RESEARCH ARTICLE

A Hybrid Metaheuritic Technique Developed for Hourly Load Forecasting

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Electricity load forecasting has become one of the most functioning tools in energy efficiency and load management and utility companies which has been made very complex due to deregulation. Due to the importance of providing a secure and economic electricty for the consumers, having a reliable and robust enough forecast engine in short-term load management is very needful. Fuzzy inference system is one of primal branches of Artificial Intelligence techniques which has been widely used for different applications of decision making in complex systems. This paper aims to develop a Fuzzy inference system as a main forecast engine for Short term Load Forecasting (STLF) of a city in Iran. However, the optimization of this platform for this special case remains a basic problem. Hence, to address this issue, the Radial Movement Optimization (RMO) technique is proposed to optimize the whole Fuzzy platform. To support this idea, the accuracy of the proposed model is analyzed using MAPE index and an average error of 1.38% is obtained for the forecast load demand which represents the reliability of the proposed method. Finally, results achieved by this method, demonstrate that an adaptive two-stage hybrid system consisting of Fuzzy & RMO can be an accurate and robust enough choice for STLF problems. © 2016 Wiley Periodicals, Inc. Complexity 21: 521–532, 2016

Key Words: complex forecasting; fuzzy inference; radial movement optimization; electricity demand

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1. INTRODUCTION

Due to deregulation of the electric power systems predicting the demand load behavior has become a very complex and chaotic [1,2]. Nowadays, electricity

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distributer companies feel a need for electrical load forecasting to certainly enhance the ability to manage the production and demand at the same time, securely, and economically. Normally, load forecasters are classified into three types: Short-term Load forecast (STLF), Middle-term Load Forecast, and Long-term Load forecast [3–6]. Short-term Load forecast with the ability of hourly prediction seems to be the most challenging, complex, and difficult among them due to the fast changes in values and unpredictable behavior of the users of electrical appliances and units. During the past years, a wide variety of approaches and techniques have been hired to tackle this problem [7–9]. Forecasting techniques can be divided into two main categories: classic and modern approaches. Most classic techniques are based on time series estimation which mainly includes approaches based on statistical methods such as Box and Jenkis [6] double exponential smoothing, halt-winter, autoregressive (AR), and autoregressive moving average (ARIMA) [10,11]. Quite the opposite, modern forecasting techniques provide faster convergence and more accurate forecasts [12,13]. Among the modern forecasting algorithms, machine learning and artificial intelligence (AI)-based techniques are of interest, due to their remarkable performance compared with the classic methods [14–16].

Fundamentally, classical methods rely on linear analysis, while the load series are usually nonlinear functions of the exogenous variables. It results in lack of accuracy in developing a model which correlates the load and a series of nonlinear factors such as daily time rhytms. For some of which require nonlinear models such as ARIMA, the main concern is the utilization of a search process that requires a few iterations and occationally may not converge. To avoid this, adjusting step sizes arbitrary and determining stoppage criteria which may devalue the search process are necessary [17,18]. Consequently, to include the nonlinearity, the AI techniques have attracted scientists' and researchers' attention in load forecasting problems [19,20]. As examples of such techniques, Neural Networks [21,22], Fuzzy Inference [23–26], Particle Swarm Optimization [27–30], Genetic Algorithm, and Support Vector machines can be mentioned [31–36].

Among the AI techniques, artificial neural networks (ANN) and its have attracted many researchers' attention and therefore a lot of research has been focused on their application in STLF. To mention some of them, Ringwood et al. [37], modeled the short, medium and long term load demands using a neural network (NN) technique by employing an auto-correlation function as a network structure. By comparing the proposed NN-based models with some conventional methods such as Box-Jenkins, better performance was reported. However, they still provided lower quality results compared with some similar research reports such as [38–40]

The benefit of using ANN is its learning ability from the input data in a train process. However, conventional ANN models mostly suffer from overfitting or suboptimization problems which result in unsatisfactory experimental forecasting accuracy [3]. Conversely, the process of parameters and network architecture selection consoderably affects the performance of the forecast model; that is, to achieve acceptable results, it requires in depth knowledge of the neural networks. Moreover, the trial and error and tedious tuning process makes its optimization hard and uncertain.

Hybrid technique of PSO with radial basis function (RBF) neural network was applied to load forecasting problem which improved the traditional RBF model [40]; however, the quality of results was far from being considered as satisfactory. Hybrid of genetic algorithm (GA) and ANN has also been utilized for load forecasting problems [41,42]. The GA technique provides a global search engine which has been widely used for different optimization problems. In this hybrid strategy, GA globally optimizes the architecture of the ANN by finding the best numbers for the input neurons and the hidden layers. Although GA is a powerful optimization tool, the systems use GA are mostly suffering from high computational costs and efforts which is generally not suitable for short time frame problems such as STLF.

Fuzzy inference system has also been applied to the STFL problem [42–46]. The weakness of fuzzy inference system is that it returns uncertainty and again requires in depth knowledge of its structure, as the number and boundaries of membership functions is one of the main challenges.

