Fuzzy Modeling and Similarity based Short Term Load Forecasting using Evolutionary Particle Swarm Optimization

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***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. One of the important aspects to operate power system in such 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 evolutionary particle swarm optimization (EPSO) 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 days and their 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 EPSO technique on the training data set of the considered data and tested. The results of load forecasting shows that the proposed EPSO tunes fuzzy system provides better results than the fuzzy stand alone system (without EPSO).**

***Index Terms*--Euclidean norm, Evolutionary particle swarm optimization, Fuzzy logic approach, Particle swarm optimization, Short term load forecasting, Similar day method.**

I. 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 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].

The load is composed of two components; one is weather dependent, and the other is weather independent. In some traditional methods, each component is modelled separately and the sum of these two gives the total load forecast. The behaviour of weather independent load is usually represented by Fourier series or trend profiles in terms of the time functions. The weather sensitive portion of the load is arbitrarily extracted and modelled by a predetermined functional relationship with weather variables. 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, 14]. However, these models take long computational time and have some deficiency in the case of the load changed abruptly. Evolutionary and behavioural random search algorithms such as genetic algorithm (GA) [15]-[17], particle swarm optimization (PSO) [18, 19], etc. have been previously implemented for different problems. In spite of its successful implementation, GA does pose some weaknesses such as longer computation time and premature convergence accompanied by a high probability of entrapment into the local optimum [20, 21].

Feed forward neural net structures like multi layer perceptron, functional link, wavelet, recurrent or feedback structures like Hopfield, Elman, Multi Feedback and hybrid structures using fuzzy neural networks have been widely proposed for non-stationary forecasting applications [22]. But in STLF, actual load data put forth many challenges to design a predictive neural network. Prominent of these challenges are, data pre-processing, input parameter selection, type of neural net structure selection, and training algorithm. Computational complexity, which is important for real time implementation of algorithms in power systems, is dependent on the structural complexity and training algorithm. 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. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs and in this sense fuzzy logic is one of a technique for mapping inputs to outputs. S. J. Kiartzis et al [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].

In this paper, we propose an approach for the short term load forecasting using similarity and the fuzzy parameters tuned by the evolutionary particle swarm optimization (EPSO) algorithm. 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, the load curve

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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 logic system tuned with EPSO. This tuned fuzzy system is developed using the information about the previous forecast day and its similar days that have errors and developed fuzzy inference system is used for the reducing the error. The suitability of the proposed approach is verified by applying it to a typical data set. This paper contributes to the short term load forecasting by using evolutionary particle swarm optimization (EPSO) in the proposed method.

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

II. 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.

For this paper the data taken from EUNITE Network has been used, which as per authors information, was provided to participants for a competition many years ago (see acknowledgement). The analysis on the monthly load and weather data helps in understanding the variables, which may affect load forecasting. The data analysis is carried out on data containing hourly values of load, temperature, and humidity of 7 months. In the analysis phase, the load curves are drawn and the relationship between the load and weather variables is established [38]. Also, the week and the day of the week impact on the load is obtained.

A. Load Curves

The load curve for the month of May is shown in Fig 1. The observations from the load curves are as follows:

1. There exists weekly seasonality but the value of load scales up and down.
2. The load curves on week days show similar trend
3. The load curves on the weekends show similar trend.

In the present study, days are classified based on the following categories:

a. Normal week days (Tuesday - Friday)
b. Monday
c. Sunday
d. 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.

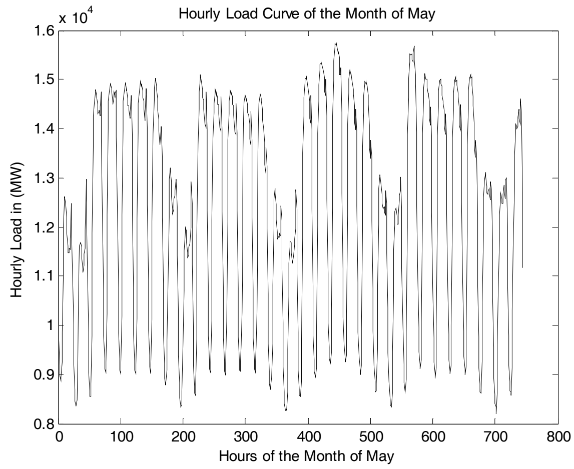

Fig. 1 Load curve for the month of May

B. Variation of Load with Temperature

The variation of the temperature variable results in a significant variation in the load. Fig 2 shows a plot between the maximum temperatures versus average demand. In Fig. 2 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. demand increases as the temperature increases.

