

Fuzzy Modeling and Similarity based Short Term Load Forecasting using Swarm Intelligence-A step towards Smart Grid

Amit Jain¹, M Babita Jain²

¹ Lead Consultant, Utilities, Infotech Enterprises Limited, Hyderabad, Andhra Pradesh, India

² Professor, Rungta Engineering College, Raipur, Chattisgarh, India

{Amit.Jain@infotech-enterprises.com; jain.babita@gmail.com}

Abstract. There are a lot of uncertainties in planning and operation of electric power system, which is a complex, nonlinear, and non-stationary system. Advanced computational methods are required for planning and optimization, fast control, processing of field data, and coordination across the power system for it to achieve the goal to operate as an intelligent smart power grid and maintain its operation under steady state condition without significant deviations. 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, and energy pricing strategy. One of the important aspects for the power system to operate in such a manner is accurate and consistent short term load forecasting (STLF). This paper presents a methodology for the STLF using the similar day concept combined with fuzzy logic approach and swarm intelligence technique. A Euclidean distance norm with weight factors considering the weather variables and day type is used for finding the similar days. Fuzzy logic is used to modify the load curves of the selected similar days of the forecast by generating the correction factors for them. The input parameters for the fuzzy system are the average load, average temperature and average humidity differences of the forecasted previous day and its similar days. These correction factors are applied to the similar days of the forecast day. The tuning of the fuzzy input parameters is done using the Particle Swarm Optimization (PSO) and Evolutionary Particle Swarm Optimization (EPSO) technique on the training data set of the considered data and tested. The results of load forecasting show that the application of swarm intelligence for load forecasting gives very good forecasting accuracy. Both the variants of Swarm Intelligence PSO and EPSO perform very well with EPSO an edge over the PSO with respect to forecast accuracies.

Keywords: Euclidean norm, Evolutionary particle swarm optimization, Fuzzy logic approach, Particle swarm optimization, Short term load forecasting, Similar day method.

1 Introduction

Short term load forecasting (STLF) is a time series prediction problem that analyzes the patterns of electrical loads. Basic operating functions such as unit

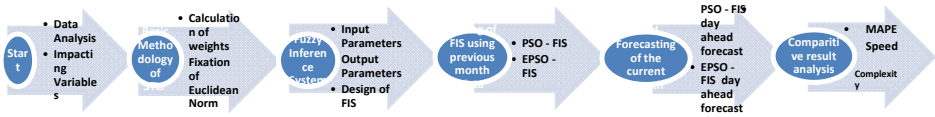


Fig. 1 Overview of the methodology followed

commitment, economic dispatch, fuel scheduling and maintenance can be performed efficiently with an accurate load forecast [1]-[3]. STLF is also very important for electricity trading. Therefore, establishing high accuracy models of the STLF is very important and this faces many difficulties. Firstly, because the load series is complex and exhibits several levels of seasonality. Secondly, the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day and because there are many important exogenous variables that must be considered, specially the weather-related variables [4].

Traditional STLF methods include classical multiply linear regression, automatic regressive moving average (ARMA), data mining models, time-series models and exponential smoothing models [5]-[13]. Similar-day approach and various artificial intelligence (AI) based methods have also been applied [4, 5, 7 and 14]. Evolutionary and behavioural random search algorithms such as genetic algorithm (GA) [15]-[17]-[20, 21], particle swarm optimization (PSO) [18, 19], etc. have been previously implemented for different problems.

There also exist large forecast errors using ANN method when there are rapid fluctuations in load and temperatures [4, 23]. In such cases, forecasting methods using fuzzy logic approach have been employed. S. J. Kiartzis et al [22, 24], V. Miranda et al [25], and S. E. Skarman et al [26] described applications of fuzzy logic to electric load forecasting as well as many others [27]-[29].

The above discussed literature aims at making an accurate STLF for helping the grid work efficiently. For making the distribution grid smarter it is required to deploy communications and leverage advanced controls that are commonplace in substation automation, remedial action schemes, power management systems, and industrial closed-loop power automation [38]-[40].