Although hybrid techniques mostly provide higher accuracy and better convergence profile for the training algorithm, they are mostly computationally expensive and time consuming methods [47–49]. Conversely, their complexity are rather high and debugging and adjusting the parameters may lead to improper results. Therefore, robust adjusting the parameters and handling the uncertainties of such techniques may need another approach which makes it more complex and reduces the overall reliability of the method. In light of this fact, there is a cry for a robust yet simple hybrid search engine which is able to provide robust and accurate forecast results while provides acceptable computational cost and reduces complexity of the system.

This research project aims to perform a short-term load forecast in Iran (Mashhad) by employing a fuzzy engine. To develop such a forecasting system, the hourly load profile of 10 years are collected and used for the train and test purposes. The fuzzy platform is typically optimized in rule base by expert systems and a gradient method for membership function optimization. However, to achieve good forecasting results in this study, a novel

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fast and efficient netaheuristic algorithm called Radial Movement Optimization (RMO) is applied on the fuzzy system to obtain the best solution for rule bases and membership functions. Eventually, the designed system is demonstrated to be exact and accurate as 1.38% MAPE, which considered as a satisfactory and reliable result for a 1 h ahead load forecaster. It is apparently shown that the suggested Fuzzy system guarantees a robust response with high nonlinearity detection. RMO algorithm used in this case, has a significant role to achieve a fast convergence for fuzzy platform which enables the system adopt any new database. Overall, the proposed hybrid Fuzzy-RMO technique provides more accurate and more robust results by optimizing the membership function number and boundaries of the fuzzy inference system. At the same time, it diminishes the uncertainty from the fuzzy inference system and removes the confusion from choosing the fuzzy inference input sets and parameters in the design structure. The contributions of this article are twofold:

1. To propose a novel hybrid method for short term load forecasting problem which is simple yet robust with low complexity;
2. to improve the hourly forecasting accuracy, taking into account the prominent results exiting in the literature.

The rest of the article is organized as follows. Section 2 presents the proposed approach to forecast wind power. Section 3 provides the different criterions used to evaluate the forecasting accuracy. Section 4 provides the numerical results from a real-world case study. Section 5 outlines the conclusions.

2. MATERIALS & METHODS

2.1. Case Study

Mashhad is the capital city of Razavi Khorasan province and located in the northeast of Iran with metropolean area of 3946 km^2 and total area of 850 km^2. It is the largest electricy consumer in Iran with about 15,542,000 MWh per year and also the second most populous city of this country. Currently its population is 3,131,586 persons where 2,567,243 are living in the city. The population growth was 1.81% and 1.90% between 2007 to 2008, and 2008 to 2009, respectively.

It is predicted that the electricity consumption of Mashhad will raise to 2500 MW per year by 2025. In 2006, Iran consumed 199,800,000 MWh per year with annual increment of 8% in electricity consumption while the world's average increase was 3.7% per year. Meanwhile, Mashhad by itself keeps an annual increment of 6% in electrical energy consumption.

Since it hosts over 20 million tourists and pilgrims per year in addition to the growth of population and industrial sections, the electricity forecast of the load demand is very complex and yet very crucial for the future municipalization and investments.

2.2. Fuzzy Inference System

Sugeno method which adopted for the methodology in this study is described in this section [50]. Although, Mamdani method is known as the most common fuzzy inference system used by researchers, Sugeno method is more suitable in some specific applications. Compared to Mamdani method, Sugeno is computationally efficient and provides a more compact representation which is very useful whenever an adaptive technique is being used for constructing the fuzzy model [51,52]. Since the fuzzy inference model is being optimized, in this research, Sugeno inference model is employed to be customized. In terms of operation, Sugeno and Mamdani methods are quite similar in the first two parts of the fuzzy process, which are fuzzifying the inputs and applying the operators to the fuzzified inputs. The main difference is in the output membership functions which is always linear for Sugeno inference system [53].

A typical rule is Sugeno fuzzy model is shown as follows:

$$\begin{array}{ll} \text{if} & x, y \rightarrow \text{inputes}, \\ \text{then} & z_i = a_i x + b_i y + c_i \rightarrow \text{output} \end{array} \tag{1}$$

where a_i *and* b_i are equal to zero for a zero-order Sugeno model in which the output level z_i is always a constant.

The output level z_i is defined for each rule and weighted by the firing strength of the rule, w_i. As an instance, considering an AND rule with inputs of x *and* y, the firing strength is obtained using the Boolean dot as follows:

$$w_i = AND(F_1(x), F_2(y)) = F_1(x).F_2(y) \tag{2}$$

where F_1 *and* F_2 are membership functions for inputs x and y. The final output of the system is the weighted average of all rule outputs, computed as:

$$\text{Final; Output} = \frac{\sum_{j=1}^{N} w_j.z_j}{\sum_{j=1}^{N} w_j} \tag{3}$$

The operational block diagram of Sugeno rule is shown in Figure 1.

