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Research Article

Renewable Generation (Wind/Solar) and Load Modeling through Modified Fuzzy Prediction Interval

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The accuracy of energy management system for renewable microgrid, either grid-connected or isolated, is heavily dependent on the forecasting precision such as wind, solar, and load. In this paper, an improved fuzzy prediction horizon forecasting method is developed to address the issue of intermittence and uncertainty problem related to renewable generation and load forecast. In the first phase, a Takagi-Sugeno type fuzzy system is trained with many evolutionary optimization algorithms and established coverage grade indicator to check the accuracy of interval forecast. Secondly, a wind, solar, and load forecaster is developed for renewable microgrid test bed which is located in Beijing, China. One day and one step ahead results for the proposed forecaster are expressed with lowest RMSE and training time. In order to check the efficiency of the proposed method, a comparison is carried out with the existing models. The fuzzy interval-based model for the microgrid test bed will help to formulate the energy management problem with more accuracy and robustness.

1. Introduction

Intermittent, disperse, and dilute nature of renewable sources like wind and solar give new challenges for the integration of these sources in the microgrid planning and control [1, 2]. The task is even harder in islanded operation of the microgrid. One of the proposed solutions is to use the energy storage system for smoothing the uncertain behavior of generation for energy management system and to minimize the operational cost of the system. Nevertheless, the aforementioned problem is still not accurately solved and reliable unless or until a proper generation prediction method is not employed to address these issues [3].

In islanded operation of a microgrid, the task for smoothing the fluctuations produced by renewable sources is more challenging because limited generation options are available in the system [4]. Therefore, in standalone systems, this creates a critical demand supply and power quality problem unlike big geographical power systems.

To address the uncertainty and intermittence problem, many researches have been carried out under stochastic and robust forecast system [5–9], but the reliability of the system and actual implementation as compared to simulation results are the big concern in all over the world which will lead in doing more efforts in this field.

The forecasting of renewable resources such as wind and PV is strongly coupled with accuracy of the weather prediction model because usually the wind speed and irradiance information is utilized to forecast wind and PV power, respectively, using empirical formula. Factors such as location, surrounding terrain, and climatology showed a strong relation with accuracy of weather parameter, namely, temperature, vapor pressure, precipitate, cloud coverage, solar radiation, wind speed/direction, and humidity. A short-term wind power forecast is shown in [1]; the authors used sparse vector autoregressive sVAR model for the wind farm in Australia. A logit normal transformation is combined with the spatiotemporal weather data and compared with ARIMA and VAR methods in order to show the authority of the proposed method. Wind speed is predicted in [10], authors mentioned, to develop a weather warning system for more extreme wind speed predictions which leads to high fluctuation in wind power. However, the paper did not address neither implementation nor simulation details. The ARMA-based-enhanced boosting technique is mentioned for day-ahead wind power prediction in a wind farm at Jiangsu province, China, in [11]. The method showed improvement in 15.5% MAE with respect to the ARMA model and 3.21% MAE for the persistence model. Nonetheless, the validation accuracy check is not performed against more accurate techniques such as wavelet-ARIMA and hybrid Kalman filter in statistical domain. An interval-based fuzzy inference wind forecast is performed in [12], using empirical and nonparametric approach. Proposed method is applied on a Danish wind farm to predict different prediction intervals on adaptive resampling-based coverage rates for confidence interval. Authors used beta probability distribution function to calculate wind power forecast error in [13]; they argued that the fat-tailed forecast error pdf is more accurately modelled by beta distribution. However, the model is restricted to the particular dataset only.

Wavelet decomposition is utilized for solar radiation into low- and high-frequency band then SVM is applied to classify the pattern by Xiyun et al. in [14]. Historical solar radiation and atmospheric pressure are successfully used to get 3.78% RMSE and 12.83 MAE. Another technique [15] is mentioned in literature for 6 h ahead the backpropagation neural network-based solar power predictor; authors performed correlation analysis on several weather parameters and finally solar radiation and air temperature are used to develop predictor for solar power forecast, and the proposed method is deployed as a software package at Ljubljana, Slovenia, for testing and validation. Autoregressive exogenous ARX model is successfully integrated with numerical weather prediction which has 35% more accuracy than persistence models in [16]; AR works as a short-term predictor and the model can predict 4 h to several days of solar thermal power. Another ANN-NWP framework is mentioned in [17] with a confidence interval up to 95%.

Machine learning techniques are very useful in solving forecasting issues particularly neural network application in load prediction [2, 18]. Neural network has a high capability to capture nonlinear effects in the dataset, but the selection of proper neurons, hidden layers, computational time for training, and the possibility to fall in local minima is the main challenge to improve in NN type models. Felice et al. in [2] discussed a neural network with regularized negative correlation learning RNCL methodology, as the neural network has high sensitivity for its initial condition; therefore, this method is combined with the output of different networks which gives better performance over error reduction. Intrusive and nonintrusive load monitoring and prediction approaches are mentioned in [18]. Fuzzy regression model is proposed by Hong and Wang [19] for STLF; the authors used historical, weekday, and temperature information for the 3-year dataset and then formulated three fuzzy linear regression models. Mean absolute percentage error (MAPE) was in the range of 2.6–4.58% for hourly peak load. However, the authors did not show enough data to support the complete effectiveness of the proposed method and gathering large dataset is a difficult task in practical systems. The Takagi-Sugeno method is used to generate scenarios in the grid-connected microgrid by adding error probability distribution values in point forecast [20]; the method reduced the forecasting error in RG and load, plus authors also developed a robust EMS with two-step relaxation and Benders algorithm in order to maximize the exchange cost between microgrid and utility. Finally, the system is tested with the Monte Carlo simulation for the feasibility study. An efficient and model independent support vector machine-based method is discussed in [21], but the selection of kernel function, computation time, and parameter selection is the shortcoming for SVM-based approaches. A variety of statistical prediction methods is applied for building load demand, such as ARIMA and multiple exponential smoothing functions which are also applied using dry bulb temperature data in [22, 23] for long-term forecast, but LTF is mostly utilized for investment and planning purposes. Hybrid approaches for STLF also applied in various researches, such as a cooling load of a building, are predicted using ARIMA followed by SVM in [24]; it is used to reduce the error by 50% as compared to the individual algorithm. A mean square error is also minimized in [25] using general NN + wavelet transform + genetic algorithm- (GA-) based fuzzy inference system (GNN-W-GAF) for real-time data, where the NN is used to get initial prediction using wavelet information, and then GA is used to adjust the weights of the fuzzy inference system in the second stage of prediction. Hybrid approach using PSO-NN is applied in [26] by clustering data into three inputs, namely, weekday, weekend, and holidays. However, none of the above paper represents the uncertainty associated with modeling of the forecast problem and STLF issues where the density forecast is irrelevant and sequential time stamps are highly correlated.

