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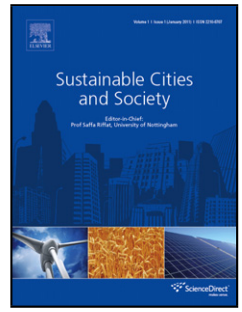

Title: An Intelligent Hybrid Short Term Load Forecast Model For Seasonal Prediction of Smart Power Grid

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An Intelligent Hybrid Short Term Load Forecast Model For Seasonal Prediction of Smart Power Grid

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Highlights

1. A novel hybrid heuristic search optimization based neural network model is proposed for short term load forecast (STLF).
2. Study, analyze and selection of highly correlated historical load and weather variables based on load demand study.
3. Global best Particle swarm optimization (GPSO) is used to update the weight biase values of feedforward neural network.
4. The proposed PSO based NN forecast model is compared to contemporary techniques such as back propagation (BP) and Levenberg marquardt (LM) NN based forecast models in order to analyze the performance.
5. The proposed forecast model demonstrates higher forecast accuracy, training performance of the NN and faster convergence than the comparative contemporary techniques for STLF.

Abstract: An accurate load demand forecasting is always very important for efficient planning and energy management, in buildings, distribution and power systems. Millions of dollars can be saved annually by increasing a small degree of improvement in prediction accuracy. However, it is a difficult task as multiple factors affecting on it, such as inability of prediction model and variables affecting on load (meteorological and exogenous variables). Therefore, a novel feedforward neural network (FNN) based load demand forecast framework is proposed. As conventional backpropagation technique stuck into local minima during training process of FNN, which increase the prediction error significantly. In this paper, new global best particle swarm optimization (GPSO) algorithm is applied as new training technique to enhance the FNN prediction performance. Fitness function and weight bias encoding/decoding scheme are applied to for FNN training. The influential meteorological and exogenous variables are applied as model inputs along with correlated lagged load demand data. New-ISO England grid data is used to validate and verify the performance of proposed model. The proposad forecast model provides significanly higher forecast accuracy compared with contemporary techniques in sesonal a week ahead case studies. In adidition, proposed model also provides better seasonal prediction, convergence rate and training performance than comparative models.

Keywords: Short term load forecasting (STLF), Neural Network (NN), Global best particle swarm optimization (GPSO), Back propagation (BP), Levenberg marquardt (LM), Meteorological and exogenous variables, Mean Absolute percentage error (MAPE).

1. INTRODUCTION

Load forecasting is enormously important for efficient and reliable operation of power system, which leads to uninterruptable power supply to the consumers [1]. Power system operations such as scheduling, maintenance, adjustment of tariff rates and contract evaluations can be efficiently carried out by a precise load forecast [2]. Accurate load forecasting can also be helpful for energy policy-making decisions and efficient energy management system.

In the last decade, widespread research has been published on load forecasting due to its potential to be utilized in smart buildings, grids and cities [3]. The importance of load forecast is further increased as efficiency of power system is affected due to an under and overestimation of load demand. The underestimation of the electrical load demand may show a very negative effect on the demand response, moreover it is also difficult to manage overload conditions as a large backup storage almost impractical for economic reason. In case of overestimation, it may increase the power surplus and production cost leading to very inefficient system operation [4]. Load demand forecast also play a vital role in optimum unit commitment, control of spinning reserve, evaluation of sales and purchase contracts between various energy companies.

The multiple decisions of energy management system such as power system operation, maintenance and planning can be carried out on basis of accurate load demand forecast [5]. Effective planning of power systems can save millions of dollars, which plays a significant role in the economic growth of a country. To implement the concept of smart grids, and buildings, an accurate load forecasting plays a vital role. In the last decade, a large number of researches have been proposed short-term load forecast (STLF) models due to its impact on the reliable operation of power systems and the economy. Some of research studies divulge load forecasting techniques into different categories based on their working principle [6]. Load demand forecast techniques can be classified into different categories named persistence method, physical techniques, statistical techniques, hybrid models and new ensemble network. In literature, hybrid Kalman filters [7], autoregressive models [8], ARMAX model [9, 10] and statistical techniques [11] were applied to forecast the load demand. Theses techniques give good forecast results under less uncertain load demand situation. However, forecast error is significantly increased as several exogenous and meteorological variables are affecting on it. Also, large penetration of solar in terms rooftop PV units and large wind farms add more uncertainty in load demand. Therefore, the existing forecast models are not highly adaptive in nature to deal with uncertain metrological and sociological events. Consequently, it leads to higher forecast error.

Artificial intelligence (AI) based techniques for load forecasting have been getting much attention by researchers since the mid 1990’s. It is due to AI suitability for nonlinear inputs model and prediction problems. The AI techniques have the ability to solve complex problems with higher accuracy under uncertain condition. Several AI techniques have been applied to STLF, such as support vector regression techniques [12], artificial immune system [13], radial basis function [14], Hybrid Monte Carlo algorithm based ANN forecast model [15] and forward neural networks [16-17]. In [18], authors purposed Genetic algorithm and backpropagation combinational neural network based load demand forecast technique. The proposed forecast technique shows a better forecast results in most of the case studies. However, backpropagation (BP) learning does not ensure global optimum solution for neural network training. BP learning technique of neural network stuck in local and doesn’t optimize the NN weight bias values during the training process. As result, it affects the NN performance and leads to higher forecast error. Therefore, global best particle swam optimization (GPSO) techniques is proposed to optimize the NN weight bias values during the training process. In addition, there is a strong impact of metrological variables on load demand. These variables are temperature, relative humidity, dew point, dry bulb and wind speed. The historical load data as well as metrological variables are need to apply as a forecast model inputs for better training performance and higher predication accuracy. Therefore, metrological and exogenous variables are also applied as forecast model inputs along with historical lagged load demand values. These input variables enhance the training performance of the proposed model, which leads to enhanced forecast accuracy.

This paper is organized as follows: Section II examines the impact of ANN forecast model architecture and inputs. It also demonstrates the impact of correlated load and weather inputs on load demand. Section III describes the PSO algorithm, pseudo code of GPSO, training of neural network with GPSO algorithm, fitness function and weight encoding scheme. Section IV provides the seasonal forecast results of proposed model accuracy, convergence and regression analysis. These results are compared with back propagation (BP) and Levenberg marquardt (LM) based NN forecast model for validation. Conclusions and contributions of the paper are highlighted in Section V.

2. NEURAL NETWORK FORECAST MODEL INPUTS AND TOPOLOGY

2.1. DATA OBSERVATION:

In this study, ISO New England (Regional Transmission Organization) grid hourly load is used to predict the future load demand. Also, metrological variables such as dry blub and dew point are also used to train the forecast model. One year 2008 hourly load and weather data form 1st January to 31st December is used as input to the forecast model. Figure 1 depicts the hourly load pattern of year 2008. From the load profile analysis, seasonality trend can be observed in load data series. The seasonality is formed by the repeated cycle of load demand patterns. Furthermore, a variation is load demand can be observed due to change in seasonal temperature. Load demand in summer is significantly higher than the autumn and spring. It is due to change of individual energy consumption and air conditioning etc.

