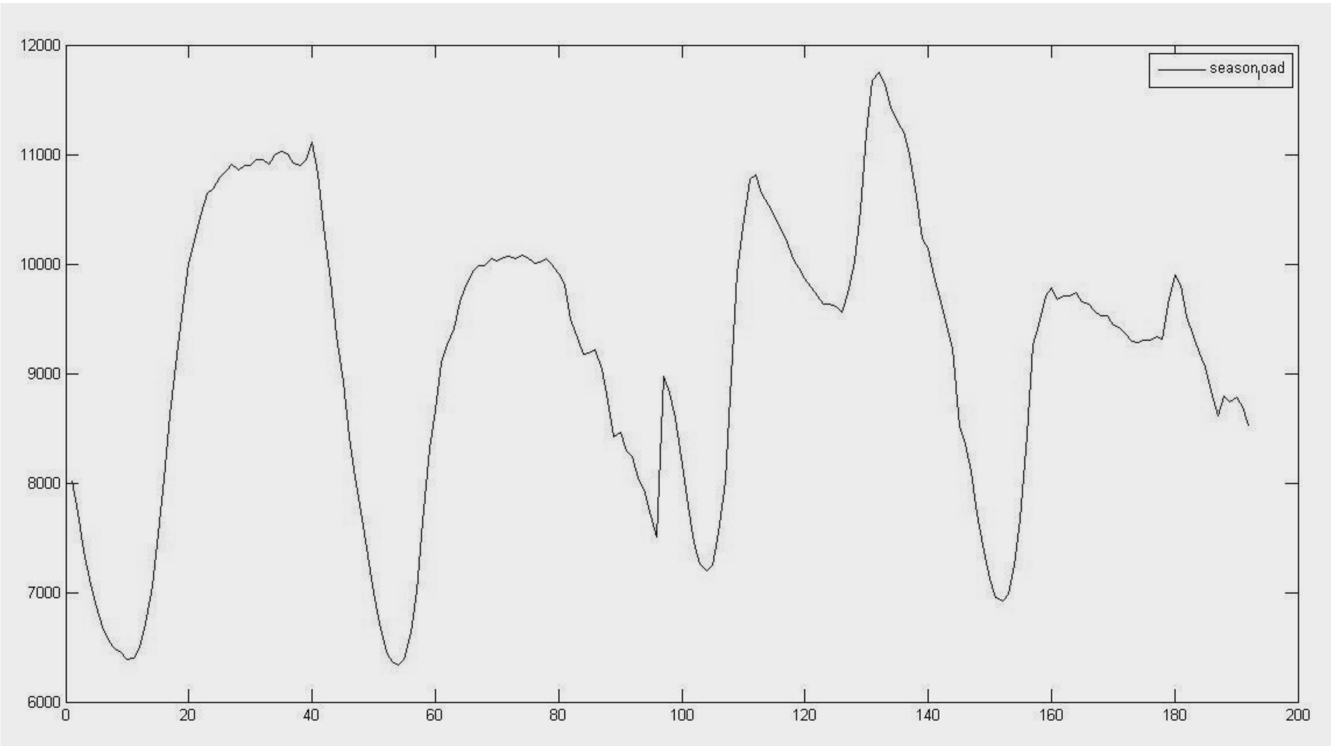

Figure 10: Hourly load demand cure

Here, we have considered an IEEE 69-bus radial distribution system which is shown in Figure 11.