Stochastic and uncertain behavior of wind and PV are not mentioned in most of the literatures as discussed earlier; hence, this study will show the details for modelling uncertainty by using fuzzy interval prediction-based approach. A similar method is used in the study [27], where the covariance of the error vector is used to develop the fuzzy regression model without mentioning the training method which will deeply affect the accuracy of the forecast, whereas this paper proposed evolutionary-based training for linear regressors in fuzzy interval in order to get better accuracy than existing least square and backpropagation-based method of [27], plus performance indicators such as coverage grade and interval band for lower and upper intervals are also introduced in order to check the quality of the forecast.

The rest of the paper is arranged in the following order. Section 2 provides the description of a grid-connected microgrid and the importance of prediction in energy management efficiency enhancement. Section 3 provides the detail on the mathematical model of the fuzzy interval and fuzzy PSO-based prediction interval algorithm. Section 4 provides the results and application description for wind, PV, and load forecasts which are tested on the Goldwind Microgrid test

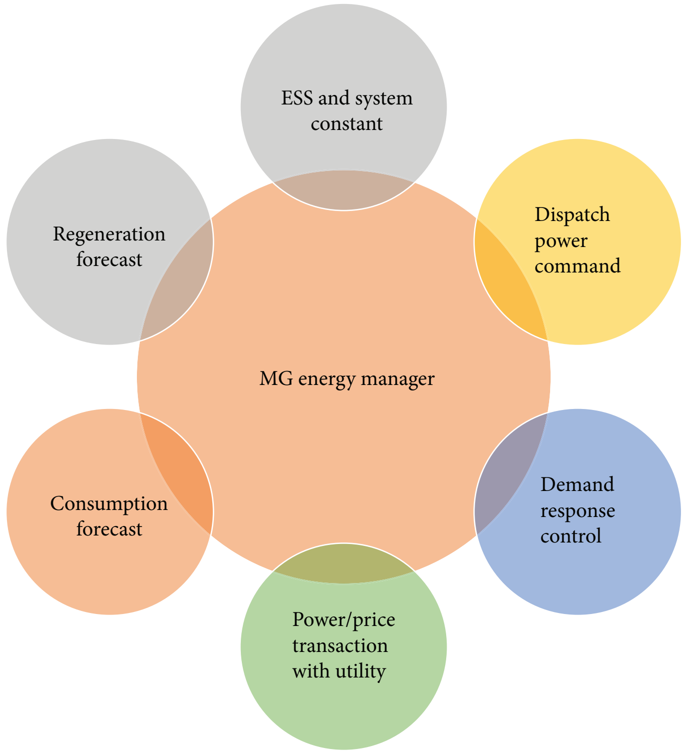

Figure 1: Microgrid energy manager.

bed, Beijing. Finally, Section 5 gives conclusion and future recommendation for this work.

2. Importance of Prediction in Energy Management

Energy management system (EMS) is the backbone of any microgrid infrastructure; it is responsible for a reliable and economical operation. It has three types of control methods, one is centralized in which all the data gathered at a one central processing unit, then it dispatches the control commands under a system constraint back to the primary controllers for execution. Second method is decentralized, where all units collect local information and communicate with each other for proper decision-making. Last method is hybrid control, where local controllers collect local information and also execute central controller commands as an upper-level controller and provide a perfect coordination among all the controllers. Also in Figure 1, a smart energy manager (SEM) features are highlighted for the grid-connected and isolated microgrid. The responsibilities of EMS in a microgrid system include solving the optimization problem for economic dispatch, gathering technical and physical constraints of the network, generating units and loads, then selecting the best possible dispatching signals for satisfying objectives which are set by the operator. Centralized secondary control is more suitable for an isolated microgrid where the infrastructure is fixed plus the demand and supply problem is crucial. Whereas a distributed scheme is more suitable for a plug-in play type of functionalities just like in a grid-connected microgrid with multiple owners. The following are the operations of EMS:

(i) Generation prediction for all uncontrollable DERs, such as wind turbine and PV panels, is usually done by the EMS/secondary controller in next day/hour-based timestamps.

(ii) Load forecast and demand-side management policies for all consumers are usually developed at the secondary controller in next day/hour-based timestamps.

(iii) State of charge (SOC) for battery and other battery management constraints usually handled by the battery management module (BMM).

(iv) Connection status for grid and price forecast for utility in next hour/day format is performed at the secondary controller.

(v) System diagnostic, security, state estimation, black start, self-healing, and other active/reactive power adjustment checks are usually done by the secondary controller.

Considering uncertainties in the renewable generation source, spinning reserve becomes a necessary part of the microgrid as an energy buffer to mitigate the fluctuation plus smoothing the overall voltage and power profile. This spinning reserve also creates economic and management-related hurdles which lower the motivation to invest in microgrid-related systems. Hence, an accurate prediction of these uncertain units is necessary in a sliding horizon fashion in order to get the forecast from several minutes to several days. Similarly, load uncertainty is purely unavoidable, due to the fact that usually in a traditional power system the customer has no participation in the decision-making process, which makes it very difficult to predict and control. Forecasting techniques can be divided into different time horizons, such as very short-term (1 min–1 hr), short-term (1 hr–1 week), medium-term (1 month–1 year), and long-term (1 year and above), different spatial resolutions (0.01 km to 100 km), and techniques, for example, statistical, machine learning, and physical/numerical. Numerical weather prediction (NWP) is concerned with the weather forecast and related with the analysis of a number of variables in multidimensional calculation space; it followed the relation of thermodynamics, fluid dynamics, and chemical reaction of the air particles. For lower temporal and spatial resolution, NWP prediction is very accurate. Statistical forecasting methods rely on consistent historical data and are very computationally efficient and fast but for nonlinearity machine learning techniques they are appropriate. Machine learning usually falls into an overfitting problem for training dataset, but up to this date it is very reliable, as well as it is improving by the passage of time. Hence, an EMS for the microgrid system must be accounted for the uncertainties in the forecast in order to take better decisions.