In this paper, we propose an approach for the short term load forecasting using similarity and the fuzzy parameters tuned by the PSO and EPSO algorithms for better power generation and distribution management aiming to make the power system a smart grid. In this method, the similar days to the forecast day are selected from the set of previous days using a Euclidean norm based on weather variables and day type [30]. There may be a substantial discrepancy between the load on the forecast day and that on similar days, even though the selected days are very similar to the forecast day with regard to weather and day type. To rectify this problem load curves on the similar days are corrected to take them nearer to the load curve of the forecast day using correction factors generated by a fuzzy inference system which is tuned with two techniques PSO and EPSO. This tuned

fuzzy inference system (FIS) is developed using the history data. The suitability of the proposed approach is verified by applying it to a real time data set. This paper contributes to the short term load forecasting by developing a PSO and EPSO tuned FIS for reducing the forecasting error and finally coming out with the best suitable technique for STLF. The overview of the methodology followed is shown in the Fig. 1.

The paper is organized as follows: Section II deals with the PSO and EPSO for STLF and data analysis; Section III gives the overview of the proposed forecasting methodology; Section IV presents the tuning of fuzzy parameters using PSO; Section V presents the tuning of fuzzy parameters using EPSO Section VI presents comparison of simulation results of the proposed forecasting methodology i.e. PSO and EPSO tuned fuzzy parameters results followed by conclusions in Section VII.

2 PSO and EPSO for STLF and Variables Impacting Load Pattern

EPSO is a general-purpose algorithm, whose roots are in Evolutions Strategies (ES) [31]-[33] and in Particle Swarm Optimization (PSO) [34] concepts. The PSO is an optimization algorithm that was introduced in 1995 and some researchers have tried its application in the power systems field with reported success [35, 36]. The EPSO technique, a new variant in the meta-heuristic set of tools, is capable of dealing with complex, dynamic and poorly defined problems that AI has problem with, has an advantage of dealing with the nonlinear parts of the forecasted load curves, and also has the ability to deal with the abrupt change in the weather variables such as temperature, humidity and also including the impact of the day type. PSO has recently found application in STLF where PSO has been applied to identify the autoregressive moving average with exogenous variable (ARMAX) model of the load [37]. According to a thorough literature survey performed by authors, any application of EPSO to STLF has not been reported in literature as of today.

The analysis on the monthly load and weather data helps in understanding the variables which affect load forecasting. The data analysis is carried out on data containing hourly values of load, temperature, and humidity of 3 years. In the analysis phase, the load curves are drawn and the relationship between the load and weather variables is established [38].

2.1 Variation of Load with Day type

The load curves for a winter test week (12th – 18th Jan, 1997) and summer test week (13th – 19th July, 1997) are shown in Fig 2. The observations from the load curves show that there exists weekly seasonality but the value of load scales up and down and the load curves on week days show similar trend and the load curves on the weekends show similar trend. It can also be seen that this weekly seasonality feature holds good for all the seasons of the year. The only variation is in the load which is more in summer than in winter due the increased temperatures of summer and this correlation can be seen in the Fig.2.

Based on the above observations in the present study, days are classified as four categories. First: normal week days (Tuesday - Friday), second: Monday, third: Sunday and the fourth category being Saturday. Monday is accounted to be different to weekdays so as to take care for the difference in the load because its previous day is a weekend.

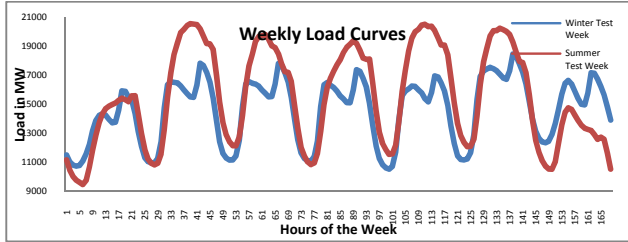


Fig. 2 Weekly Load curves of winter and summer test weeks

2.2 Variation of Load with Temperature and Humidity

The variation of the temperature and humidity variables results in a significant variation in the load. Fig 3 shows a plot between the maximum temperatures versus average demand and average humidity. The graph shows a positive correlation between the load and temperature and load and humidity i.e. demand increases as the temperature and humidity increases.