2.3. Radial Movement Optimization

Radial Movement Optimization (RMO) is a swarm-based metaheuristic global optimization technique proposed by Rahmani and Yusof [54,55] as a fast, simple and efficient tool for global optimization of complex and

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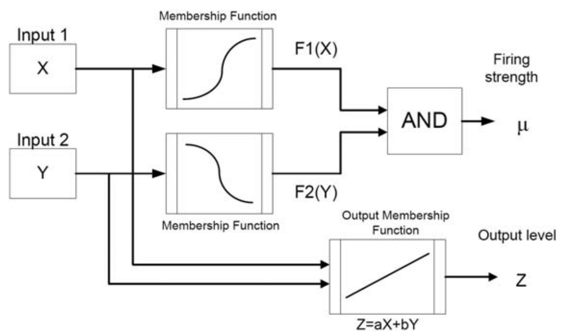
FIGURE 1

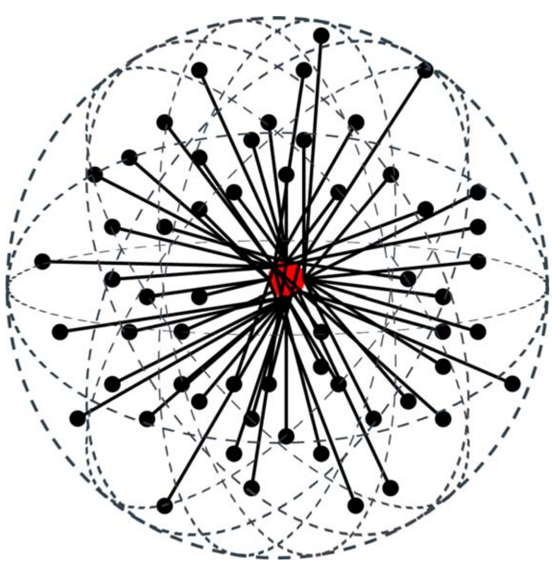


A two input and single output Sugeno inference system with linear output.

nonlinear optimization problems. It starts with initializing the particles inside the problem search-space that each of them proposes a solution to the problem. The evaluation function is called objective function and calculates the fitness value of all the particles at each single step. The generation of resultant movement vector is dependent to two "best" values besides a random vector for the particles.

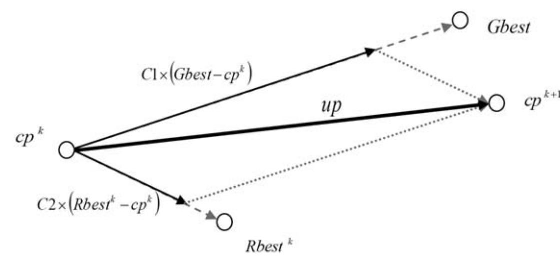
The location of particles is represented by a matrix where nop indicates the number of particles and *nod* is the number of dimensions. The number of particles is elective and depends on the user, but *nod* denotes the number of variables which are going to be optimized. The location matrix of the algorithm is shown in Eq. (4).

FIGURE 2



The particles sprinkled along the radii where $V_{\max}$ is the radius of the sphere [54].

FIGURE 3



A simple diagram for updating the *cp through up* vector [54].

$$X_{i,j}=\begin{bmatrix} X_{1,1} & X_{1,2} & \dots & X_{1,\mathrm{nod}} \\ X_{2,1} & \ddots & \dots & \vdots \\ \vdots & \dots & \ddots & \vdots \\ X_{\mathrm{nop},1} & X_{\mathrm{nop},2} & \dots & X_{\mathrm{nop},\mathrm{nod}} \end{bmatrix} \tag{4}$$

where $i=1,2,3,\dots,\mathrm{nop}$ and $j=1,2,3,\dots,\mathrm{nod}$.

2.3.1. Initialization

The first choice for initializing the particles in the solution space of the problem is to assign locations to the particles randomly. This random assignment should be performed such that covers the whole nop×nod dimensional search space. A sample of this initialization is shown in below:

$$X_{i,j}=X_{\min(j)}+\mathrm{rand}(0,1)\times\left(X_{\max(j)}-X_{\min(j)}\right) \tag{5}$$

where $i=1,2,3,\dots,\mathrm{nop}$ and $j=1,2,3,\dots,\mathrm{nod}$. $X_{\min(j)}$ and $X_{\max(j)}$ are the constraints for the jth dimension which are determined based the search-space. The rand(0,1) can be obtained from a normal distribution function, such as the *Gaussian Distribution*, between 0 and 1. However, the initialization method shown in Eq. (6) is used is this study. The reason is sharing the particles in the search space uniformly to decrease the possibility of getting trapped in local optima.

$$\mathrm{step}_j=\frac{X_{\max(j)}-X_{\min(j)}}{\mathrm{nop}}$$
$$\begin{cases} \text{for } i=2,\dots,\mathrm{nop} \\ \text{for } j=1,2,\dots,\mathrm{nod} \end{cases} \Rightarrow \begin{cases} X_{1,j}=X_{\min(j)} \\ X_{i,j}=X_{i-1,j}+\mathrm{step}_j \end{cases} \tag{6}$$

2.3.2. Movements of the Particles

Once the *cp* has been obtained, the next step is to sprinkle the particles from the *cp* along the radii. This would make the particles move along the radii in straight lines from the *cp* based on $V_{i,j}$ vector. The $V_{i,j}$ vector is a