3. Fuzzy Takagi-Sugeno Modelling

Fuzzy prediction interval (FPI) modelling is utilized in a variety of studies in the past, and it is used to forecast power output for nondispatchable sources. FPI is useful for approximation of nonlinear dynamic system, and it facilitates to develop robust EMS formulation which is the ultimate scope of this study. The number of rules is minimized in this study which makes the partition of output variable space that is projected onto the input variable space in order to get the optimal solution for fuzzy sets and rules. Fuzzy clustering approach is used to make that partition and get the premise parameter. Fuzzy c-mean clustering is applied to develop initial clusters, minimizing the intracluster variance, and assigning initial weights that will be adjusted in later stages in order to avoid local minima. The Takagi-Sugeno-based fuzzy model is helpful to achieve consequence parameters based on the least square method.

A linear membership-based fuzzy rule space is developed by Takagi-Sugeno in [28, 29], which is capable of estimating a variety of nonlinear systems. The idea is to partition the space of input andoutput variables into separate linear fuzzy subspaces and then combine into normalized membership function β; this method is called premise parameter selection by Takagi-Sugeno in [28]. Let us suppose that a linear relationship is established between the input and output variable.

$$\begin{aligned} z &= \sum_{i=1}^{n} \beta_i \left(a_0^i + a_1^i x_1 + a_2^i x_2 + \cdots + a_k^i x_k \right), \\ &= \sum_{i=1}^{n} \left(a_0^i \beta_i + a_1^i x_1 \beta_i + a_2^i x_2 \beta_i + \cdots + a_k^i x_k \beta_i \right), \end{aligned} \tag{1}$$

where β_i is the normalized membership function of ith rule R_i $(i = 1 \cdots n)$, input/output dataset $x_{1j}, x_{2j}, \ldots, x_{kj}$ maps to z_j at interval k, j is the measurement vector from 1 to m, the total output vector is $Z = [z_1, z_2, \ldots, z_m]^T$, and the coefficients of linear functions $a_0^i, a_1^i, \ldots, a_k^i$ are solved by the least square method to find the optimal minima of these weights and n denotes the total number of rules. Extension of this rule (1) for multivariable can be written as $\widehat{\mathbf{z}} = [x, y, w]$; here, $\widehat{\mathbf{z}}$ is the predicted vector which depends on x, y are inputs, and w is a control vector.

$$\begin{aligned} \widehat{\mathbf{z}} = \sum_{i=1}^{n} \beta_i \Big(& a_0^i + a_1^i x_1 + a_2^i x_2 + \cdots + a_k^i x_k + b_0^i \\ & + b_1^i y_1 + b_2^i y_2 + \cdots + b_k^i y_k \Big). \end{aligned} \tag{2}$$

More explicitly for the given problem of forecasting in this paper, the T and S framework (2) can be extended to matrix notation t timestamps.

$$\begin{aligned} \widehat{\mathbf{z}}_t &= f^{\mathrm{TS}}(x_{t-1}, y_{t-1}, w_{t-1}), \\ &= \beta_i x_{t-1} [1 \; y_{t-1} \; w_{t-1}] A, \\ &= \Upsilon^T A, \end{aligned} \tag{3}$$

where the $t-1$ subscript shows the historical data vector, $A = [a_0, \ldots, a_k, b_0, \ldots, b_k]^T$, where $a_0 = [a_0^1, \ldots, a_0^n]^T$ which are the weight vectors which are used for error reduction in the proposed method later in this paper and Υ is the fuzzy regression matrix. The set of predictions can be shown as error vector e for forecast:

$$\widehat{\mathbf{z}}_t = \Upsilon^T A + e_j. \tag{4}$$

Fuzzy partitioning method is used in this paper to minimize the number of rules based on fuzzy c-mean clustering approach.

(1) *Interval identification*: In order to approximate function families for various sets of intervals because the deterministic solution is not reliable in renewable/load predictions, hence, the author calculated forecasting intervals with certain interval bandwidth σ and fuzzy covariance model of error.

$$\widehat{\mathbf{z}}_t^{\,U} = f^{\mathrm{TS}}(x_{t-1}, y_{t-1}, w_{t-1}) + \sigma^U \mathrm{Cov}_e^{\mathrm{TS}}(x_{t-1}, y_{t-1}, w_{t-1}), \tag{5}$$

$$\widehat{\mathbf{z}}_t^{\,L} = f^{\mathrm{TS}}(x_{t-1}, y_{t-1}, w_{t-1}) + \sigma^L \mathrm{Cov}_e^{\mathrm{TS}}(x_{t-1}, y_{t-1}, w_{t-1}), \tag{6}$$

where σ is the interval width and can be adjusted for the given dataset with certain coverage grade CG and $\mathrm{Cov}^{\mathrm{TS}}$ is the covariance of the target and predicted data model as $\mathrm{Cov}^e = (y_j - \widehat{y}_j)$ same as T and S mentioned earlier.

Hence, the fuzzy regression model Υ parameters are identified by clustering and with (5) and (6), the coefficient A and covariance matrix Cov^e is trained using evolutionary search algorithms such as the least square combined back propagation (FR), particle swarm optimization (PSO), firefly (FF) optimization, cultural algorithm (CA), and genetic algorithm (GA)

(2) *Interval band*: Interval band is introduced in term of σ, where the lower the value of σ indicates the smaller bandwidth of the interval and lower the probability of missing real measurement value from the predicted values.

$$\gamma = \frac{\mathrm{RMSE}_{\max} - \overbrace{\left(\sum_{p=1}^{q} \mathrm{RMSE}_{\mathrm{error}_p}\right)}^{\alpha}}{\mathrm{RMSE}_{\max}}. \tag{7}$$

In the above relation, α represents the point error RMSE of the historical prediction q. $\mathrm{RMSE}_{\max}$ is the maximum training root mean square value. Interval band is directly related with γ such as $\sigma = 1 - \gamma$.