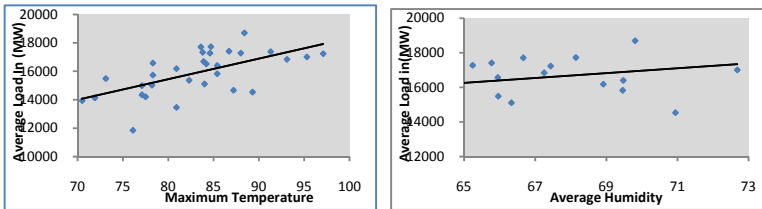


Fig. 3 Maximum Temperature Vs Average Load Curve for the month of July'97 and Average Humidity Vs Average Load Curve for the month of July'97

3 Short Term Load Forecasting using Fuzzy Logic

This section presents in detail the architecture details and implementation procedure of the fuzzy inference system for the proposed STLF. A very important observation is made from the Fig. 4 which shows the annual load curves of 1997, 1998 and 1999 generated using their daily average loads. It can be seen that the similar months of different years follow a similar load curve pattern. Hence for the selection of similar days the previous year's similar months will also have considerable effect. The load forecasting at any given hour not only depends on the load at the previous hour but also on the load at the given hour on the previous day and also on the load of the previous day of previous years'. Assuming same trends of relationships between the previous forecast day and previous similar

days as that of the forecast day and its similar days, the similar days can thus be evaluated by analyzing the previous forecast day and its previous similar days. Also the Euclidean Norm alone is not sufficient to obtain the similar days; hence the evaluation of similarity between the load on the forecast day and that on the similar days is done using the adaptive fuzzy inference system.

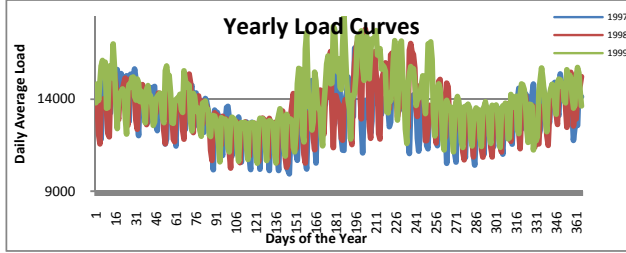


Fig. 4 Daily Average Load curves of Year 1997, 1998, 1999

In the fuzzy inference system (FIS), difference of the previous forecast day and its similar days' load, temperature and humidity are fed as input, resulting in correction factors, which are used to correct the similar days of the forecast day and then averaged to obtain the load forecast. The parameters of the fuzzy inference system used for the forecast of the current month are already optimized using the data of previous month and its history using PSO and EPSO.

3.1 Calculation of Weights and selection of Similar Days

The first task in building the FIS is to identify the similar days of the forecast previous day and the similarity is judged on the basis of the Euclidean Distance Norm given by the formula:

$$EN = \sqrt{W_1(\Delta T_{max})^2 + W_2(\Delta H_{avg})^2 + W_3(\Delta D)^2} \quad (1)$$

Where

$$\Delta T_{max} = T_{max} - T_{max}^p, \Delta H_{avg} = H_{avg} - H_{avg}^p \text{ and } \Delta D = D - D^p$$

Where, T_{max} and H_{avg} are the forecast day maximum temperature and average humidity respectively. Also, T_{max}^p and H_{avg}^p are the maximum temperature and average humidity of the searched previous days, D and D^p are the day type values of the forecast day and the searched previous days and w_1 , w_2 , w_3 are the weight factors determined by least squares method based on the regression model constructed using historical data.

The data available is 38 months data. For weight calculation first 26 months data is used. The equations when formulated using matrix algebra form: $L = AY$, where A is a $[790][5]$ matrix, L is a $[790][1]$ and Y is a $[5][1]$ matrix. Y is the weight matrix.

3.2 Formulation of Fuzzy System

The formulation of the developed Fuzzy Inference System comprises of three input membership functions: ΔE_L , ΔE_T , ΔE_H , average load difference, average temperature difference and average humidity difference respectively of the forecast day and its selected similar days and one output membership function i.e. the correction factor. The limits of all these membership functions are initially fixed and are later optimized once for the day ahead load forecasting of one month. For building the FIS to forecast load of a given month (we call it as the 'current forecast month') the proposed methodology uses 120 days of history data. This history data comprises of two months data (60 days) prior to the current month, one month data (30 days) of second prior month of previous year of current month and one month data (30 days) of the second prior month of the second previous year of current month. For example if the current forecast month is July'99, the history data of 120 days used for building the FIS would be June'99, May'99, May'98 and May'97.