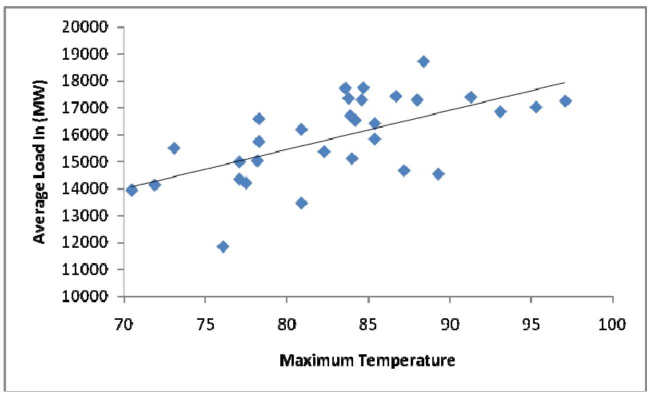

Fig. 2 Maximum Temperature Vs Average Load Curve for the month of July

C. Variation of Load with Humidity

Fig 3 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.

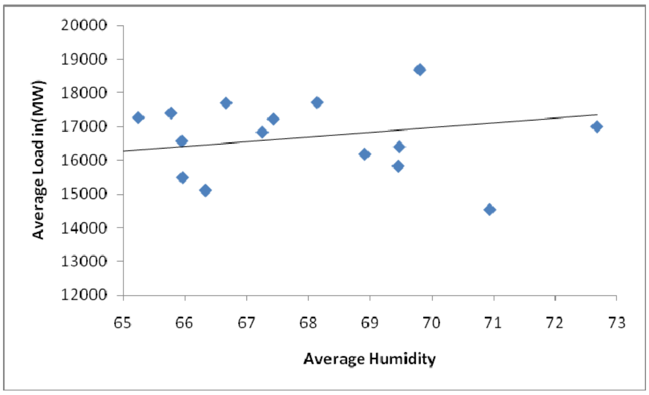

Fig. 3 Average Humidity Vs Average Load Curve for the month of July

III. Short Term Load Forecasting using Fuzzy Logic

A. Similar Day selection

In this paper, Euclidean norm is used which provides the similarity for the forecast day by using an expression where smaller the value of Euclidean norm the more similar are the days to the forecast day. Besides temperature, humidity, especially when there is fast or abrupt variation in its value, also has positive impact on load as shown in section II C. In the present work, we have proposed a Euclidean norm, which uses the maximum temperature, average humidity and day type with weight factors to evaluate the similarity of the previous days with respect to forecast day. The expression for the Euclidean norm is as follows:

$$EN= \sqrt{(w_1(\Delta T_{max})^2 + w_2(\Delta H_{avg})^2 + w_3(\Delta D)^2)} \quad (1)$$

$$\Delta T_{max} = T_{max} - T^p_{max} \quad (2)$$

$$\Delta H_{avg} = H_{avg} - H^p_{avg} \quad (3)$$

$$\Delta D = D - D^p \quad (4)$$

Where, T_{max} and H_{avg} are the forecast day maximum temperature and average humidity respectively. Also, T^p_{max} and H^p_{avg} are the maximum temperature and average humidity of the searched previous day, D and D^p are the day types of forecast day and the searched previous day 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 [29]. The day type values considered in this work are 4 (Tuesday-Friday), 3 (Monday), 2 (Saturday), 1 (Sunday). The similar days are selected by searching from the previous 30 days of the forecast day. For this, Euclidean norm values are calculated for each of previous 30 days using the maximum temperature, average humidity and day type values for forecast day and each previous day out of previous 30 days. This gives 30 Euclidean norm values for 30 previous days and 5 days with least Euclidean norm values are considered as 5 similar days of the forecast day. The search for similar day is limited to previous 30 days to account for the seasonality of the data as seasonality is important so that there is not much variation in weather conditions when similar previous days are searched and also correction factor is calculated from the data of the days from same season.