(3) *Coverage grade*: In order to classify the forecast system based on performance, the authors in this paper introduced the coverage grade CG system. This performance evaluation method with interval band gives the insight into the accuracy of predictions. The levels of CG is divided into 3 levels, namely, A, B, and C.

$$\mathrm{CG} = \frac{\sum_{j=1}^{m} \kappa}{m}. \tag{8}$$

Coverage grade is calculated to adjust the σ value and is the interval; κ is the binary parameter which shows that whether the measurement data lies inside of the interval or not. Lower values of RMSE in point forecast gives the bandwidth for respective grades such as A grade ($90\% < \mathrm{CG} \leq 100\%$) coverage, B grade ($70\% < \mathrm{CG} \leq 90\%$) coverage, and C grade ($\mathrm{low} < \mathrm{CG} \leq 60\%$) coverage. Based on defined parameters, the proposed method will constantly improve the performance of the forecast using interval band and coverage grade tuning with (7) and (8). For example in terms of CG_q, a forecaster with A_{30} label indicates the operator that the algorithm is running on best performance for past 30 historical points.

3.1. Particle Swarm Optimization for FPI. Swarm-based optimization techniques are very much dependent on the initial conditions, but the ability of avoiding local minima is much higher provided that the parameters are carefully selected and initialized. Particle swarm is a well-known global optimization technique which mimics the bird flocking approach like other swarm optimization techniques. All birds are looking for food (min/max objective) in different directions, and a bird close to the food will be followed (distance and velocity are set on every step) by the swarm and finally, it converges on the solution in [30].

$$\begin{aligned} \mathrm{Vel}_{\mathrm{particle}}^{t+1} = {} & w_{\mathrm{int}} \mathrm{Vel}_{\mathrm{particle}}^{t} + c_{\mathrm{pl}} r_{\mathrm{dist}}^{1} \left(p_{\mathrm{partlocal}}^{t} - x_{\mathrm{particle}}^{t}\right) \\ & + c_{\mathrm{gl}} r_{\mathrm{dist}}^{2} \left(p_{\mathrm{partglobal}}^{t} - x_{\mathrm{particle}}^{t}\right), \end{aligned} \tag{9}$$

where Vel, p, and x are the velocity, best position, and position, respectively, for each particle at the t interval. Furthermore, w_{int}, c_{pl}, and c_{gl} are inertial weight, local learning coefficient, and global learning coefficient, respectively. r_{dist}^{1} and r_{dist}^{2} are the random distribution of the particle. The complete PSO-based training algorithm for fuzzy model tuning is mentioned in Algorithm 1.

4. Case Study

4.1. Microgrid Test Bed. This paper used the data from the Goldwind Microgrid test bed which is located (3945′23.6′N, 11631′56.3″E) in the suburb of Beijing, China. The microgrid system consists of a wind turbine which is rated at 2.5 MW; two photovoltaic system, one is 250 kW and the other one is 200 kW capacity; two battery systems connected with bidirectional converters; four fuel generators include diesel and natural gas fuel type; and the maximum rated load of 3 MW for the office building on the site. Simplicity of this forecast scheme is the reduce input variable set which is easily available and faster to predict, and it can modify for the next step predictions, for example, wind velocity and historical wind power are used for future wind power prediction; similarly, historical load data is used for future load forecast. The impact of other weather parameters is embedded in the historical power output, but in case of load, it is more related to the time of the day rather than the weather data. All the NWP [weather research and forecasting model (WRF)] information for the next day such as wind velocity and solar irradiance are acquired from the FTP server of Goldwind Technology, whereas the other historical information is collected from the SCADA system. PSO algorithm is used to modify the weight matrix of the fuzzy set of functions which are separated into 5 clusters and then interval bands are obtained with different coverage grades in order to check the forecast performance. The results are presented in 10 min sampling time with one step to one day (144 steps) ahead predictions. One day ahead prediction is performed every 10 min interval based on the input data for real and predicted values.

Flowchart is shown in Figure 2 for the PSO-based fuzzy prediction interval scheme; two step training is applied on every time stamp. In the first step, historical data is acquired and fuzzy set of membership functions is initialized in clusters using fuzzy c-mean clustering method. After that, PSO is applied in order to get optimal-trained fuzzy model with lowest RMSE value, and it sends the power reserve signal to the EMS module in case of a higher RMSE than the set points. In the second step, the model acquires next day ahead weather parameters in order to get the initial forecast; later on, the coverage grade is calculated and checked against the set point of CG value (in percentage), if the value is above the set point then the interval band adjusts and again calculates the next step ahead the forecast else, the model will train and update again accordingly. Finally, an Intel i5, 2.53 GHz quad-core processor with 4 GB RAM laptop is used to compute the results of this study.

4.2. Wind Prediction. Wind power prediction is done by FPI, June 11, 2016, to July 26, 2016, data are used to train and July

```
Get Initial Parameters (fuzzy model weights, cost function,
variables count, variables range, max iteration, population
size, inertial weight and damping ratio, personal and
global learning coefficient)
for 1 to population size do
    Initialize the position [30], velocity, personal and global
    best of each particle based on the cost function.
end for
repeat
    for 1 to population size do
        Update velocity of a particle using (9)
        Update position, velocity and cost of each particle
        Apply minor limits for the velocity of each particle
        if particle cost ≤ particle best cost then
            update personal best
            if particle best cost ≤ best solution cost then
                Update global best
            end if
        end if
    end for
    Best cost of iteration ← best solution cost
    Update inertial weight
until Maximum iteration & minimum error achieve
```