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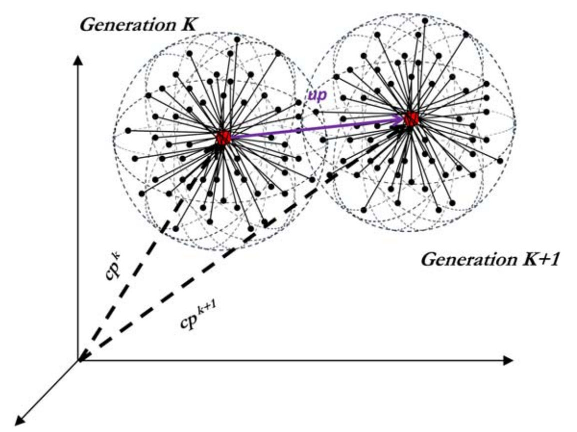


Updating the *cp by up* vector.

$nop\times nop$ random vector obtained based on the following equation:

$$V_{i,j}=\mathrm{rand}(0,1)\times V_{\max(j)} \Rightarrow \begin{cases} V_{\max(j)}=\dfrac{X_{\max(j)}-X_{\min(j)}}{k} \\ i=1,2,\ldots,\mathrm{nop} \\ j=1,2,\ldots,\mathrm{nod} \end{cases} \tag{7}$$

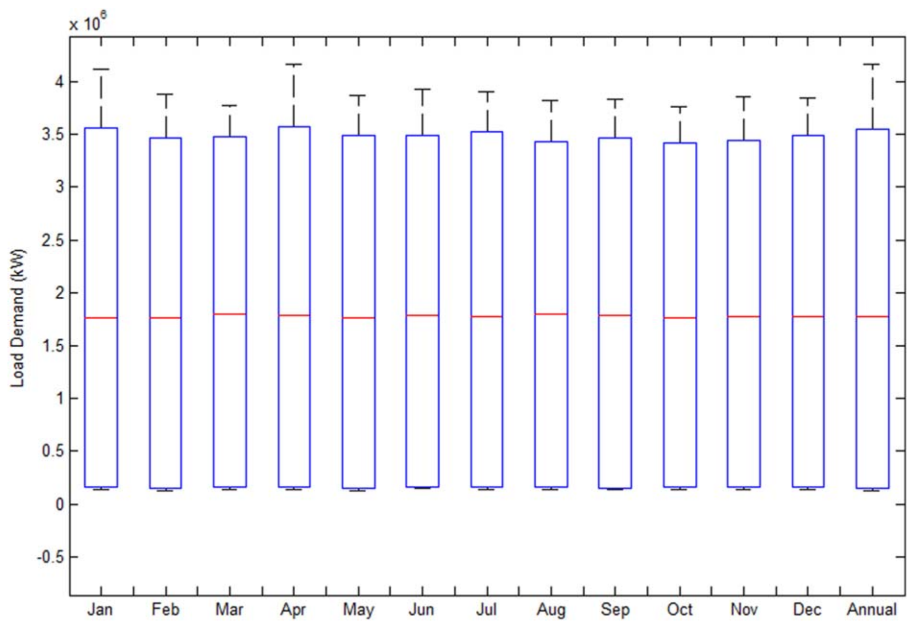
The coefficient k must be an integer number. The trials on different cases show that the best values for k is in a range of 2 to 5. However, it still depends on the other parameters which are going to be introduced. For the test cases, k is considered equal to 5. Normally, in such methods that particles are hired to search the solution-space, an inertia weight is defined to consider the convergence issue. In RMO, the inertia weight is shown with W and reduces throughout the generation run. Equation (8) shows the relation between W and the generation steps.

$$W_k=W_{\max}-\left(\frac{W_{\max}-W_{\min}}{\mathrm{Generation}_{\max}}\right)\times \mathrm{Generation}_k$$
$$V_{i,j}^k=W_k\times \mathrm{rand}(0,1)\times V_{\max(j)} \tag{8}$$

Unlike other global optimization techniques such as PSO and DE, the particles in RMO do not fly over the solution-space, so there is no need to save their current location for the next step. As the value of velocity vector $V_{i,j}^k$ is dependent on W_k, the values of $W_{\max}$ *and* $W_{\min}$ determine the impact of the velocity vectors on the movement of the particles (see Figure 2). In the figure, the radial movement of the particles from the center point, *cp* is shown. The boundaries of the sphere where the particles are sprinkled is equal to $V_{\max}$. In this study, the $W_{\max}$ is set to 1 and $W_{\min}$ is set to 0.1.

Next, the objective function is used to evaluate the fitness of all the particles. The radial particles with the best fitness value will be taken as the radial best (*Rbest*). The location of this particle with its associated value fitness value represents the *Rbest* particles. Among the radial best

FIGURE 5



Statistical graph for the available load data of Mashhad.