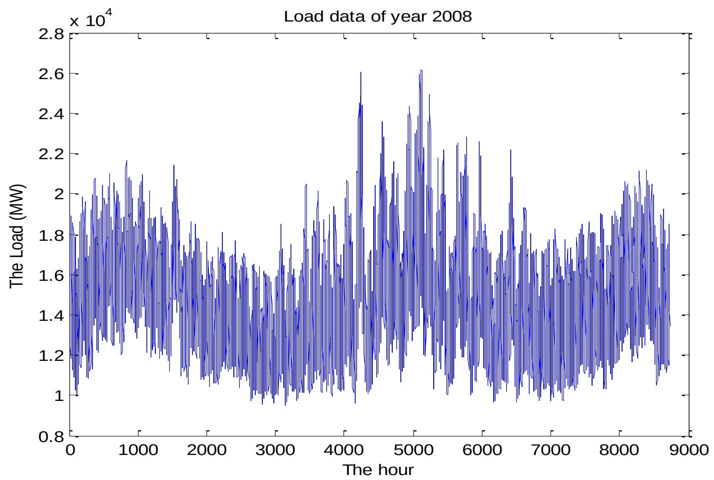

Figure 1: One year 24 hourly load demand of the ISO New England grid in 2008.

2.2. Proposed ANN based forecast model and inputs:

Two years (2008 and 2009) load and weather data with 15 min resolution of New-ISO England power grid is collected to train and test the proposed forecast model as utilized in [19]. Input data of forecast NN forecast model is divided into training, testing and validation data sets. Training data is used to train the forecast model. Seasonal data of 2009 is used for testing and measuring the accuracy of the forecast model. Type and number of Inputs of forecast model is very important to enhance the forecast model performance. There are no specific defined rules for input selection of forecast model but suitable selection can be carried out based on the field experience and expertise [20]. In this research, forecast models are selected based on correlation of specific input variable on load demand. The proposed inputs of ANN model inputs for hourly load forecast are shown in Figure 2.

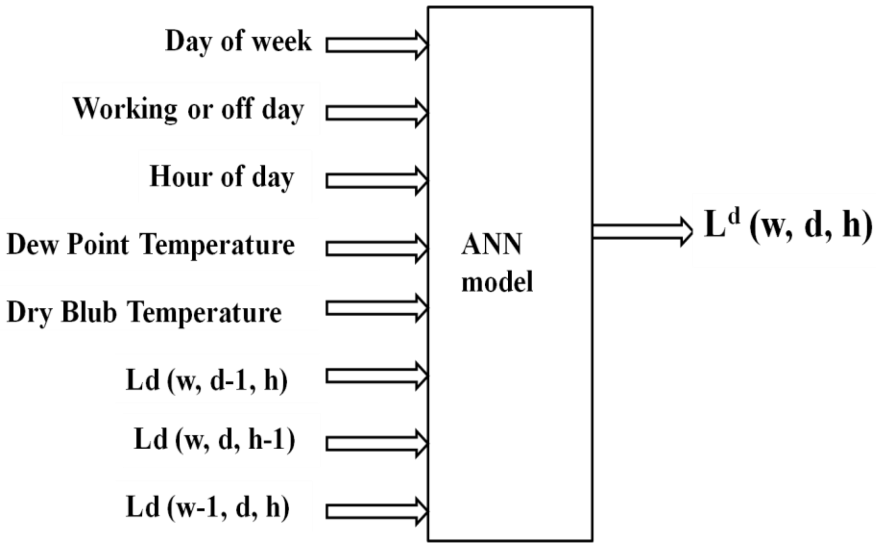

Figure 2: Selected correlated inputs of proposed forecast model.

In order to enhanced training performance of the model, historical lagged values of load demand, meteorological and exogenous variables as given below. As shown in Fig. 2, L_d (w, d, h) represents the predicted load demand of a particular hour of the same day and week.

- L_d (w, d, h-1): represents the load demand for pervious hour of the same day and week.
- L_d (w, d-1, h): represents the load demand for same hour of the week in previous day.
- L_d(w-1, d,h): represents the load demand for same hour of a day of the previous week.
- Day of week (day of week represents either it is first day or second day or any other day of week)
- Working day or off day (type of day)
- Hour of day
- Dew point temperature
- Dry blub temperature

2.3. Working day or off-day:

It is observed that, load demand in working and off-day is different due to variation in human activities. Therefore, in order to increase the forecast accuracy type of day is considered as NN forecast model input.

2.4. Day pointer D (k) and hour pointer H (k):

The load demand also varies in different time of day and day of week. Load profile analysis depicts that, the variation in load demand from Monday to Sunday and morning to night. Figure 3 depicts that, the change in load demand according to hour of day and day of week.

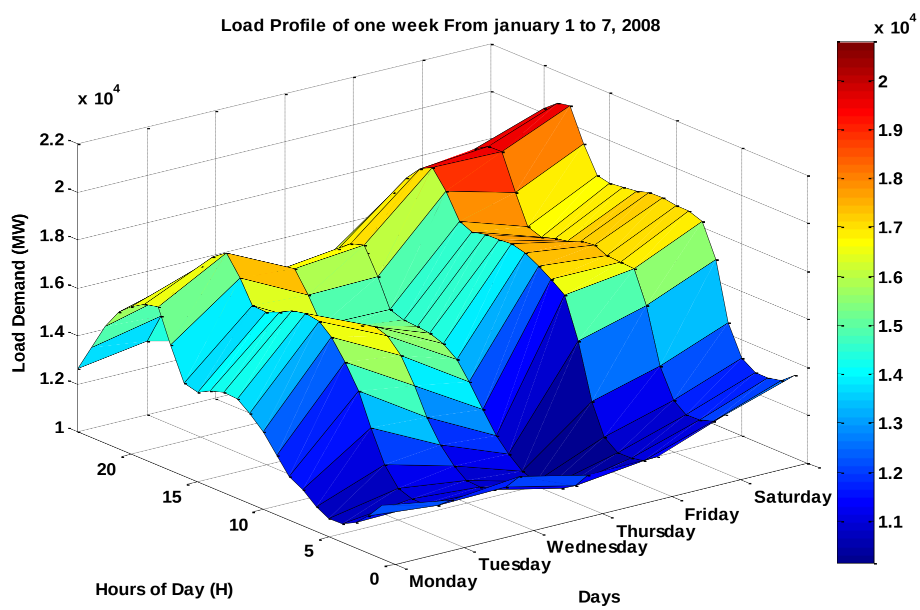

Figure 3: One-week load profile of ISO New England grid (January 1 to 7, 2008).