Table 1. Fuzzy Rules of the Inference System

Rule No	E_L	E_T	E_H	Output Value
R1	H	H	H	PVB (Positive Very Big)
R7	M	M	H	PB2 (Positive Big 2)
R14	M	M	M	ZE (Zero Error)
R23	L	L	H	NB1 (Negative Big 1)

4 Optimization of Fuzzy parameters using Particle Swarm Optimization

4.1 Insight into Particle Swarm Optimization

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In each iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbours, the best value is a local best and it is called lbest.

After finding the two best values, the particle updates its velocity and positions with equations (2) and (3).

$$v[i] = v[i] + c1 * rand() * (pbest[i] - present[i]) + c2 * rand() * (gbest[i] - present[i]) \quad (2)$$

$$present[i] = present[i] + v[i] \quad (3)$$

$v[i]$ is the particle velocity, $present[i]$ is the current particle (solution). $pbest[i]$ and $gbest[i]$ are defined as stated before. $rand()$ is a random

number between (0,1). c_1 , c_2 are learning factors. usually $c_1 = c_2 = 2$.

Particles' velocities on each dimension are clamped to a maximum velocity V_{max} . If the sum of accelerations would cause the velocity on that dimension to exceed V_{max} , which is a parameter specified by the user then the velocity on that dimension is limited to V_{max} .

4.2 PSO Implementation for FIS optimization

Optimization of the fuzzy parameters a_1, \dots, a_6 is done using the particle swarm optimization technique. For the data set considered the fuzzy inference system has been optimized for six parameters (maxima and minima of each of the input fuzzy variable E_L , E_T , E_H), considering 49 particles. Hence each particle is a six dimensional one. The initial values of the fuzzy inference system are obtained by using the 120 days data as discussed in Section III. These values are incorporated into the fuzzy inference system to obtain the forecast errors of forecast previous month (in the example case forecast previous month is June '99).

The particle swarm optimization function accepts the training data i.e. 120 days, and the objective is to reduce the RMS MAPE error of the 30 forecast days (June '99) using the 90 days history data (details given in Section III-C). The MAPE is taken as the fitness function and the particle swarm optimizer function is run for 100 iterations (by then the RMS MAPE is more or less fixed and comes less than 3%). After each iteration, the particle swarm optimizer updates the latest particle position using the optimizer equations based on the PBest and Gbest of the previous iteration if the fitness function value is better than the previous one. The parameters thus obtained after the PSO optimization are the final input parameters of the designed FIS. These fuzzy parameter values are set as the input parameter limits of the fuzzy inference system and this FIS is used to forecast the load of the current forecast month (in the example case current forecast month is July '99).

4.3 Forecast of current forecast month load

The data of the current forecast month (Example: July1 to July30) is taken as the testing dataset for the problem at hand. The short term load forecasting for the month of July is now done using the FIS optimized by the PSO i.e PSO-FIS. The five similar days are selected from the history 90 days (for July1 the history 90 days are June'99, June'98, June'97) of the forecast day and the hourly correction factors to these similar days are obtained by the five similar days of the forecast previous day (for June 30 the previous 90 days are May31 to June 29 of 99, 98 and 97) and the PSO-FIS. These five correction factors are then applied to the five similar days of the forecast day and the average of the corrected five values is considered as the load forecasting for each hour. The same procedure is done for all the 24 hours of the day. The same procedure is followed for all days of July i.e. Jul 1 to Jul 30. The MAPE is calculated for the each day of the 30 days of forecast of the Jul data (using the actual hourly values and the forecast hourly values). The FIS is formulated and optimized for every month of 1999 using the same methodology and is then implemented for the load forecasting of all the months of 1999

year. The results obtained for the STLF using PSO-FIS have been quite satisfactory and further analysis and study of the performance of the PSO-FIS for STLF is done in Section VII.

5 Optimization of Fuzzy parameters using Evolutionary Particle Swarm Optimization

5.1 Insight into Evolutionary Particle Swarm Optimization

The *particle movement* rule for EPSO is that given a particle x_i , a new particle x_i^{new} results from:

$$x_i^{new} = x_i + v_i^{new} \quad (4)$$

$$v_i^{new} = w_{i0} * v_i + w_{i1} * (b_i - x_i) + w_{i2} * (b_g^* - x_g) \quad (5)$$

This formulation is very similar to classical PSO – the movement rule keeps its terms of inertia, memory and cooperation. However, the weights, taken as object parameters, undergo mutation which is not the case with PSO:

$$w_{ik}^* = w_{ik} + \mu N(0,1) \quad (6)$$

Where $N(0, 1)$ is a random variable with Gaussian distribution, 0 mean and variance 1.