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TABLE 1

Coefficients of the RMO Algorithm

$C1$	$C2$	w_{max}	w_{min}	Number of Particles (nop)
0.8	0.7	1	0.1	50

particles, comparisons are made to obtain the fittest particle which is known as global best (*Gbest*) particle. The locations of the *Gbest and Rbest* particles are used to update a new best center point location using the *Update* (*up*) vector, as shown in Eqs. (9) and (10). The vector diagram of the mentioned equations is shown in Figure 3.

$$cp^{k+1}=cp^k+up \tag{9}$$

$$up=C1\times\left(Gbest-cp^k\right)+C2\times\left(Rbest-cp^k\right) \tag{10}$$

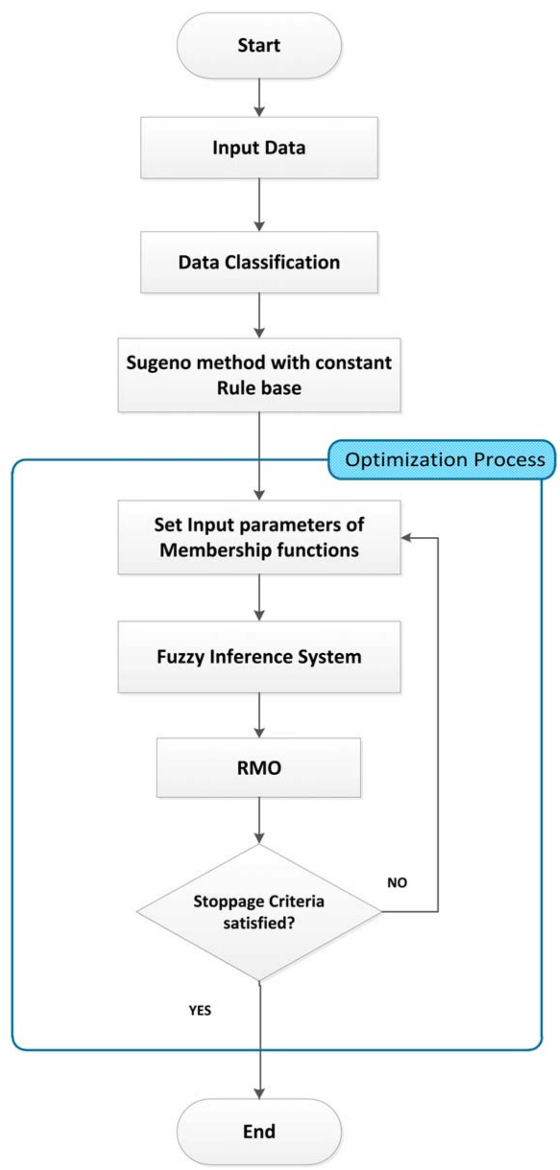
*C*1 *and C*2 are the coefficients which must be set prior to running the simulation. After the *cp* is updated, the particles will be sprinkled again from the new *cp*. In the following iteration, the value of the *Gbest* is replaced with the value of the *Rbest* obtained, only if it is better than the existing one; which means, If any of the *Rbest* proposes a better solution than *Gbest*, the location of *Gbest* must be swapped with *Rbest*. The stoppage criteria in this study is the maximum iteration. Figure 4 shows the optimization scenario of two tandem generations based on Eq. (10) where the *up* vector updates the location of the *cp*.

3. IMPLEMENTATION OF THE HYBRID TECHNIQUE

In this study, hourly load demand data of Mashhad is analysed, trained and tested for 10 years from 2004 to 2014. This large amount of data can lead to a complete cognition of load attributes in this city. The forecaster is designed to predict the on hour ahead load demand in terms of dependence to previous load values. Figure 5 shows statistical graph of the available data for the load demand of Mashhad, in which the parts of each candle from bottom to top represent values for the lowest daily load recorded, average of daily lowest values, the average value, average of daily highest values, and the highest load recorded for each month; respectively. The point to mention is that since the heating system in autumn and winter is mainly based on gas appliances and the cooling systems in summer are mostly water-based air cooler, the overall electricity consumption is not affected by the seasonal changes. According to the graph, the highest peak load was recorded in April with 4,170,818 kW while the lowest peak recorded was in September with 3,762,681 kW. Moreover, the highest and lowest variations in the load demand belong to August and April, respectively.

In the first stage, the input data is classified into two groups: Six previous day and hour parameters. Moreover, other parameters, such as last 24 h average temperature and humidity, month, day, and hour of forecast, and the last 6 h average load are also taken into account to increase the robustness of the predicted model. Nevertheless, the effects of other parameters in hourly load are neglected. Meanwhile, this input selection is common in most STLF techniques and will give a good observation of load scheme to forecaster.

FIGURE 6



Flowchart of the proposed hybrid Fyzzy-RMO technique.