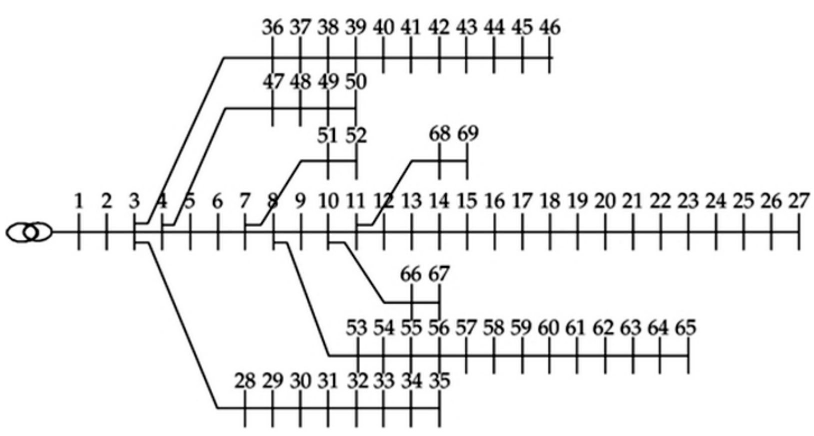

Figure 11: IEEE 69-bus radial distribution system

For 69-bus system, the real power losses without the placement of DG were obtained from Equation (7) and the total real power loss was obtained as 216.6168 kW. The corresponding real power losses and the hourly demand curves are shown in Figure 12.

Now, by the addition of DG in the system, and at different load levels, various values of losses and the corresponding DG sizes were obtained according to those demand level as specified by Equation (12). The minimum total power loss in the system was obtained to be 125.9816 kW where the loading was 11.753 MW. The location for the placement of DG was 61 and the size of the DG was 1.001 MW.

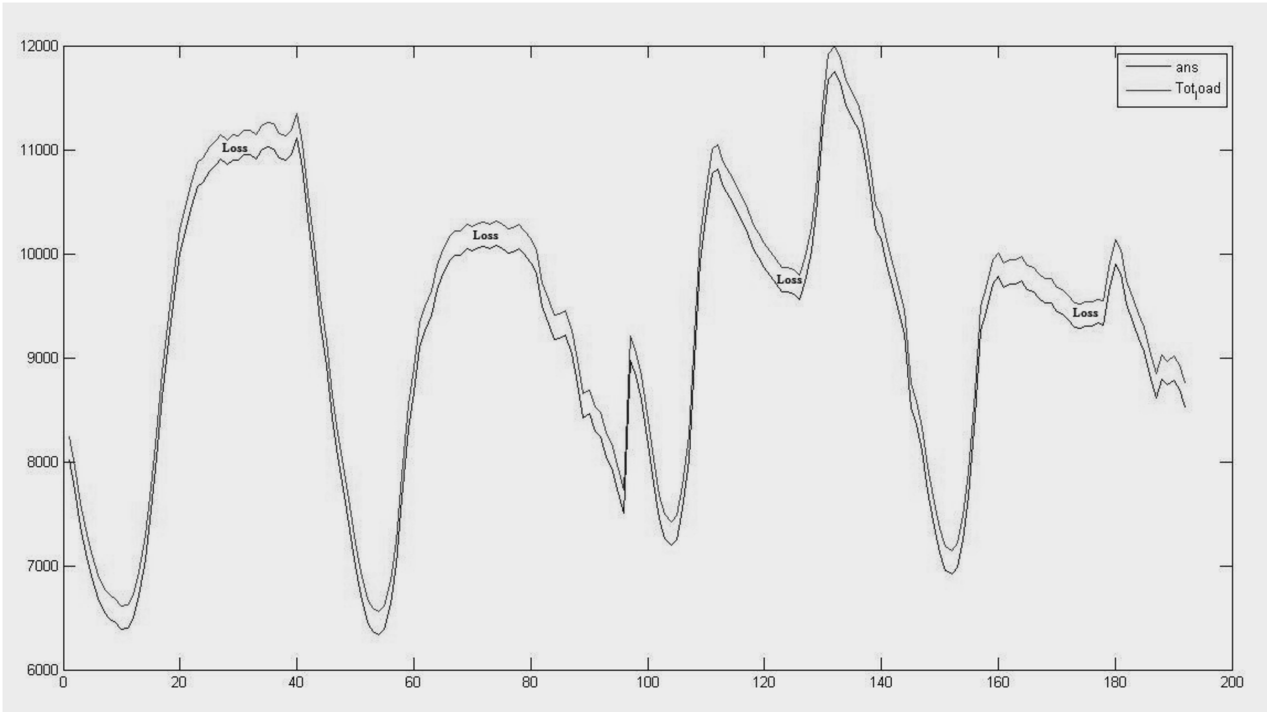

Figure 12: Hourly load demand and power loss curves

The variation of size of DGs according to the variation of the load can also be noticed which specifies that the DG size should not be kept constant at the peak load, as it may lead to further losses at the in the system. The hourly load demand and generation curves are shown in Figure 13.