Algorithm 1

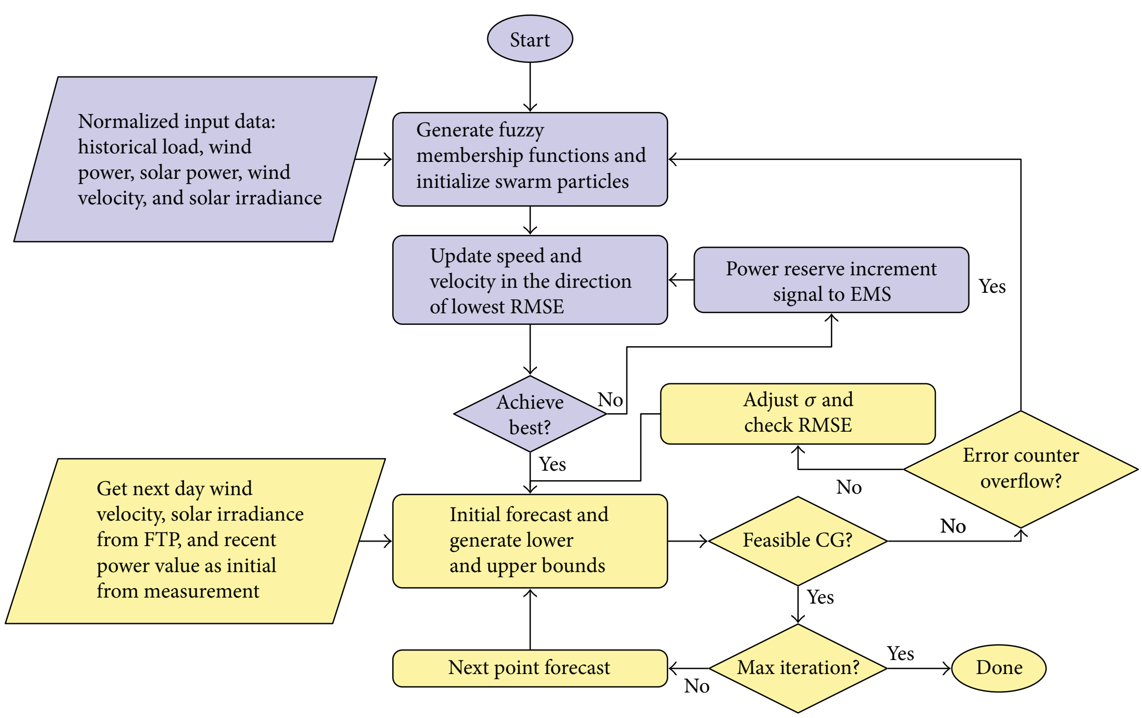

Figure 2: Flowchart of the proposed method.

27 to Aug 12, 2016, data are used for validation purposes. All the data are gathered from the SCADA of the Goldwind Microgrid test bed, Beijing. The rated capacity of this single PMSG type wind turbine is 2.5 MW. Wind velocity and historical power are the training inputs with 10 min of sampling time. The linear regressor for input variable (wind speed) and output variable (wind power) are v_r and p_r, respectively, in discrete time. As in interval prediction, the output of exogenous variable is related to the last historical values $(t-1)$ then, in accordance with the notation $z_r = [v_{r-1}^3, p_{r-1}]$ where r is the discrete variable. Hence, the ith rule for the membership function in terms of linear regressors for the wind

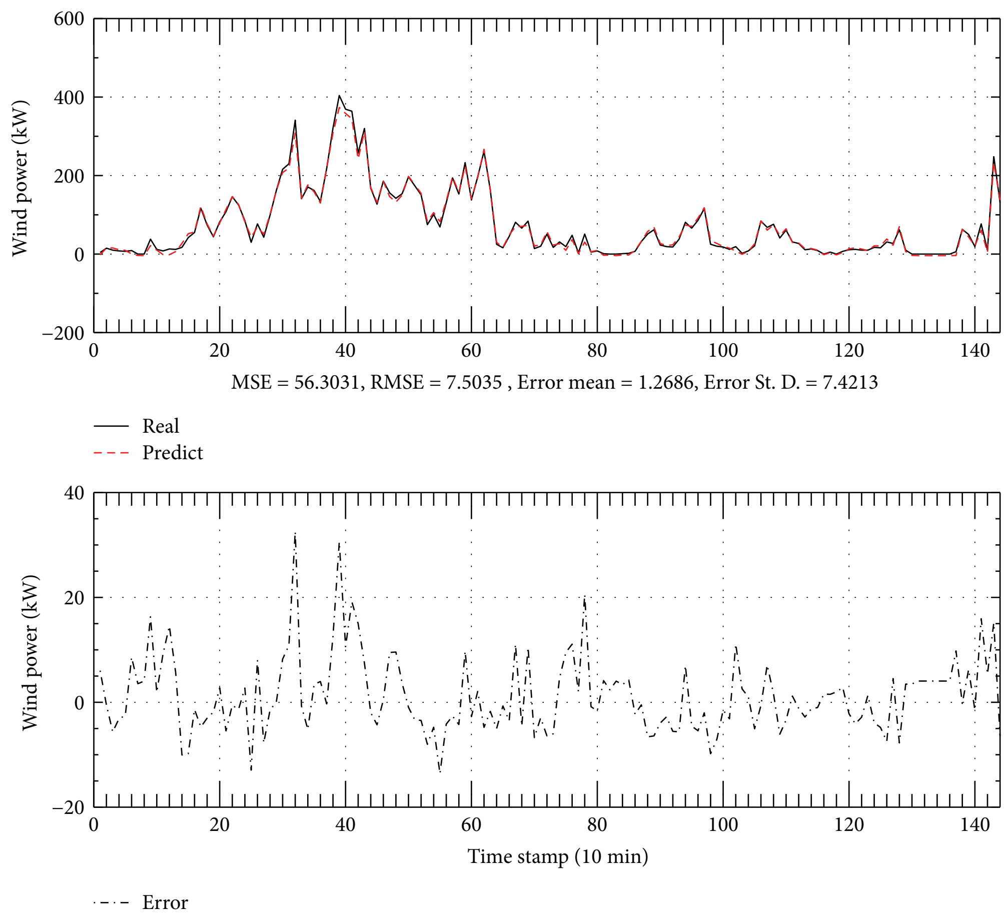

Figure 3: One day ahead RMSE value of wind forecast.

energy prediction is defined by clustering approach which is mentioned in Section 3.

$$\hat{\mathbf{z}}_r = P_w(r) = \sum_{i=1}^{n} \beta_i \left(a_0^i + a_1^i v_{r-1}^3 + a_2^i v_{r-2}^3 + \cdots + a_k^i v_{r-k}^3 + b_0^i + b_1^i p_{r-1} + b_2^i p_{r-2} + \cdots + b_k^i p_{r-k}\right). \tag{10}$$