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FIGURE 7

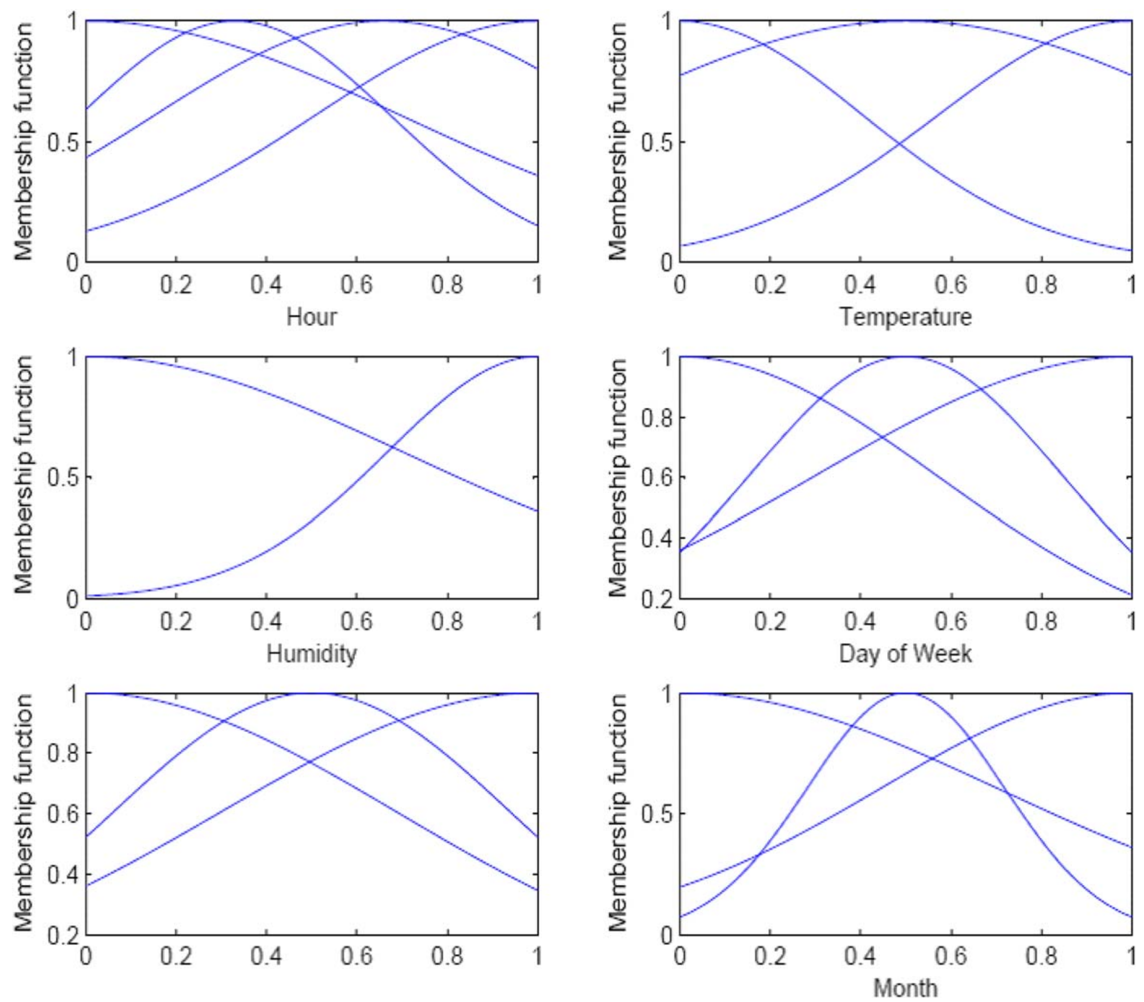
1-18 input bandwidths	19-36 input centers	output coefficients

A sample particle used in PSO procedure for membership function recognition.

The approach taken for designing and optimizing the fuzzy forecaster consists of two stages. At first, to obtain an appropriate rule base, a simple Sugeno system with constant output membership functions is used. Second, to optimize the rule base of forecaster, the RMO algorithm is employed in discrete mode. This stage is similar to a clustering problem in which the input data is collected into N sections where N is the number of fuzzy rules. Also the input variables are fuzzified using symmetric Gaussian membership functions. The number of sets for the temperature, day, month and previous loads is three while the hour and humidity are chosen to have 4 and 2 sets of membership functions respectively. Moreover, the output is divided into five symmetric constant levels.

The second stage is to optimize input and output membership functions using the sample data and the optimized rule base. The output membership function in this stage, is supposed to be a linear combination of input values; this will eventuate a higher dependence of output to inputs and admittedly more accurate results in output. Table 1 tabulates the coefficients of the RMO algorithm used in this study. In addition, a flowchart of the proposed hybrid technique is demonstrated in Figure 6.

FIGURE 8



Optimized input membership functions using the RMO algorithm.