A cyclic pattern can be observed in one-month load plot of demand during the hours of days and days of month as shown in Figure 4. Figure 4 illustrates that, the load demand in on weekends is relatively higher than weekdays. It can be concluded that, load demand in weekends is fairly different than working as shown in one week and month load profile. In order develop an accurate forecast model, the type and hour of day can be included as forecast model input.

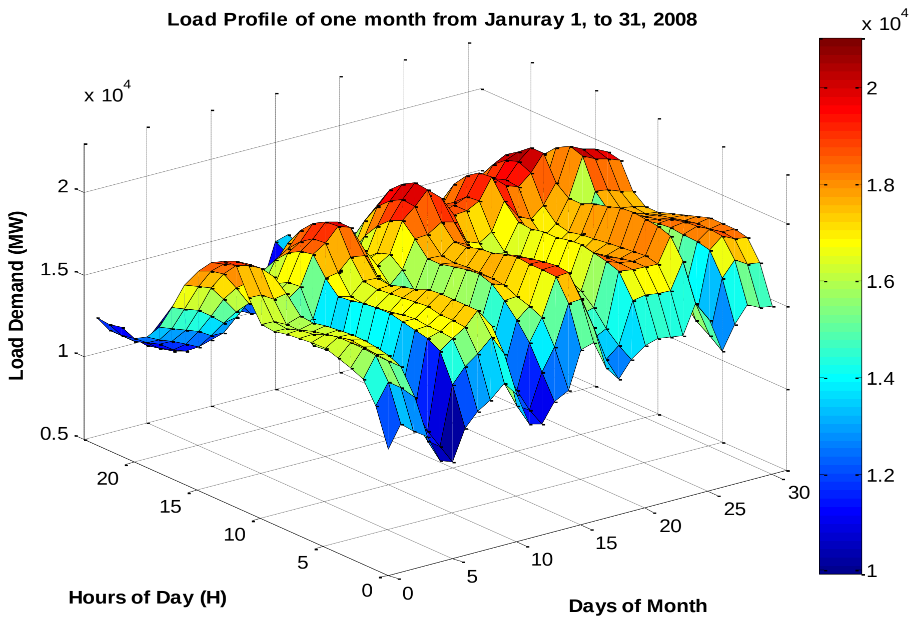

Figure 4: One month load profile of ISO New England grid (January 2008).

2.5. WEATHER INPUT VARIABLES:

The impact of metrological conditions on load demand has been reported in [20-23]. It is reported that, load demand varies with change in temperature, season and other metrological variables. ISO new grid web database also provide the dew point and dry bulb temperature along with historical load demand data. Figure 5 represents the relationship between the dry blub and load demand. The graph shows that as the value of the dry blub increases, the power system demand also increases and vice versa. The human perception study shows that the dry blub in the range of 45F to 65F is suitable for humans. The load demand is low within this range of dew point.

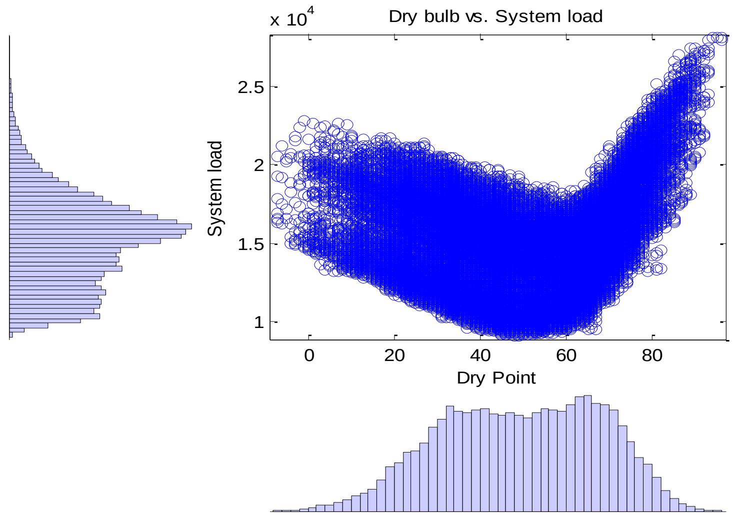

Figure 5: Relationship dry blub vs. power load demand.

3. PROPOSED ANN ARCHITECTURE:

A three-layer feed forward neural network having one input, a hidden and an output layer is used to forecast the load demand. A large number of configuration experimented with different settings for the various parameters of the neural network architecture (e.g., number of hidden layers, number of neurons per hidden layer, different types of network transfer function). Moreover best-suited inputs of NN with lowest forecast error are selected and model performance is also analyzed with different network parameters. The proposed neural network architecture is 8-20-1, which contains the neurons 8-20-1 in input, hidden and output layer respectively as shown in Figure 6.

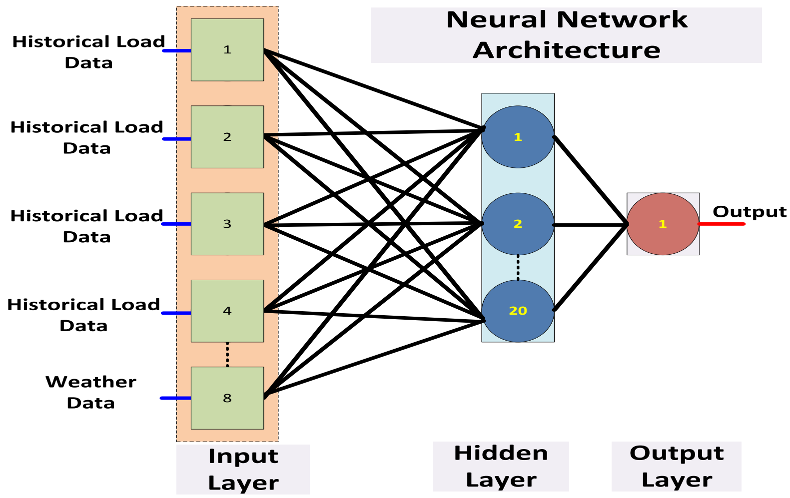

Figure 6: Proposed ANN architecture of forecast model.

3.1. Particle swarm optimization:

Particle swarm optimization (PSO) is a heuristic search approach based on population, which ensures the global optimal solution. Eberhart, an electrical engineer and Kennedy, a social physiologist were developed this evolutionary computation technique in 1995 [24]. Literature review shows, PSO proves itself as a powerful optimization tool, which is applied to several different real world problem [25]. PSO is population based optimization technique which inspired by sociological behaviour of birds or fishes moving in search of food. The birds or fishes tries to find the food by own best search experience as well social experience.