The global best b_g is randomly disturbed to give:

$$b_g^* = b_g + \mu' N(0,1) \quad (7)$$

The logic behind this modification from PSO is the following: a) if the current global best is already the global optimum, this is irrelevant; but b) if the optimum hasn't yet been found, it may nevertheless be in the neighbourhood and it makes all sense not to aim *exactly* at the current global best – especially when the search is already focused in a certain region, at the latter stages of the process.

The μ , μ' are learning parameters (either fixed or treated also as strategic parameters and therefore subject to mutation-fixed in the present case).

5.2 EPSO implementation for FIS optimization

Same as in the case of PSO-FIS the fuzzy inference system has been optimized for six parameters (maxima and minima of each of the input fuzzy variable E_L , E_T , E_H), considering 49 particles. Hence each particle is a six dimensional one. The initial values of the fuzzy inference system are obtained by using the 120 days data as discussed in Section III. These values are incorporated into the fuzzy inference system to obtain the forecast errors of forecast previous month.

5.3 Forecast of July month load

The procedure here is same as in the case of PSO-FIS given in Section IV-C with the only difference that the EPSO-FIS is used instead of PSO-FIS. The MAPE is less than 3% for maximum days of forecast of the whole year of 1999. The results obtained for the STLF using EPSO-FIS have been quite satisfactory and further analysis and study of the performance of the EPSO-FIS for STLF is done in Section VII.

6 Simulation Results

The performance of the proposed PSO optimized FIS and EPSO optimized FIS for the STLF is tested by using the 38 months data, Nov'96 to Dec'99 of a real data set. The PSO, and EPSO implementation has been done using the MATLAB coding and the Fuzzy Inference System has been developed using fuzzy logic toolbox available in MATLAB and load forecasting is done for the all days of all months of the year 1999.

The parameters of the PSO and EPSO algorithms used for the tuning of fuzzy input variables are given in Table 2. The forecasted results of one winter week and one summer week are presented. These two weeks include four categories of classified days of week in the present methodology namely Saturday, Sunday, Monday, and Tuesday and also the effectiveness of the technique for all seasons.

Table 2. Parameters of the PSO and EPSO algorithms

Parameters	PSO	EPSO
Population Size	49	49
Number of Iterations	100	50
$C1/w_{i0}$ (initial)	2.0	0.6
$C2/w_{i1}$ (initial)	2.0	0.1
$V(0)/w_{i2}$ (initial)	1.0	0.3
$\mu=\mu'$	NA	1.5

The figure 5 shows the graphical representation of the comparative load forecasted of a winter test week for all day types by the two proposed methodologies in comparison with the actual load.

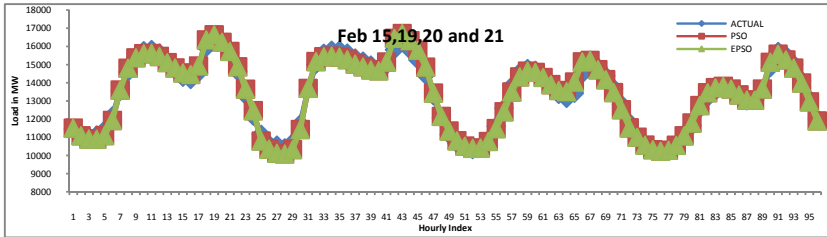


Fig. 5 Winter Week load forecast of PSO-FIS and EPSO-FIS

The forecast results deviation from the actual values are represented in the form of MAPE, which is defined as in the equation 8 and the MAPE plots of the actual hourly load, forecasted hourly load with PSO-FIS and EPSO-FIS for the 4 representative days of the summer test week of June '99 representing four categories of classified days of week for all the three cases are given figure 6.

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|P_A^i - P_F^i|}{P_A^i} \times 100 \quad (8)$$

P_A , P_F are the actual and forecast values of the load. N is the number of the hours of the day i.e. 24 and $i = 1, 2, \dots, 24$.