B. Fuzzy Inference System

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. Assuming same trends of relationships between the previous forecast day (i.e. previous day forecasted from its similar days) and its similar days as that of the forecast day and its similar days, the similar days for forecast days can thus be corrected to get better load forecast for the forecast day.

The fuzzy inference system (FIS) is used to evaluate the similarity between the previous forecast days and their similar days, resulting in correction factors that are used to correct the similar days of the forecast day to obtain the final load forecast. To evaluate this degree of similarity, three fuzzy input variables for the fuzzy inference system are defined [30].

$$E_L^k = L_p - L_{ps}^k \quad (5)$$

$$E_T^k = T_p - T_{ps}^k \quad (6)$$

$$E_H^k = H_p - H_{ps}^k \quad (7)$$

Where, L_p and L_{ps} are the average load of the previous forecast day and the previous k^{th} similar day, and in the same manner T_p, T_{ps}, H_p, H_{ps} show the value corresponding to average temperature and average humidity respectively. E_L, E_T, E_H take three fuzzy set values; Low (L), Medium (M), High (H). The membership functions of the input variables and output variable are shown in Fig 4 and Fig 5. The fuzzy rules for the inference system for the given fuzzy variables are based on the generalized knowledge of the effect of each variable on the load curve [38] and some examples of fuzzy rules are given in Table I. If the membership of E_L is μ_{EL}, that of E_T is μ_{ET} and that of E_H is μ_{EH}, the firing strength, μ, of the premise is calculated based on the min operator. The firing strength of each rule is calculated as follows:

$$\mu_i = \min(\mu_{EL}i, \mu_{ET}i, \mu_{EH}i) \quad (8)$$

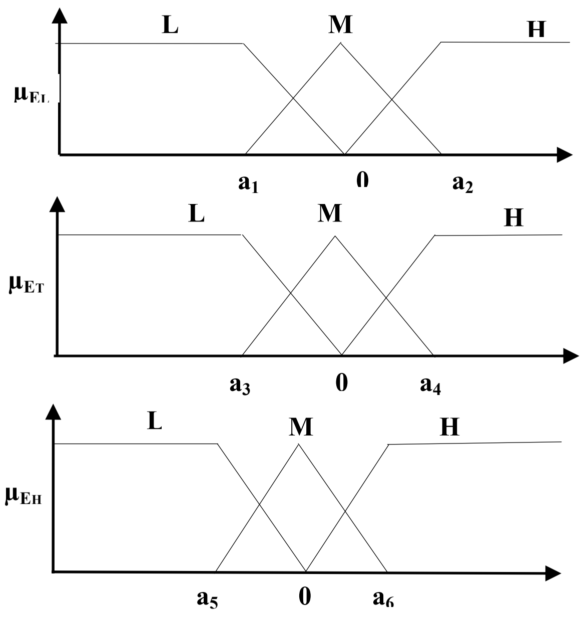

Fig. 4 Membership functions of the fuzzy input variables

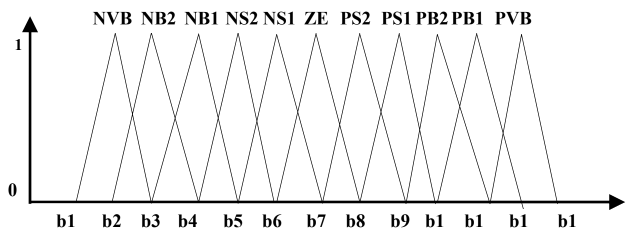

Fig. 5 Membership functions of the fuzzy output variables

TABLE I
FEW 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)

The membership function of an inferred fuzzy output variable using a fuzzy centroid defuzzification scheme translates fuzzy output statements into a crisp output value, W_k using the firing strength μ_i and the de-fuzzification coefficient α_i of the fuzzy rule applicable to the input data.

$$W_k = \sum_{i=1}^{27} \alpha_i \mu_i^k \Big/ \sum_{i=1}^{27} \mu_i^k \qquad (9)$$

The output value is expressed by W_k which is the correction factor for the load curve on the k^{th} similar day to the shape on the forecast day. W_k is applied to each similar day and corrects the load curve on similar days. The forecast next day load curve L (t) is then given by averaging the corrected loads on similar days.

$$L(t) = \frac{1}{N}\left[\sum_{k=1}^{N} (1 + W_k) L_s^k(t)\right] \qquad (10)$$

Where $L_s^k(t)$, is the load at t'o clock on the k^{th} corrected similar day, N is the number of similar days and t is hourly time from 1 to 24.