Here, $A = [a_0, \ldots, a_{r-144}, b_0, \ldots, b_{r-144}]^T$ is same as mentioned earlier and considers $P_w^U(r)$ and $P_w^L(r)$ as the lower and upper bounds related to $P_w(r)$ such that $P_w^L(r) \le P_w(r) \le P_w^U(r)$ for all r in discrete space. Furthermore, $A^U = [a_0^U, \ldots, a_{r-144}^U, b_0^U, \ldots, b_{r-144}^U]^T$ is for $P_w^U(r)$ and $A^L = [a_0^L, \ldots, a_{r-144}^L, b_0^L, \ldots, b_{r-144}^L]^T$ is for $P_w^L(r)$. These parameters, namely, A^U and A^L can be adjusted based on training with PSO. The prediction intervals now can be written as

$$P_w^U(r) = f^{\mathrm{TS}}\left(v_{r-1}^3, p_{r-1}\right) + \sigma^U \mathrm{Cov}_{\mathrm{wind}}^{\mathrm{TS}}\left(v_{r-1}^3, p_{r-1}, \mathrm{Cov}_{r-1}^e\right), \tag{11}$$

$$P_w^L(r) = f^{\mathrm{TS}}\left(v_{r-1}^3, p_{r-1}\right) + \sigma^L \mathrm{Cov}_{\mathrm{wind}}^{\mathrm{TS}}\left(v_{r-1}^3, p_{r-1}, \mathrm{Cov}_{r-1}^e\right), \tag{12}$$

$$\mathrm{Cov}_{\mathrm{wind}}^{\mathrm{TS}} = \sum_{i=1}^{n} \beta_i (z_{r-1}) \mathrm{Cov}_{r-1,i}^e, \tag{13}$$

where covariance of past error Cov_{r-1}^e is integrated with the fuzzy interval of input and error as $\mathrm{Cov}_{\mathrm{wind}}^{\mathrm{TS}}$. Next, the lower and upper bounds for the fuzzy interval-based wind power P_w are calculated based on the coverage grade, and interval band is adjusted accordingly.

Figure 3 shows the one day ahead forecast of wind power and error value for 144 steps. This can be easily judged from the graph that the error increases more at the sharp changes in measured wind power. The value of mean square error (MSE), root mean square error (RMSE), error mean, and standard deviation gives insight about the forecast, for example, the RMSE [kW] is 7.5035 which is very satisfactory result achieved through the PSO integration in the T and S model.

In Figure 4, case 1 presents the gradual variation in one day ahead wind forecast and measured power with different coverage grades based on different values of σ. It should be noted here that the CG of level C has a narrower band with some data points whereas the grade A level CG can be accounted for almost all data points but the uncertainty is higher, whereas level B has fewer data points compared to

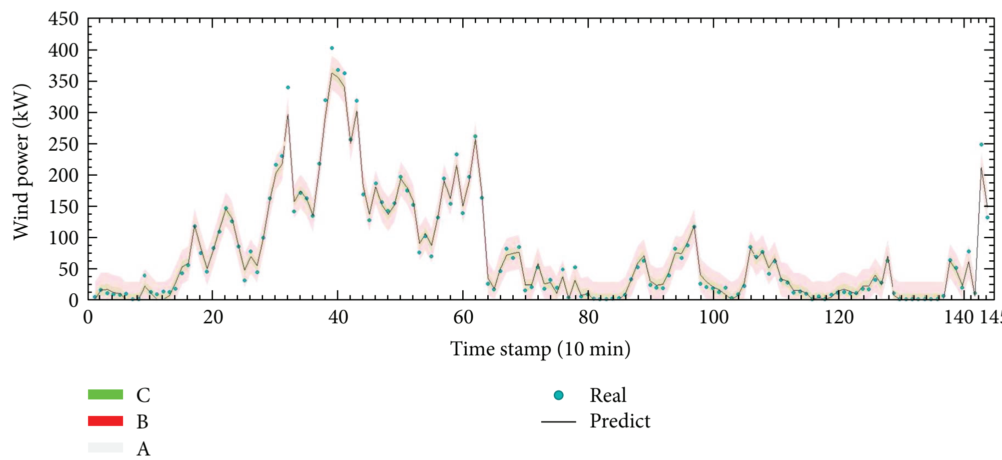

FIGURE 4: Fuzzy interval prediction for one day ahead (case 1) wind power with coverage grades.

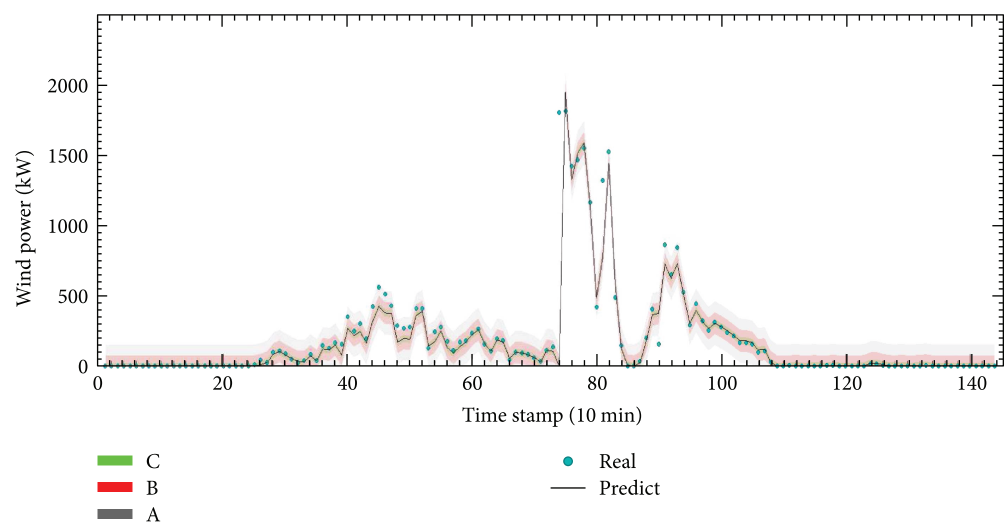

FIGURE 5: Fuzzy interval prediction for one day ahead (case 2) wind power with coverage grades.