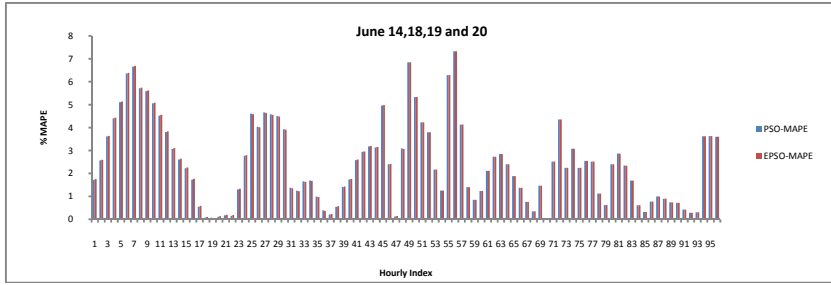


Fig. 6 June 14, 18, 19 and 20 '99 hourly MAPE comparison of PSO-FIS, EPSO-FIS

Table 3. Comparative MAPE of Winter and summer test weeks

Forecast Day	PSO-FIS	EPSO-FIS	Forecast Day	PSO-FIS	EPSO-FIS
15 Feb '99(Mon)	1.858	1.8559	14 Jun '99(Mon)	2.8487	2.8476
16 Feb '99(Tue)	2.4176	2.4125	15 Jun '99(Tue)	2.8723	2.8001
17 Feb '99(Wed)	0.9752	0.9747	16 Jun '99(Wed)	1.7475	1.7423
18 Feb '99(Thur)	2.7089	2.7085	17 Jun '99(Thur)	2.4978	2.4965
19 Feb '99(Fri)	2.6117	2.6113	18 Jun '99(Fri)	1.9928	1.9908
20 Feb '99(Sat)	1.6188	1.61	19 Jun '99(Sat)	1.6905	1.6815
21 Feb '99(Sun)	0.9379	0.9295	20 Jun '99(Sun)	1.2601	1.2514

The MAPE values for the winter test week and summer test week for both the cases are given in Table 3. The results show that the MAPE has been low in the EPSO-FIS in comparison of the PSO-FIS this demonstrates the superiority of the EPSO tuned fuzzy algorithm.

7 Conclusions

This paper proposes a novel method for comparative short term load forecasting using two different variants of particle swarm technique which are PSO and EPSO optimized fuzzy inference system. 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, and energy pricing strategy the proposed architecture is a step towards efficiently managing the real time demand and managing the intermittent power supplies by making a very accurate STLF and hence helping

the grid work smarter. Also, a new Euclidean norm including temperature and humidity and day type is proposed, which is used for the selection of similar days. For the first time the distance based fuzzy system has been optimized using the swarm intelligence and applied for the short term load forecasting. All the two proposed systems are used to evaluate the correction factor of the selected similar days to the forecast day using the information of the previous forecast day and its similar days. The results clearly indicate that all the proposed two systems are very robust and effective for all day's types and all seasons. Still, the fuzzy inference system with EPSO algorithm is proved to be the better compared to PSO-FIS as we observed during our simulation study where weather variables, temperature as well as humidity, are used, as it gives load forecasting results with very good accuracy. The reason analyzed for the excellent performance of EPSO-FIS is the ability to update the object parameters, which are the particles to be optimized and also it updates its strategic parameters which helps in faster convergence and better accuracy as can be seen in the results shown in Table 3. The EPSO-FIS is able to produce very accurate load forecast in lesser number of iterations in comparison to the PSO-FIS. The use of three years of historical data is also greatly responsible for the very good quality results indeed for both of the techniques with almost all the MAPE values very much less than 3%. The selection of the similar days from 90 days of history data comprising of the forecast previous month of the same year, of the previous year and also of the two years' previous year is a novel concept which helps in getting the similar most load curves with respect to temperature, humidity, day type to be selected for optimized fuzzy correction. Authors hope that the proposed methodology will further propagate research for short term load forecasting using swarm intelligence and new optimization techniques to get even more improvement in forecasting results.