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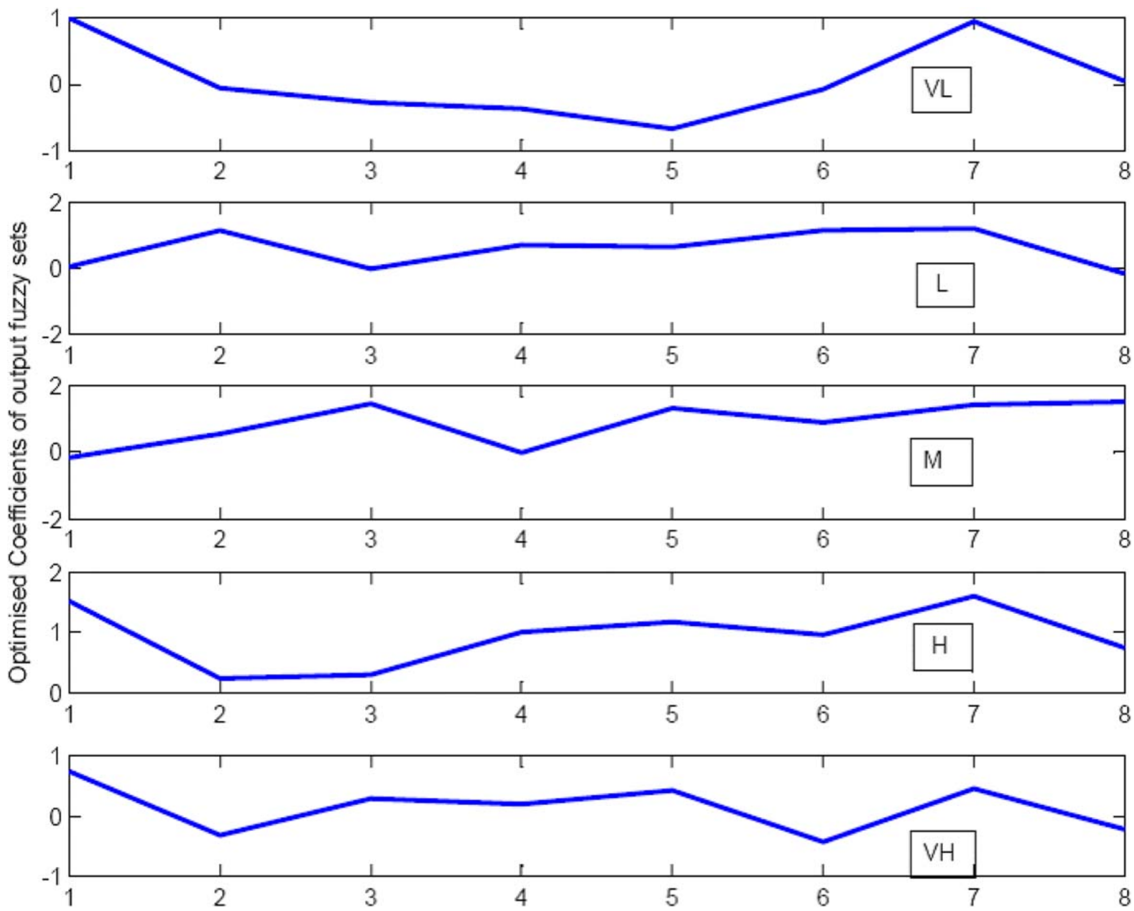
FIGURE 9



Optimized coefficients of the five output fuzzy sets.

4. RESULTS AND DISCUSSION

4.1. Rule-Based Generation

To find a proper rule base for the Sugeno system, the RMO technique is used. The effectiveness of RMO in this problem is its fast convergence which can handle the process of large data in a short time. Therefore, in this case study it is tried to find the full-sized rule base which contains all combinations of input fuzzy sets. The search space of the problem consists of 23 dimensions though which indicates the summation of all the input and output sets. Training procedure is done using 1000 random samples. Given 100 iteration steps as the precondition to terminate the training of the network study for 50 particles. The *location matrix* of the RMO would be a 50 × 23 dimensional matrix to handle the location of all the 50 particles. Samples are chosen randomly to contain the overall load scheme in it. Symmetric Gaussian functions are used for all the input membership functions.

4.2. Membership Function Evaluation

Having the desired rule base, the Sugeno system is trained in this stage to obtain the best membership functions for this special problem. Input fuzzy sets are allowed to change their bandwidth and centre, whether the output variable is supposed to be generated by a linear combination of input values. Equation (11) illustrates the form of each output fuzzy set, in this stage.

$$\mu(i)=\sum_{j=1}^{6} a_{ji}x_j=a_{1i}x_1+a_{2i}x_2+\ldots+a_{6i}x_6+a_{7i} \qquad (11)$$

where $i=1,2,\ldots,5$ are number of output fuzzy sets; x_j is the input variable; a_{ji} is the output linear coefficient.

A sample designed particle is shown in Figure 7 where the first and second eighteen places are appertained to fuzzy sets bandwidth and centers respectively. And the next 35 columns are supposed to contain the output

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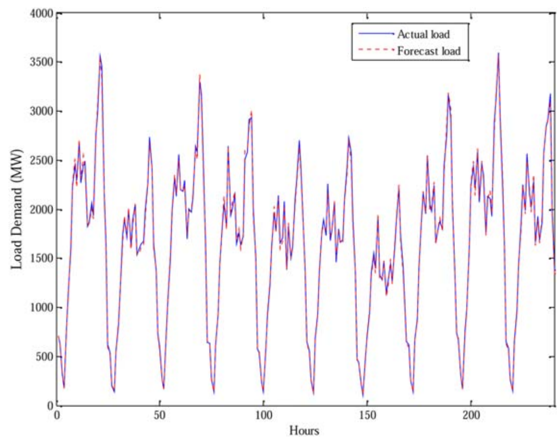
FIGURE 10



Actual and forecast loads of Mashhad for the first 10 days of 2014.

coefficients. In this way, both input and output fuzzy sets are tuned and optimized.