IV. OPTIMIZATION OF FUZZY PARAMETERS USING EPSO

PSO is a population-based optimization method first proposed by Eberhart and Colleagues [34, 36]. Like evolutionary algorithms, PSO technique conducts search using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO system, particles change their positions by flying around in a multidimensional search space until computational limitations are exceeded.

Although a population is used for searching the search space, there are no operators inspired by the human DNA procedures applied on the population. Instead, in PSO, the population dynamics simulates a 'bird flock's' behavior, where social sharing of information takes place and individuals can profit from the discoveries and previous experience of all the other companions during the search for food. Thus, each companion, called particle, in the population, which is called swarm, is assumed to 'fly' over the search space in order to find promising regions of the landscape. For each particle, at the current time step, a record is kept of the position, velocity, and the best position found in the search space so far. PSO faces drawbacks like, sometimes deviating from the goal and going in the wrong direction and carrying the unhealthy particles together without any mutation. EPSO attempts to overcome these drawbacks of PSO.

A. Basic algorithm

The idea behind EPSO [39] is to grant a PSO scheme with an explicit selection procedure and with self-adapting properties for its parameters. The variables in an EPSO formulation are divided, according to the vocabulary used in the Evolution Strategies community, composed of *object parameters* (the X variables) and *strategic parameters* (the weights w). At a given iteration, consider a set of solutions or alternatives that we will keep calling particles. A particle is a set of object and strategic parameters [**X, w**]. The general scheme of EPSO is the following:

REPLICATION - each particle is replicated r times

MUTATION - each particle has its weights **w** mutated

REPRODUCTION - each mutated particle generates an off spring according to the *particle movement* rule

EVALUATION - each offspring has its fitness evaluated

SELECTION - by stochastic tournament or elitist selection, the best particles survive to form a new generation

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

$$X_i^{new} = X_i + V_i^{new} \qquad (11)$$

$$V_i^{new} = w_{i0}^* V_i + w_{i1}^*(bi - X_i) + w_{i2}^*(bg^* - Xg) \qquad (12)$$

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:

$$w_{ik}^* = w_{ik} + \mu N(0,1) \qquad (13)$$

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:

$$bg^* = bg + \mu' N(0,1) \qquad (14)$$

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). This scheme benefits from two "pushes" in the right direction: the Darwinist process of selection and the particle movement rule; therefore, it is natural to expect that it may display advantageous convergence properties when compared to ES or PSO alone.

B. Dealing with constraints

In EPSO, constraints are dealt with as it is usual in ES models: by adding penalties to the fitness function.

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), considereing 49 particles. Hence each particle is a six dimensional one.The initial limits for these paprameters of the fuzzy inference system are obtained by using the May and June data. These values are incorporated into the fuzzy inference system to obtain the forecast errors of June month.

The evolutionary particle swarm tuner function accepts the training data i.e. May and June, with the objective to reduce the Mean Absolute Percentage Error (MAPE) fitness function of the forecast days (June) using May data by tuning the fuzzy input parameters. The evolutionary particle swarm tuner function is run for 50 iterations and by then the MAPE of all days of June attain a fixed value. After every iteration the

EPSO tuner function updates the latest particle position (which in the present case are the input parameter limits) using the optimization equations based on the global best bg of the previous iteration provided the fitness function value is better than the previous one. The parameters obtained after the EPSO optimization of the FIS are the final fuzzy input parameter limits for the FIS inputs E_L, E_T, E_H and these are used to forecast the load of the testing data set i.e. July month.