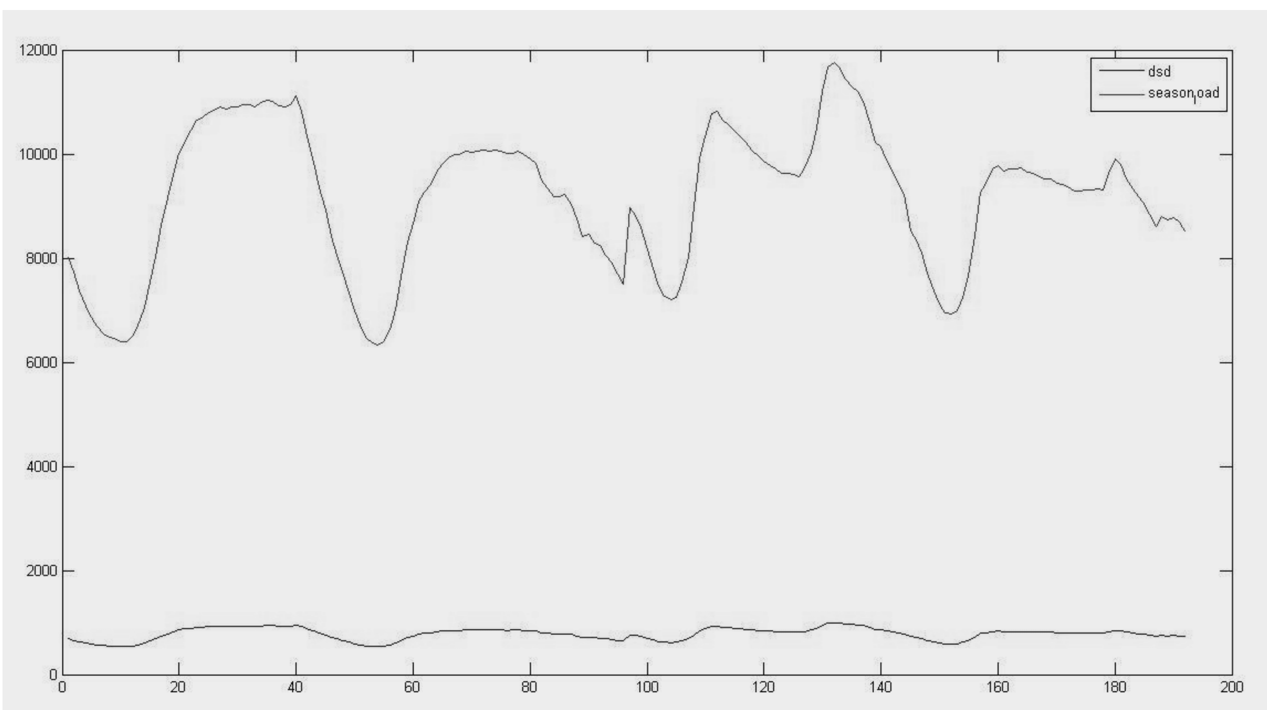

Figure 13: Hourly load demand and generation curves

So, it can be observed how the load forecasting data can be used by the distributors to schedule their generation and to optimize the amount of generation required at every load level. The distributors can gain technically and economically by catering to the optimum generation at every point.

6. CONCLUSION

This paper has emphasized on the need of load and price forecasting in the real time scenario. The load forecasting has been carried out by linear regression, single and multi hidden layer ANN and ARIMA modeling. ANN alone proved to be a great success in finding out the load and price forecasting and clearly outperforms ARIMA and a two level ARIMA-ANN. Further is has been seen that a single hidden layer ANN with more number of neurons gives a better result than the one having lesser number of neurons in the hidden layer. But the use of multi layer ANN proved to yield even better results as compared to single layer ANN. Further, this paper also presents a methodology to determine the optimal sizing and placement of DG units based on the minimization of the total power losses in the system. Here, it has also been appreciated to take into consideration the time varying characteristics of the load, as obtained from the forecasted data and thus suggesting a similar trend in the generation as well. The methodology has been applied to 69-bus test distribution system and the corresponding variations in the values due to the change in load level have been observed and appreciated.

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