8 References

- [1] O.A. Alsayegh, "Short-Term Load Forecasting Using Seasonal Artificial Neural Networks", *International Journal of Power and Energy Systems*, vol. 23, 2003.
- [2] Tomonobu Senjyu, Hitoshi Takara, Katsumi Uezato, and Toshihisa Funabashi, "One Hour-Ahead Load Forecasting Using Neural Network", *IEEE Transactions on Power Systems*, vol. 17, Feb. 2002.
- [3] A.G.Baklirtzis, V.Petridis, S.J.Klartzis, M.C.Alexiadis and A.H.Malssis, "A Neural Network Short Term Load Forecasting Model for the Greek Power System", *IEEE Transactions on Power Systems*, vol.11, May 1996.
- [4] Henrique Steinhert Hippert, Carlos Eduardo Pedreira, and Reinaldo Castro Souza, "Neural Networks for Short-Term Load Forecasting: A Review and Evaluation", *IEEE Transactions on Power Systems*, vol. 16, Feb. 2001.
- [5] A. D. Papalexopoulos and T. C. Hesterberg, "A regression-based approach to short-term load forecasting," *IEEE Transactions on Power Systems*, vol. 5, pp. 1535-1550, 1990.
- [6] T. Haida and S. Muto, "Regression based peak load forecasting using a transformation technique," *IEEE Transactions on Power Systems*, vol. 9, pp. 1788-1794, 1994.
- [7] S. Rahman and O. Hazim, "A generalized knowledge-based short term load-forecasting technique," *IEEE Transactions on Power Systems*, vol. 8, pp. 508-514, 1993.

- [8] S. J. Huang and K. R. Shih, "Short-term load forecasting via ARMA model identification including nongaussian process considerations," *IEEE Transactions on Power Systems*, vol. 18, pp. 673-679, 2003.
- [9] H. Wu and C. Lu, "A data mining approach for spatial modeling in small area load forecast," *IEEE Transactions on Power Systems*, vol. 17, pp. 516-521, 2003.
- [10] S. Rahman and G. Shrestha, "A priority vector based technique for load forecasting," *IEEE Transactions on Power Systems*, vol. 6, pp. 1459-1464, 1993.
- [11] Ibrahim Moghram, Saifure Rahman, "Analysis Evaluation of Five Short Term Load Forecasting Techniques", *IEEE Transactions on Power Systems*, vol. 4, 1989.
- [12] K.Lru, S.Subbarayan, R.R.Shoults, M.T.Manry, C.Kwan, F.L.lewis and J.Naccarino, "Comparison of very short term load forecasting techniques", *IEEE Transactions on Power Systems*, vol. 11, 1996.
- [13] Eugene A. Feinberg and Dora Genethliou, "Applied Mathematics for Power Systems: Load Forecasting".
- [14] Kun-Long Ho, Yuan-Yih Hsu, Chih-Chien Liang and Tsau-Shin Lai, "Short-Term Load Forecasting of Taiwan Power System Using A Knowledge-Based Expert Systems", *IEEE Transactions on Power Systems*, vol. 5, Nov. 1990.
- [15] J. H. Holland, "Adaptation in Natural and Artificial Systems", Ann Arbor, MI: Univ. Michigan Press, 1975.
- [16] D. T. Pham and D. Karaboga, "Intelligent Optimization Techniques, Genetic Algorithms, Tabu Search, Simulated Annealing and Neural Networks", New York: Springer-Verlag, 2000.
- [17] L. Davis, "Handbook of Genetic Algorithms", New York: Van Nostrand Reinhold, 1991.
- [18] R. C. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory", Proceeding of the *Sixth International Symposium on Micro Machine and Human Science*, pp. 39-43, Nagoya, Japan, 1995.
- [19] J.B. Park, K.S. Lee, J.R. Shin, K.Y. Lee, "A particle swarm optimization for economic dispatch with non-smooth cost function", *IEEE Transactions on Power Systems*, vol. 20, pp. 34-42, 2005.
- [20] D.B. Fogel, "Evolutionary Computation: Toward a New Philosophy of Machine Intelligence", second ed., *IEEE Press*, Piscataway, NJ, 2000.
- [21] R.C. Eberhart, Y. Shi, "Comparison between genetic algorithms and particle swarm optimization", in: *Proc. IEEE International Conf. Evolutionary Computing*, May, 1998, pp. 611-616.
- [22] S. J. Kiartzis and A. G. Bakirtzis, "A Fuzzy Expert System for Peak Load Forecasting: Application to the Greek Power System", *Proceedings of the 10th Mediterranean Electro technical Conf.*, 2000, pp. 1097-1100.
- [23] V. Miranda and C. Monteiro, "Fuzzy Inference in Spatial Load Forecasting", *Proceedings of IEEE Power Engineering Winter Meeting*, 2, 2000, pp. 1063-1068.
- [24] S. E. Skarman and M. Georgiopoulos, "Short-Term Electrical Load Forecasting using a Fuzzy ARTMAP Neural Network", *Proceedings of SPIE*, 1998, pp. 181-191.
- [25] T. Senjyu, Mandal. P, Uezato. K, Funabashi. T, "Next Day Load Curve Forecasting using Hybrid Correction Method," *IEEE Transactions on Power Systems*, vol. 20, pp. 102-109, 2005.
- [26] P. A. Mastorocostas, J. B. Theocharis, and A. G. Bakirtzis, "Fuzzy modeling for short term load forecasting using the orthogonal least squares method," *IEEE Transactions on Power Systems*, vol. 14, pp. 29-36, 1999.
- [27] M. Chow and H. Tram, "Application of fuzzy logic technology for spatial load forecasting," *IEEE Transactions on Power Systems*, vol. 12, pp. 1360-1366, 1997.
- [28] T. Senjyu, Uezato. T, Higa. P, "Future Load Curve Shaping based on similarity using Fuzzy Logic Approach," *IEE Proceedings of Generation, Transmission, Distribution*, vol. 145, pp. 375-380, 1998.
- [29] Rechenberg, I., "Evolutionstrategie – Optimierung technischer Systeme nach Prinzipen der biologischen Evolution", Frommann-Holzboog, Stuttgart, 1973.
- [30] Schwefel, H.-P., "Evolution and Optimum Seeking", Ed. Wiley, New York NY, 1995.
- [31] Fogel, D.B., "Evolving Artificial Intelligence", Ph.D. Thesis, University of California, San Diego, 1992.