V. Simulation Results

The performance of the proposed method for the STLF is tested by using the 7 months data, from January to July of a test data set. The EPSO implementation has been done using the MATLAB coding, the Fuzzy Inference System has been developed using fuzzy logic toolbox available in MATLAB and load forecasting is done for the days of July month.

First, fuzzy parameters are fixed based on the existing training data set, as described in the section III. The initial parameters of the fuzzy membership functions are determined through the simulation of the load curve forecasting in the previous month of the forecast day. Second, the fuzzy input parameters are optimized using EPSO algorithm to find the best range for the input membership functions. The parameters of the membership functions for the input and output variables for the next-day load curve forecasting for the stand alone fuzzy system and EPSO optimized fuzzy system are given in Table II. The parameters of the EPSO algorithm used for the tuning of fuzzy input variables are given in Table III.

Last, the tuned fuzzy inference system is used to forecast the load of the days in July month for test data set. The forecasted results of 4 representative days of the July month in a week are presented. These days represents four categories of classified days of week in the present methodology namely Saturday, Sunday, Monday, and Tuesday.

TABLE II
PARAMETERS OF MEMBERSHIP FUNCTIONS OF FUZZY VARIABLES

Parameters of membership functions of input variables	(a1,a2)	(a3,a4)	(a5,a6)
Values for Fuzzy stand alone system	(-1000,1000)	(-20,20)	(-20,20)
Values for EPSO optimized fuzzy system	(-1959,6439)	(-7, 17)	(-33,44)
Parameters of membership functions of output variables	(b1,b2,b3)	(-0.3,-0.25,-0.2)	
	(b3,b4,b5)	(-0.2,-0.15,-0.10)	
	(b4,b5,b6)	(-0.15,-0.10,-0.05)	
	(b5,b6,b7)	(-0.10,-0.05,0)	
	(b6,b7,b8)	(-0.05,0,0.05)	
	(b7,b8,b9)	(0,0.05,0.1)	
	(b8,b9,b10)	(0.05,0.1,0.15)	
	(b9,b10,b11)	(0.1,0.15,0.2)	
	(b10,b11,b12)	(0.15,0.2,0.25)	
	(b11,b12,b13)	(0.2,0.25,0.3)	

TABLE III
PARAMETERS OF THE EPSO ALGORITHM

Parameters EPSO	Value
Population Size	49
Number of Iterations	50
w_{i0}^* (initial)	0.6
w_{i1}^* (initial)	0.1
w_{i2}^* (initial)	0.3
μ=μ`	1.5