In PSO population based optimization technique, in which each candidate of population is called particle and each particle tends to find the best solution based on own and neighbor experience in a multidimensional search space. A group of particles is called swarm and swarm tends to find the optimal solution for certain optimization problem. The one major advantage of PSO techniques is to adjust only two parameters which are velocity and position of particles. Each particle updates his position and velocity based on his own and social experience according to Eqs. 1 and 2 [26].

$$v_i^{(k+1)} = wv_i^k + c_1 r_1 (Pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

Where,

c_1 and c_2 are positive constants which control the personal and global component of algorithm,

r_1 and r_2 are randomly generated numbers within a range of [0,1],

w is the inertia weight,

$Pbest_i^k$ is the personal particle best position achieved, which is based on its own experience,

$gbest^k$ is the global particle best position achieved by the all particle, which is based on overall swarm's experience,

k is the iteration index.

v_i^k Current velocity of the particle.

$v_i^{(k+1)}$ New velocity of the particle.

x_i^k Current of the position.

x_i^{k+1} New particle position.

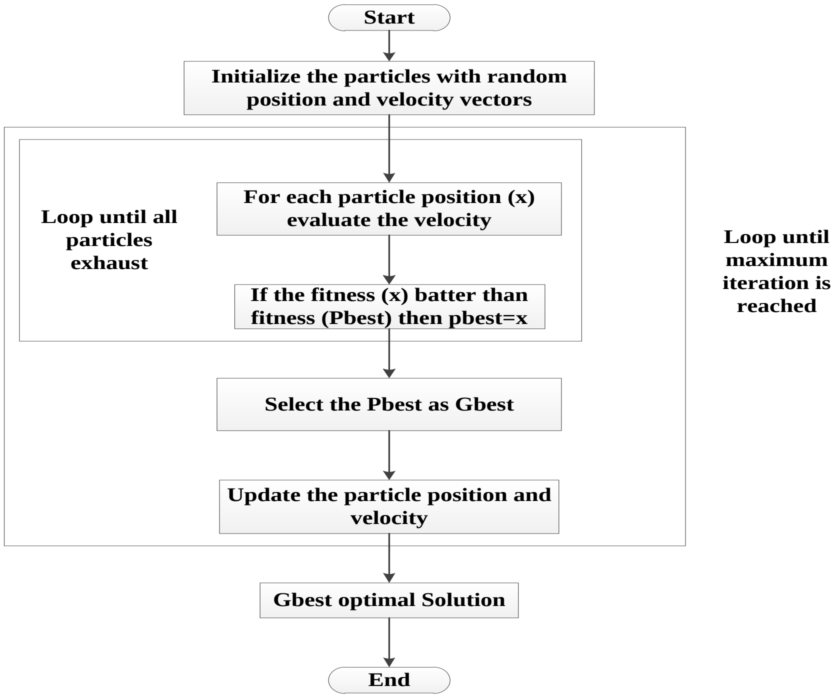

Figure 7: Flow diagram of Gbest PSO algorithm.

3.2. Global Best Particle Swarm Optimization (GPSO):

Global best or Gbest version of PSO achieves the global optimum and produce better results than the local best version local best PSO (LPSO). In Gbest PSO, the particle position is influenced by his own visited best position and best of position of neighbourhood particles. Consequently, Gbest PSO find the best solution from all particles in the swarm and most likely to achieve the global optimum according to Eqs. 3 and 4. Therefore, that in position update process reflects social influence of all particles [27].

$$v_i^{(k+1)} = wv_i^k(t) + c_1 r_1 (y_i^k(t) - x_i^k(t)) + c_2 r_2(t)(y_i(t) - x_i^k(t) \tag{3}$$

$$x_i^{(k+1)} = x_i^k(t) + v_i^{(k+1)}(t) \tag{4}$$

For Gbest PSO the velocity of particles is calculated as:

Where:

C_1 and C_2: Acceleration constants, which are used to define the contribution of social and cognitive component in velocity updating process.

R_1 and R_2: Are the random generated numbers in the range [0, 1].

$V_{ij}(t)$: Velocity of ith particle in dimension k direction at time t.

$X_{ij}(t)$: Position of ith particle in dimension k direction at time t.

In Gbest algorithm, the velocity is updated with best value of entire swarm. The first and second part in Eq. represents cognitive and social component respectively.

The pseudo code of Gbest PSO algorithm is shown in Figure 8.

```
    Create and initialize the swarm of size D
For each particle I=1,2,…,D
//set the personal best position
        If  f(D.x_i) < f(D.y_i) then
        D.y_i = D.x_i
        end
//set the global best position
        if  f(D.x_i) < f(D.ŷ_i)
        D.y = D.y_i;
        end
end
For each particle I=1,2,…,D
Update the velocity according to Eq. (3);
Update the position according to Eq. (4);
End
```

Figure 8: Pseudo code of Gbest PSO algorithm.

3.3. Neural network training using PSO:

The learning process of neural network with PSO based on the particles position, in which each particle represents the potential solution. Each particle position represents the set of weight and the number of weights associated with the network determines the dimensionality of particle in search. The particle moves in search space and each training epoch particles are trying to achieve the global minimum.

In each epoch the particle position and velocity is updated according to Eqs. 3 and 4. This process is repeated until certain threshold of learning error is not achieved.

At the global minimum point the weight values (current particle positions) generate the minimum network learning error. Figure 9 represents the learning steps of neural network with PSO [28-29]. The details of the steps are explanined next.

Step 1: The learning of the network is initialized with generation of PSO population. The initial particle position are assigned as neural network training parameters (weight, bias).

Step 2: The network is trained with particle position.

Step 3: Network will generate error by the provided network weight values in training process.

Step 4: The particle positions (weight and bias) are updated to minimize the learning error of network. The “Pbest” and “Gbest” values are used to calculate the new velocity according to Eq. 3 to get the new position of particle for targeted learning error.

Step 5: To calculate the new set particle positions (weight, bias), the value of velocity is add in previous position according to Eq. 4. Thus the difference of desired and network output produces an error which is called as mean square error (MSE) of the network. Therefore, NN training algorithm is utilized to reduce the MSE of the network until the threshold criteria met. The MSE is used as objective function in training process of neural network. This error is used to update the weight values of network to achieve the targeted output. This process will continue until stopping conditions of either minimum target learning error is achieved or maximum numbers of epochs are reached as shown in Figure 9.