Training is handled using 300 random samples, 100 iterations and 50 particles and finally the optimized input membership functions are obtained as demonstrated in Figure 8. Whilst the coefficient of each output fuzzy set can be found in Figure 9.

4.3. Forecast Results Evaluation

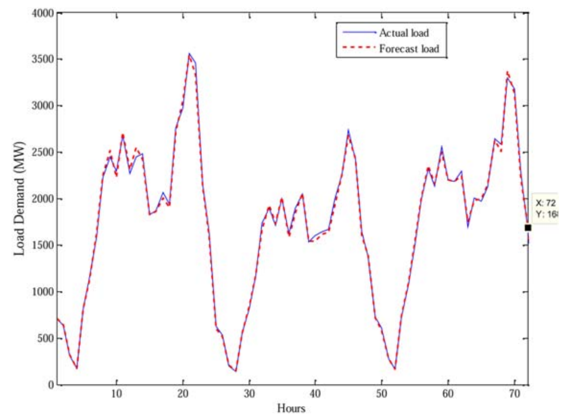
The changes were made in the fuzzy system, led to a highly accurate response for this special complex problem. Figures 10 and 11 demonstrate the quality of the proposed hybrid technique in forecasting the load demand of Mashhad, while they show the forecast loads for the first 10 days and first three days of 2014, respectively.

To assess the results quantitatively, mean absolute percentage error (MAPE) is used to calculate the accuracy of the forecast model for each month. Equation (12) demonstrates the equation for *MAPE* index where F_m is the forecast value, A_m is actual value of the load data, and N is the number of samples used for the assessment.

$$\text{MAPE}; \% = \frac{1}{N}\sum_{m=1}^{N}\left|\frac{F_m - A_m}{A_m}\right| \times 100 \qquad (12)$$

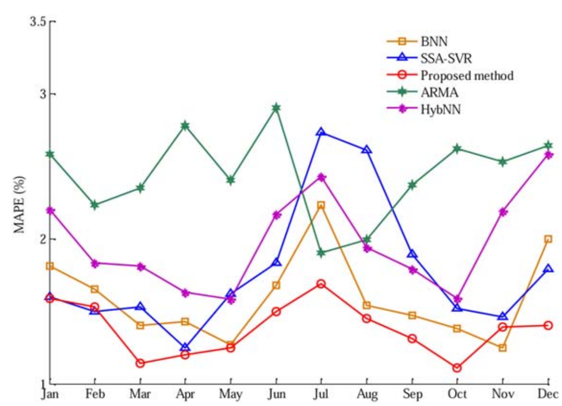
A comparative study has been performed as well by considering some of state of the art techniques applied to short term load forecasting problem, existing in the literature. Among all the techniques, we chose the ones with most popularity and highest quality of the results reported. Support vector regression machine [56], bagged neural networks [57], ARMA and a hybrid usupervised-supervised ANN [58] are used to calculate the MAPE values of every month. Figure 12 shows the results obtained, in which except February and November, the proposed fuzzy & RMO technique achieved the lowest MAPE values for the load forecast. The lowest MAPE value in the graph is obtained by the proposed method with the value of 1.11%. In contrast ARMA achieved the highest MAPE with 2.90% for June. Table 2 demonstrates the mean values of the MAPE obtained for the 12 months for all the methods. From the table, it can be observed that the proposed method is enable to present the lowest amount of MAPE among all the five methods under consideration. The proposed fuzzy & RMO technique provided the best mean MAPE of 1.38% followed by BNN and SSA-SVR with 1.59% and 1.78%, respectively. The hybNN could only perform

FIGURE 11



Actual and forecast loads of Mashhad for the first 3 days of 2014.

FIGURE 12



Comparison of MAPE values obtained for different algorithms applied for STLF problem.

TABLE 2

Mean MAPE Values Obtained for Different Algorithms Applied to STLF Problem

Technique	Proposed Fuzzy & RMO	BNN	SSA-SVR	HybNN	ARMA
Mean MAPE %	**1.38**	1.59	1.78	1.98	2.44

0.46% better than ARMA which achieved mean MAPE of 2.44%.

5. CONCLUSION

In this paper, a Fuzzy inference system is developed as a main forecast engine for Short term Load Forecasting (STLF) of a city in Iran (Mashhad). Hourly load demand data of Mashhad is analysed, trained and tested for 10 years from 2004 to 2014. This large amount of data led to a complete cognition of load attributes in this city. The forecaster is designed to predict the on hour ahead load demand in terms of dependence to previous load values. To optimize the membership functions of the fuzzy inference system and obtain a robust and reliable forecaster engine, the Radial Movement Optimization (RMO) technique is used to optimize the whole Fuzzy platform. To support this idea, the accuracy of the proposed model is analyzed using MAPE index and an average MAPE error of 1.38% is obtained for the forecast load demand which represents the reliability of the proposed method. Finally, results achieved by this method, demonstrate that an adaptive two-stage hybrid system consisting of Fuzzy & RMO can be an accurate and robust enough choice for STLF problems. Applying the proposed method in other energy forecasting problems such as solar and wind energy generation will be focus of the authors in the future. To do so, there must be performed some adaptation for real time data entry to the system.

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Conflict of interest: The authors declare that they have no conflict of interest.

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