- [32] Kennedy, J., R.C. Eberhart, "Particle Swarm Optimization", *IEEE International Conference on Neural Networks*, Perth, Australia, *IEEE Service Center*, Piscataway, NJ., 1995
- [33] Fukuyama, Y. and Yoshida, H., "A particle swarm optimization for reactive power and voltage control in electric power systems", *IEEE Proc. of Evolutionary Computation* 2001 , vol.1 , pp. 87 -93, 2001.
- [34] Yoshida, H., Fukuyama, Y., Takayama, S. and Nakanishi, Y., "A particle swarm optimization for reactive power and voltage control in electric power systems considering voltage security assessment", *IEEE Proc. of SMC '99*, vol. 6, pp.497 -502, 1999.
- [35] C. Huang, C. J. Huang, and M. Wang, "A particle swarm optimization to identifying the ARMAXmodel for short-term load forecasting", *IEEE Transactions on Power Systems*, vol. 20, pp. 1126–1133, May 2005.
- [36] S. Rahman and R. Bhatnagar, "An expert system based algorithm for short term load forecast", *IEEE Transactions on Power Systems*, vol. 3, pp. 392-399, 1988.
- [37] Miranda, V., Fonseca, N., "New Evolutionary Particle Swarm Algorithm (EPSO) Applied to Voltage/Var Control", *Proceedings of PSCC'02 – Power System Computation Conference*, Spain, June 24-28, 2002.
- [38] Markusevich, Cross-cutting aspects of Smart Distribution Grid applications, *IEEE Power and Energy Society General Meeting*, 2011
- [39] Meliopoulos, S.; Cokkinides, G.; Huang, R.; Farantatos, E.; Sungyun Choi; Yonghee Lee; Xuebei Yu, Smart Grid Infrastructure for Distribution Systems and Applications, 2011 44th Hawaii International Conference on System Sciences (HICSS)
- [40] Dolezilek, David, Case study of practical applications of smart grid technologies, 2011 2nd IEEE PES Innovative Smart Grid Technologies (ISGT Europe)

Proceedings of Seventh International Conference on
Bio-Inspired Computing: Theories and Applications
(BIC-TA 2012)

Volume 2

Bansal, J.C.; Singh, P.K.; Deep, K.; Pant, M.; Nagar, A.K.
(Eds.)

2013, XVII, 544 p. 218 illus., Softcover

ISBN: 978-81-322-1040-5