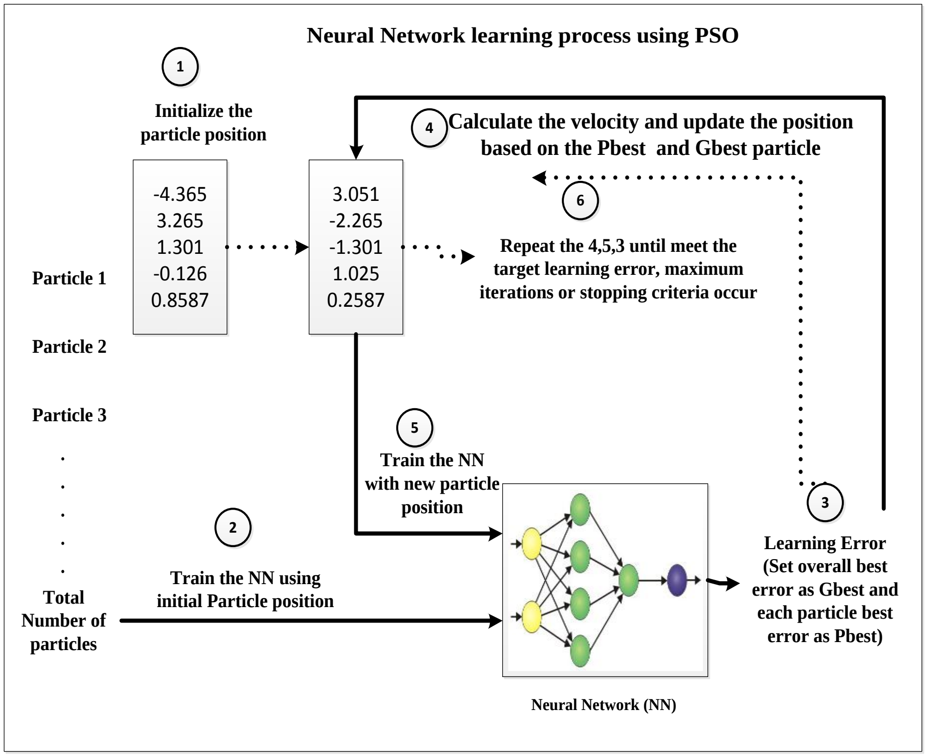

Figure 9: NN learning process using PSO algorithm.

3.4. PSO Tuning Parameters:

There are four basic tuning parameters of PSO algorithm to achieve the optimized results for optimization problem.

- Number of particles
- Time interval (Δt)
- C_1 is the acceleration constant of the (Gbest) component
- C_2 is the acceleration constant of (Pbest) component

The PSO parameters can also be adjusted based on the nature of optimization problem to achieve the higher quality of results.

The number of particles in swam should neither be very large nor very small. The large swam size increases the computational complexities of search space and computational time. The small swam size does not optimally discover the search space to find the global optimum. So, optimal selection of swarm size can also provide better network performance by achieving global optimum rather than local optima. Δt is time interval taken by the particle to move in search space. Increase in Δt by will provide lower granularity movement within the search space and vice versa.

The C_1, C_2 are the constant values used to define the weight of Pbest and Gbest in the velocity update process. If the C_1 is higher than the C_2 then particle are be inclined toward the global best solution and opposite case particle tend to moved towards local best solution. There some other parameters that may effect on the performance of PSO algorithm such as: number of iteration, stopping criteria and dimension of particles.

3.5. Fitness function

The fitness function of neural training is calculated as [30]. Figure 10 shows the three layer neural network with one input, hidden and output layer, where the number of input nodes are n, number of hidden layer nodes are h and y nodes in the output layer of the network. Assume that, the transfer functions of hidden layer and output layer are sigmoid, linear transfer function respectively.

The output of hidden layer can calculated as:

$$f(s_j) = 1 / \left(1 + \exp\left(-\left(\sum_{i=1}^{n} W_{ij}.x_i - \theta_j\right)\right)\right) \qquad (5)$$

Where j = 1, 2, 3…, h

Where $S_j = \sum_{i=1}^{j} w_{ij}.x_i - \theta_j$, W_{ij} is the connection weight of ith node of the input layer to jth node of hidden layer, x_i is the ith input, θ_k is threshold of hidden layer unit and n is the number of input nodes.

The output of kth layer calculated as:

$$O_k = \sum_{i=1}^{H} w_{kj}.f(s_j) - \theta_k \qquad (6)$$

k = 1, 2, 3,…, y

Where w_{kj} connection weight from jth hidden layer to kth is output node and θ_k is threshold of output layer.

Final Fitness function E (learning error) can be calculated as:

$$E = \sum_{i=1}^{r} E_k / (q * o) \qquad (7)$$

Where

$$E_k = \sum_{i=1}^{q} (y_i^k - d_i^k)^2 \qquad (8)$$

q is the number of training samples, y_i^k is the actual output of the ith input unit, when kth training samples is used and d_i^k is desired output of the ith input unit, when kth training samples is used.

The fitness function of ith training sample can be defined as:

$$\text{Fitness } (x_i) = E(x_i) \qquad (9)$$

3.6. ENCODING TECHNIQUE

According to [31] there are three encoding strategies, used to represent the weight values of neural network such as; vector encoding, matrix encoding and binary encoding. In this study, matrix encoding strategy is used to represent the weight values of the network as it suitable with proposed feed forward neural network (FNN) [31]. A 1-3-1 FFN architecture is shown in Figure 10 and weight bias values for each particle as an example can be written as follows.

$$\text{Particle}(:,:,i) = [W_1, B_1, W', B_2] \quad (10)$$

Where I = 1, 2, 3… total number of particle.

$$W_1 = \begin{bmatrix} W_{12} \\ W_{13} \\ W_{14} \end{bmatrix}, \quad B_1 = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}, \quad W_2' = \begin{bmatrix} W_{25} \\ W_{35} \\ W_{45} \end{bmatrix}, \quad B_2 = [\theta_4] \quad (11)$$

Where W_1 is the weight matrix of hidden layer, B_1 is the bias values of hidden layer, W_2 is the weight matrix of output layer, B_2 is the bias values of output layer and W_2' is the transpose of weight matrix of the output layer. Moreover, each particle is decoded into weight matrix for FNN output calculation.

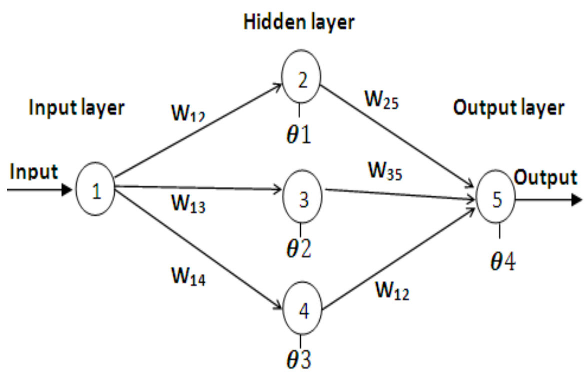

Figure 10: 1-3-2 neural network structure.

4. RESULTS AND DISCUSSION:

To assess the prediction quality of load forecast model, mean absolute percentage error (MAPE) can be measured as given in Eq. (12).

$$MAPE = 1/M \sum_{i=1}^{m} | L_{actual} - L_{predicted} | / L_{actual} \quad (12)$$

Where L_{actual} is the actual load, $L_{predicted}$ is the forecasted load and M is the number of data points.