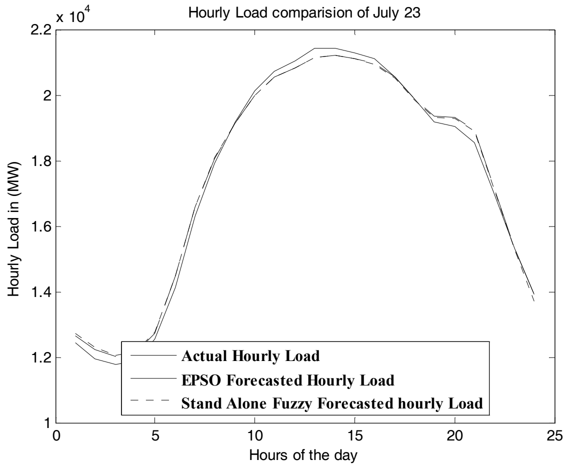

Fig. 6. Hourly Load comparisons of Fuzzy and EPSO of July 23

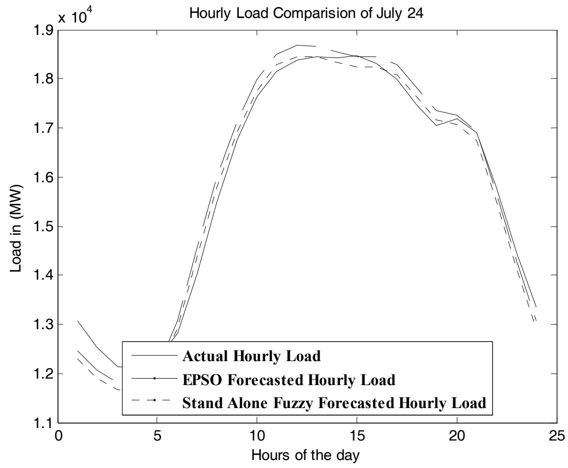

Fig. 7. Hourly Load comparisons of Fuzzy and EPSO of July 24

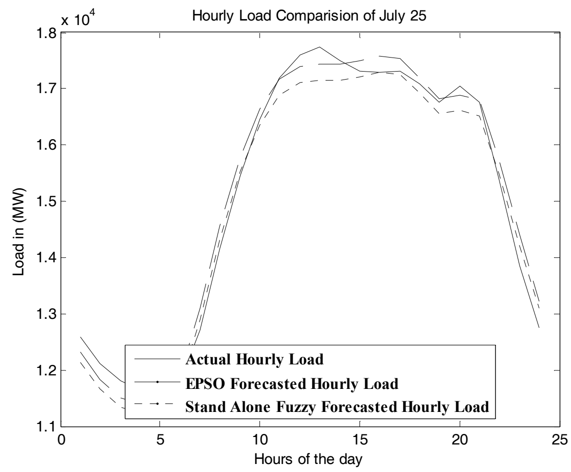

Fig. 8. Hourly Load comparisons of Fuzzy and EPSO of July 25

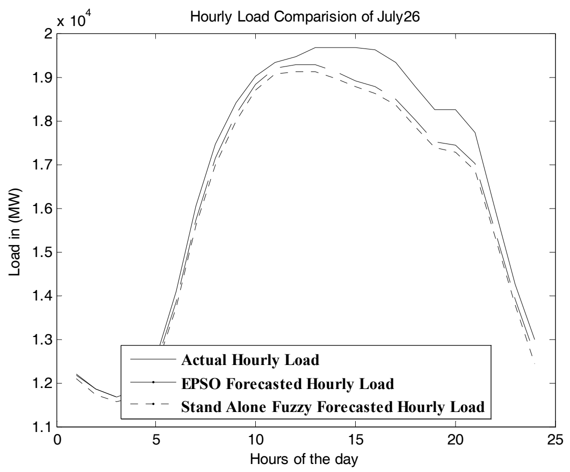

Fig. 9. Hourly Load comparisons of Fuzzy and EPSO of July 26

The forecast results deviation from the actual values are represented in the form of MAPE, which is defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_A^i - P_F^i\right|}{P_A^i}\times 100 \qquad (15)$$

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,….,.24. The plots of the actual hourly load, forecasted hourly load with stand alone fuzzy system and forecasted hourly load with EPSO tuned fuzzy system for the 4 representative days of the July representing four categories of classified days of week are shown in Fig. 6-9. The MAPE values for these sample days for both the cases are given in Table IV. The results show that the MAPE has been considerably low in the EPSO tuned FIS in comparison of the fuzzy stand alone system and this demonstrates the superiority of the EPSO tuned fuzzy algorithm.

TABLE IV
MAPE OF FORECASTED RESULTS

Forecast Day	MAPE (FUZZY ALONE)	MAPE (FUZZY+EPSO)
23 July (Friday)	2.88	1.0999
24 July (Saturday)	3.68	1.76
25 July (Sunday)	4.81	1.7616
26 July (Monday)	3.34	2.0974

VI. CONCLUSION

In this paper a methodology for short term load forecasting using EPSO algorithm is presented where optimal fuzzy inference system is designed with EPSO algorithm. Also, a new Euclidean norm including temperature and humidity and day type is proposed, which is used for the selection of similar days. EPSO tuned Fuzzy system is 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 fuzzy inference system with EPSO algorithm is better than the traditional fuzzy inference system without EPSO algorithms as we observed during our simulation study that the proposed forecasting methodology using EPSO where weather variables, temperature as well as humidity, are used, gives load forecasting results with very good accuracy.

The proposed methodology is expected to give further improvement in results quality when implemented on historical data set of many years, which we will present in our future work. Authors hope that the proposed methodology will further propagate research for short term load forecasting using new optimization techniques to get even more improvement in forecasting results.

VII. ACKNOWLEDGMENT

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