A but the uncertainty is lower than A. Hence, for a normal day with gradual change of wind velocity forecast, an operator can go with grade C or B level predictions but in case 2, the abrupt wind velocity alerts from day ahead of the NWP forecast data where the level of uncertainty is higher, so one should choose grade A or B as shown in Figure 5. Furthermore, higher variability in real values is captured accurately with the help of grade A prediction intervals; hence, the operator or EMS can adjust the spinning reserves based on the level of uncertainty required. Power reserve capability can cope against forecasting uncertainty by leaving an adequate margin for controllable units to compensate the mismatch. Here, the mechanism will only alert EMS for the possible mismatch.

Table 1 shows the comparative results obtained by applying other techniques to check the forecast error for one step (10 min) and one day ahead. The table mentioned train time, mean absolute error (MAE), and RMSE for 4 different approaches including fuzzy regression (FR) [27], cultural algorithm (CA), firefly (FF) algorithm, and genetic algorithm (GA) apart from PSO. It should be noted that longer horizon has a higher error than one step ahead except CA. Based on the results obtained, fuzzy prediction model with PSO outperforms other techniques in terms of lowest RMSE in long-horizon forecast whereas CA has the worst RMSE value and train time due to the fact of falling in local minima. GA also shows a better result in one step

TABLE 1: Comparison of prediction interval forecast for wind power.

Model	One step ahead RMSE (kW)	One step ahead MAE (kW)	One day ahead RMSE (kW)	One day ahead MAE (kW)	Train time (s)
FR	5.97	9.47	8.52	8.91	11.4
CA	189.9	10.15	39.5	26.78	131.3
FF	7.83	2.41	9.42	8.94	145
GA	1.88	8.72	10.19	8.35	60.1
PSO	4.28	6.67	7.5	9.8	56.4

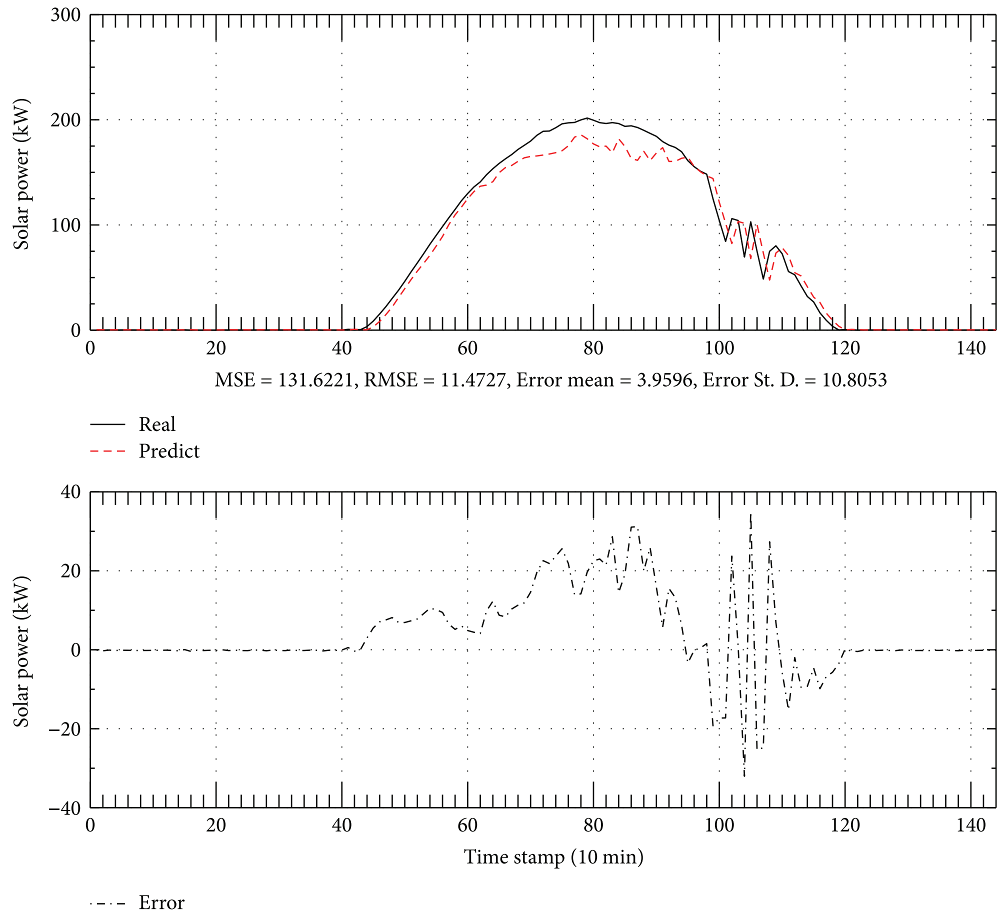

FIGURE 6: One day ahead RMSE value of solar forecast.

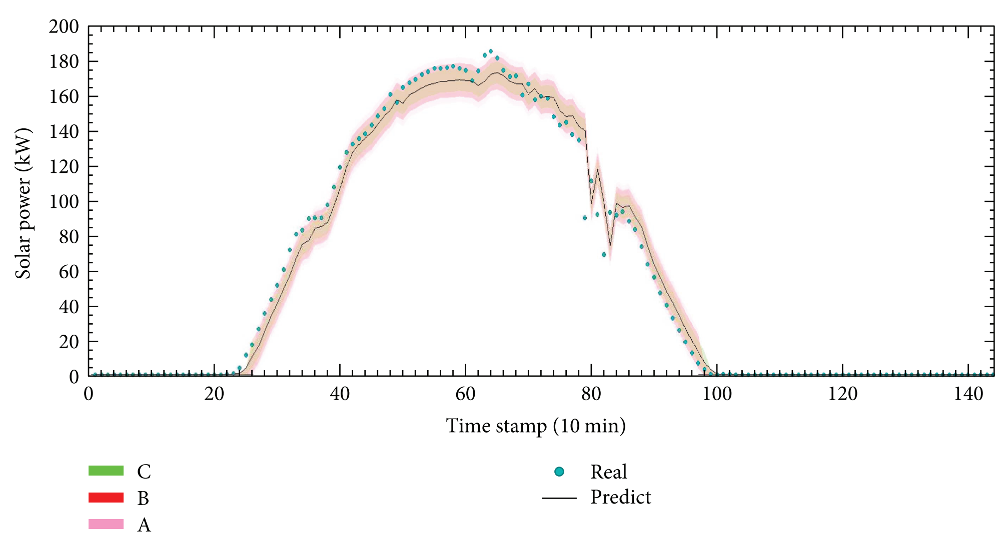

FIGURE 7: Fuzzy interval prediction for one day ahead (case 1) solar power with coverage grades.

ahead than PSO but for longer run it has higher RMSE than PSO. FR shows significant fast train time as mentioned in [27], but PSO shows superior results for one-day head forecast for local dataset.