Normally, each season have typical two months and it represents the weather behaviour of that season. Such as, December, January are considered as winter months; March, April as spring months; July, August are seen as summer months, September and October as the autumn season. In this paper, 168 hours (one week) ahead seasonal load forecast case studies are presented to analyze the forecast model performance and seasonal variation of year. The first week of January, March, July and September of 2009 is the prediction intervals for winter, spring, summer and autumn respectively [32].

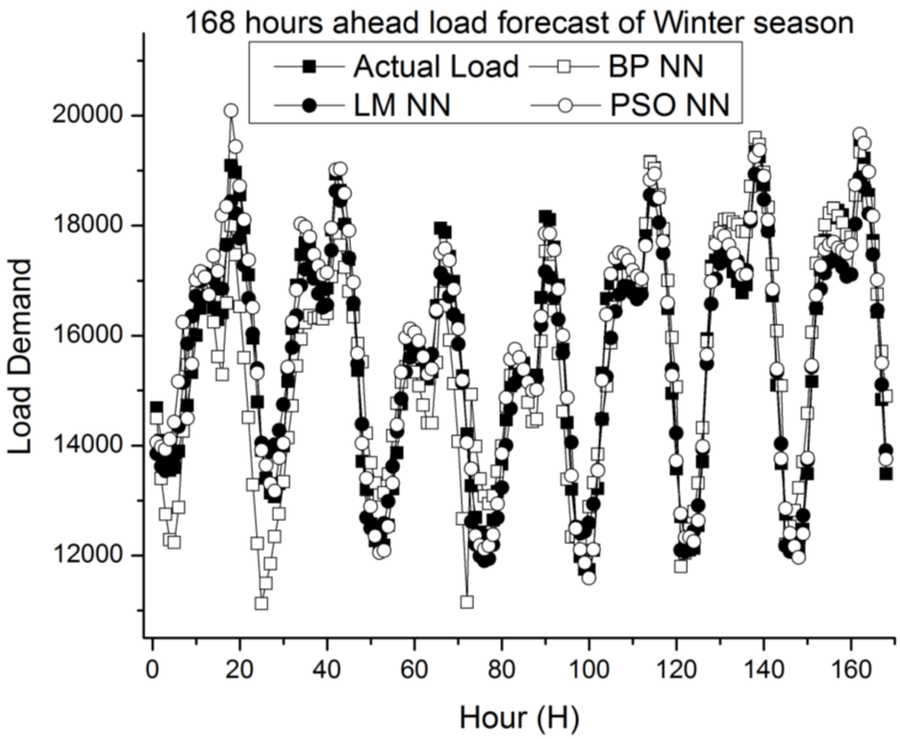

Figure 11: 168 hours ahead STLF of the winter season.

The comparison of BP, LM and PSO training techniques of ANN forecast model for 168 hours ahead load forecast are shown in Figures 11, 12, 13 and 14. The MAPE is obtained with proposed enhance PSO based forecast model and compared with BP, LM technique. MAPE of load forecast is affected due to uncertain metrological conditions and change in sociological activities.

The proposed ANN forecast model with enhance PSO training techniques shows better forecast results for all seasons of year than the BP and LM techniques. It also can be observed that, the proposed technique gives the MAPE 1.40 % in summer and other training also shows less MAPE in summer season. It is due to less variation in metrological conditions which affect the load demand. Forecast accuracy of model can be enhanced by training data, which contains less uncertainty of load demand due to weather variables and social events.

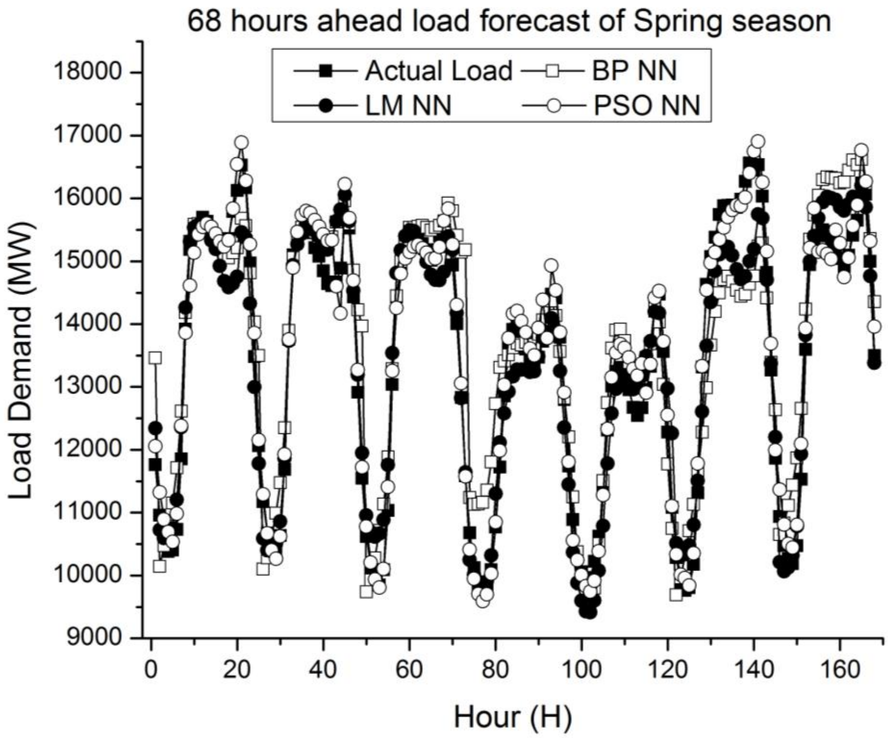

Figure 12: 168 hours ahead STLF of the spring season.

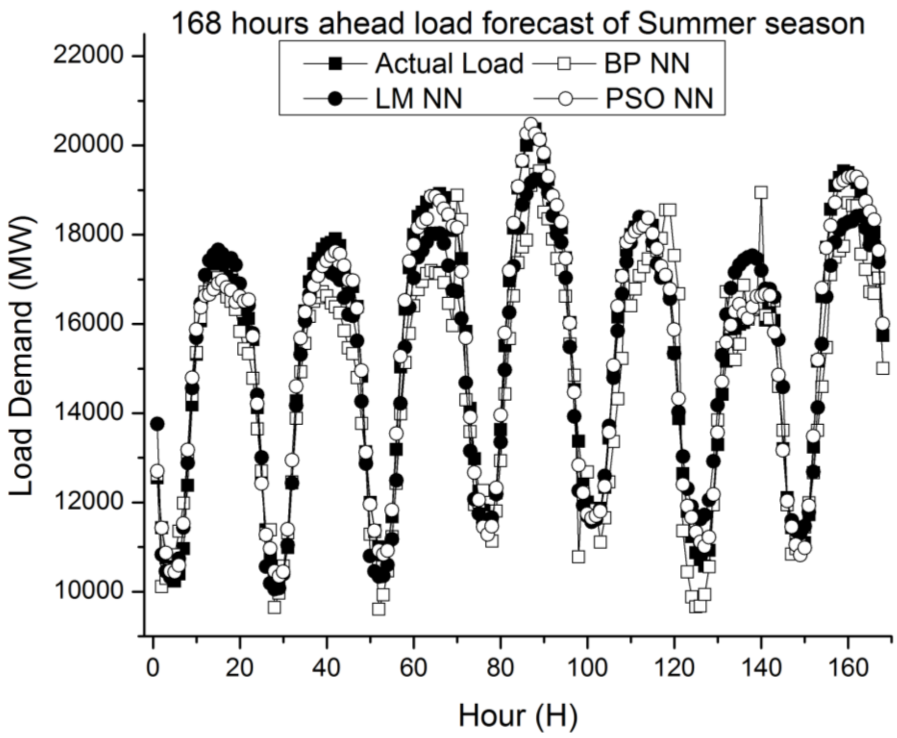

Figure 13: 168 hours ahead STLF of the summer season.

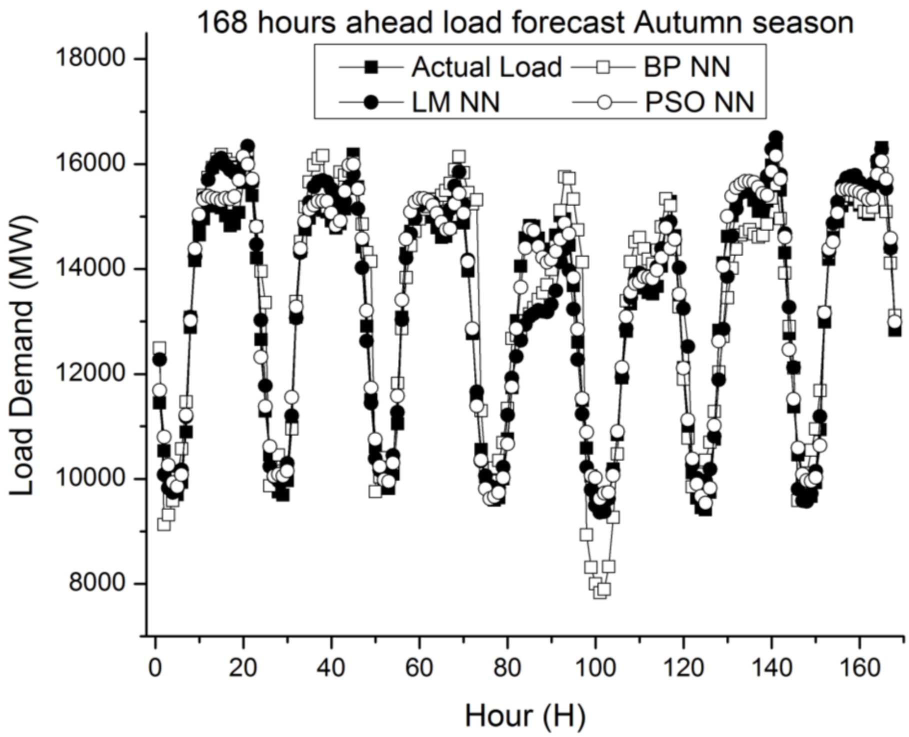

Figure 14: 168 hours ahead STLF of the autumn season.

It can be ssobserved that, the load demand in summer season is higher than the winter and autumn due to seasonal temperature variation. Consequently, the mean absolute percentage error (MAPE) in a winter season is higher with BP, LM and enhanced PSO based forecast model due sociological activities as shown in Figure 15. It means that, PSO based NN forecast model can achieve a higher accuracy due to efficient way to train the NN. It also proves that, the PSO based forecast model shows, better generalization capability over large training data of forecast model.

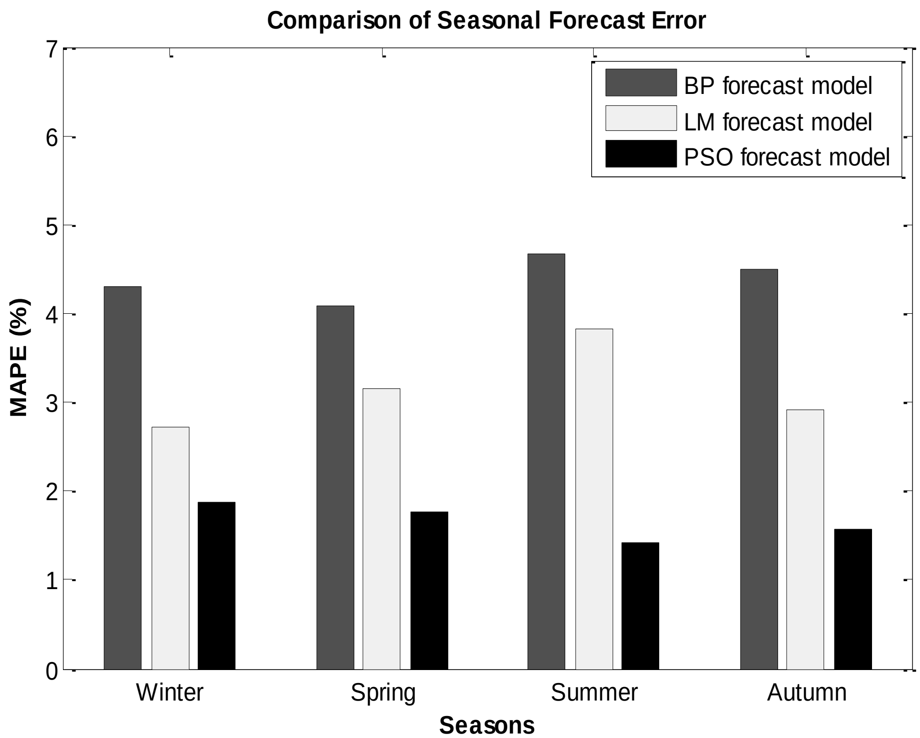

Figure 15: Seasonal MAPE comparison of BP, LM and PSO based NN forecast model.

Table 1 represents the seasonal MAPE comparison of BP, LM and PSO based forecast model, forecast horizon and date of load forecasting.

Table 1: MAPE Comparison of Seasonal Forecast

Season	*Forecast Date*	*Forecast Horizon (Hours)*	*BP MAPE (%)*	*LM MAPE (%)*	*PSO MAPE (%)*
Winter	January 1^{st} to 7^{th} 2009	168	4.303	2.726	1.869
Spring	March 1^{st} to 7^{th} 2009	168	4.088	3.163	1.760
Summer	July 1^{st} to 7^{th} 2009	168	4.665	3.823	1.408
Autumn	September 1^{st} to 7^{th} 2009	168	4.500	2.919	1.577

5. PERFORMANCE ANALYSIS OF TRAINING TECHNIQUES

A large range input data is used to train the NN based load forecast model but correlated and normalized data input sets play significant role in the training process of NN. Input data set containing outliers can affect the forecast performance of prediction models. As results, it may lead to poor network training, increased the computational cost and convergence time of the network [33]. So, these issues can resolve by training the network using highly correlated and preprocessed data set.

Figure 16 depicts the relationship between the Mean square error and the number of epochs of PSO based NN forecast model. PSO training method convergence graph shows that the NN converges for the best validation value of convergence is 251 in 111 epochs as shown in Figure 16. In comparison the BP and LM NN training takes 719 and 368 epochs to converge the forecast model for same stopping criteria.

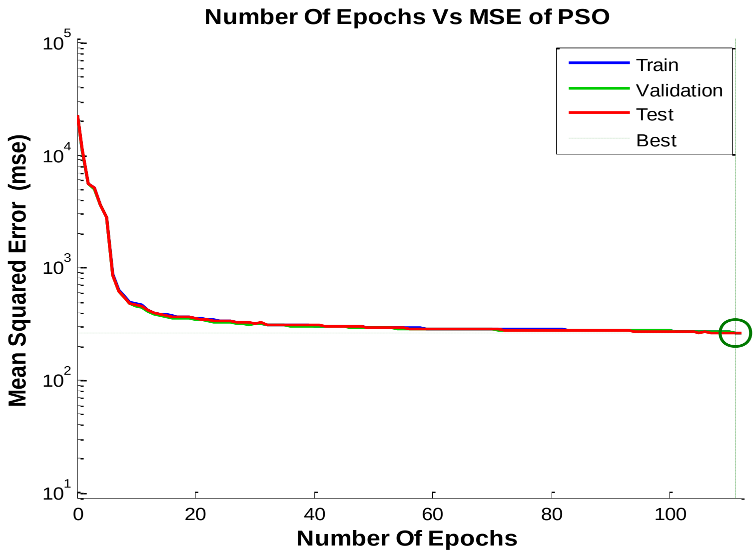

Figure 16: No. of Epochs vs. Mean Absolute error of PSO based forecast model.

BP and LM training method of neural network takes higher number of epochs than the GPSO techniques, which is computationally expensive and takes longer time to converge. In other words, the GPSO training technique achieves the required training, testing, and validation target in less number of iterations.

Table 2: Comparison of regression analysis of NN training techniques

Training Technique	*Training*	*Testing*	*Validation*	*All*
BP NN model	0.9046	0.9051	0.9022	0.9043
LM NN model	0.9562	0.9538	0.9667	0.9528
PSO NN model	0.9924	0.9917	0.9929	0.9923

Figure 17 depicts the regression analysis of GPSO training technique of the ANN method for STLF model with given inputs. The regression analysis of network provide a measure to analyze the confidence interval of training, testing, validation to the measure the overall performance of STLF model. Proposed NN based forecast model gives the highest R^2 value, which indicates that closeness of actual and forecast load demand. Moreover, confidence interval of proposed forecast model is 99% of the model; it means that 1% of estimated data is not statistically significant for neural network. A confidence interval of 99% shows our confidence in NN training process that network has adjusted according to its error.

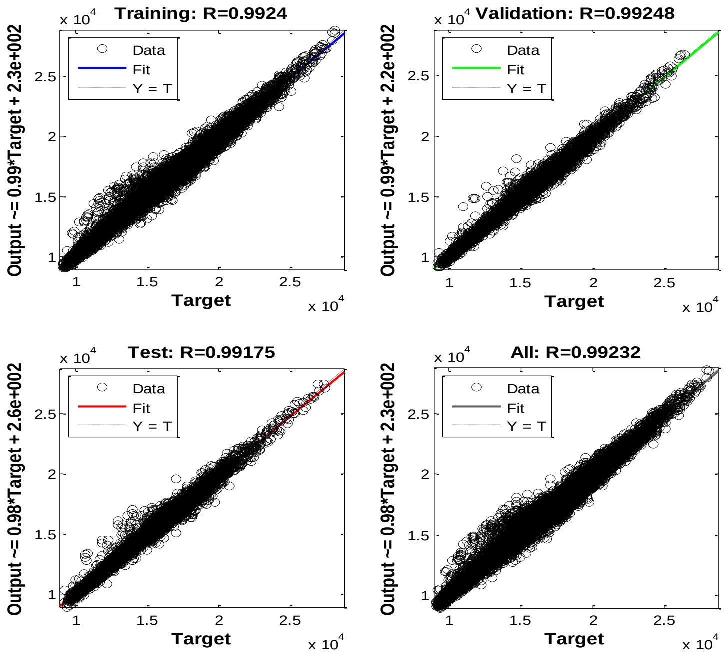

Figure 17: Regression analysis of PSO based NN forecast model

The comparison of regression of BP, LM and PSO techniques for load forecast model is presented in Table 2. As the convergence and regression analysis shows that, PSO training techniques of NN outperform than the comparative BP and LM techniques in terms of better generalization capability and learning of network [34]. The forecast accuracy of PSO based forecast model also higher than the BP and LM. Consequently, it can conclude that he proposed PSO based forecast model shows the better performance than BP and LM techniques in terms of forecast accuracy, convergence time and computational complexity. The proposed forecast can also apply to other forecast applications [35].

I. CONCLUSIONS

In this paper, a novel hybrid global best particle swarm optimization trained feedforward neural network based forecast model is proposed. The performance of proposed forecast model is compared with contemporary techniques for 168 hours (One Week) ahead seasonal load prediction. In addition, influential meteorological and exogenous variables are selected as forecast model inputs. In order to enhance the NN training performance, GPSO training algorithm is applied to update the weight and bias of the network. The seasonal load forecast model results shows that, GPSO based NN forecast model outperform in term of forecast accuracy than BP and LM training techniques. The result also shows that, the GPSO NN model give minimum forecast error (MAPE 1.408%) in summer season due to less sociological and metrological uncertainty. The GPSO based load forecast model converged in 111 epochs and regression analysis gives the R^2 value 0.99 with high confidence interval. As the regression analysis of the network shows, the overall confidence interval is 99% for training, testing and validation of the network. It can be concluded that, the PSO based forecast model shows better forecast accuracy, generalization capability and less convergence time than the comparative training techniques. This prediction model can be utilized for other forecast applications such as price, wind, PV output power and economic growth forecast. Other correlated inputs such as humidity information, wind speed, cloud cover, rainfall, and the human body index can also explore to enhance the prediction performance.

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