4.3. Solar Prediction. Solar power fuzzy model is described in this section using the data acquired from June 11, 2016, to July 26, 2016, for training and July 27 to Aug 12, 2016, for validation. The rated capacity of the PV panel at the top

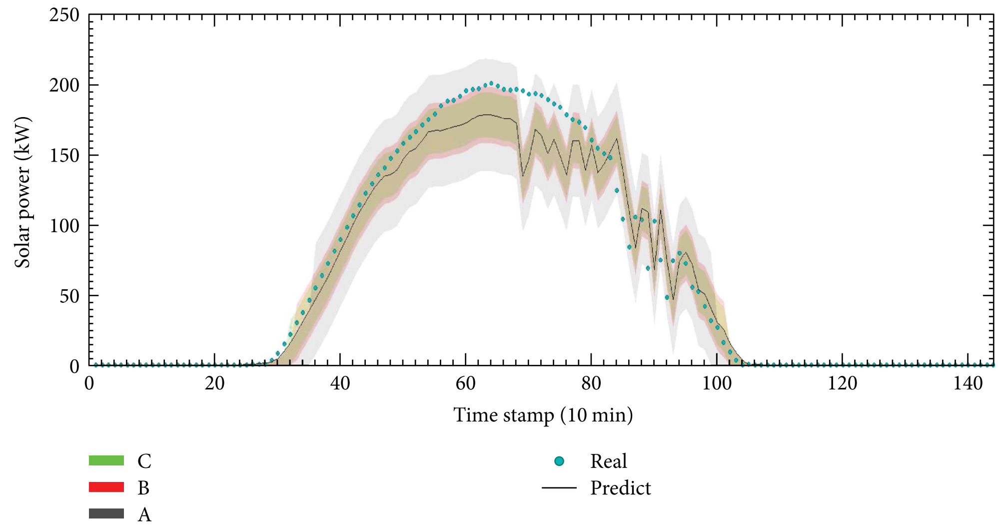

FIGURE 8: Fuzzy interval prediction for one day ahead (case 2) solar power with coverage grades.

of the Goldwind Technology office building is 450 kW, but due to efficiency issues, we can only observe power close to 200 kW at peak sunny days. Here, the input variables for the training of the proposed model are irradiance data from NWP and historical solar power output at 10 min interval (144 points in a day) $p_r = p_s$: hence, $z_r = [ir_{r-1}, p_{r-1}]$ is the relation for the identification procedure mentioned in Section 3.

$$\hat{\mathbf{z}}_r = P_s(r) = \sum_{i=1}^{n} \beta_i \left(a_0^i + a_1^i ir_{r-1} + a_2^i ir_{r-2} + \cdots + a_k^i ir_{r-k} + b_0^i + b_1^i p_{r-1} + b_2^i p_{r-2} + \cdots + b_k^i p_{r-k}\right). \quad (14)$$

Here, $A = [a_0, \ldots, a_{r-144}, b_0, \ldots, b_{r-144}]^T$ is the weight vector which is tuned with PSO and considers $P_s^U(r)$ and $P_s^L(r)$ as the lower and upper bounds related to $P_s(r)$, such that $P_s^L(r) \leq P_s(r) \leq P_s^U(r)$ for all r in discrete space. Hence, A^U and A^L are calculated for certain coverage grade and interval band.

Figure 6 shows the predicted solar output and the error value for 144 points ahead. The day starts from midnight where zero values are recorded. Additionally, the error increases at the peak period of the day and RMSE (kW) value is recorded as 11.4727.

A normal sunny day solar power forecast result is shown in Figure 7 as case 1. The forecast shows zero values at midnight and evening intervals while the peak power output is recorded around the afternoon time. Note that the predicted value is slightly lower than that of the real one in the rise up and peak period and slightly higher than the real value at the falling period due to the inaccuracy in the NWP value for day-ahead irradiance. However, the interval with grade B (70–90%) is sufficed to capture uncertainty at peak points of the day which is a more important time for the operator or EMS to properly allocate the extra power using spinning reserves. Another scenario in case 2 is shown in Figure 8; here, the abrupt and unwanted change in solar power due to irregular sunlight is completely missed by predicted value at the peak point of the day, whereas grade A (90–100%) level interval band captured this trend at the cost of higher uncertainty.

TABLE 2: Comparison of prediction interval forecast for solar power.

Model	One step ahead RMSE (kW)	One step ahead MAE (kW)	One day ahead RMSE (kW)	One day ahead MAE (kW)	Train time (s)
FR	5.44	5.41	12.97	8.2	1.22
CA	5.65	5.63	12.57	7.73	46.69
FF	5.3	5.28	13.42	8.28	45.7
GA	5.53	5.50	12.32	7.65	23.43
PSO	4.05	4.03	11.47	7.04	20.95

Table 2 shows the comparison between PSO-based fuzzy model and other fuzzy models in terms of RMSE and MAE values for solar power forecast. The results show one day ahead and 10 min ahead forecast, lowest training time obtained with FR, whereas the lowest RMSE for one day and one step ahead is achieved with PSO, which again showed better performance than other techniques.

4.4. Load Prediction. For load predictor modeling, a dataset consisting of 10 min samples is acquired from 4 May to 28 April 2016 for training and 28 April to 16 May 2016 for the validation purpose. Load data consist of historical power demand of the office building at Goldwind Technology, Beijing. The maximum load demand of the building is about 3 MW. With the help of correlation analysis, the temperature correlation with demand is almost vanished because of very short duration for spring and autumn in Beijing; hence, the air conditioning and heating loads are

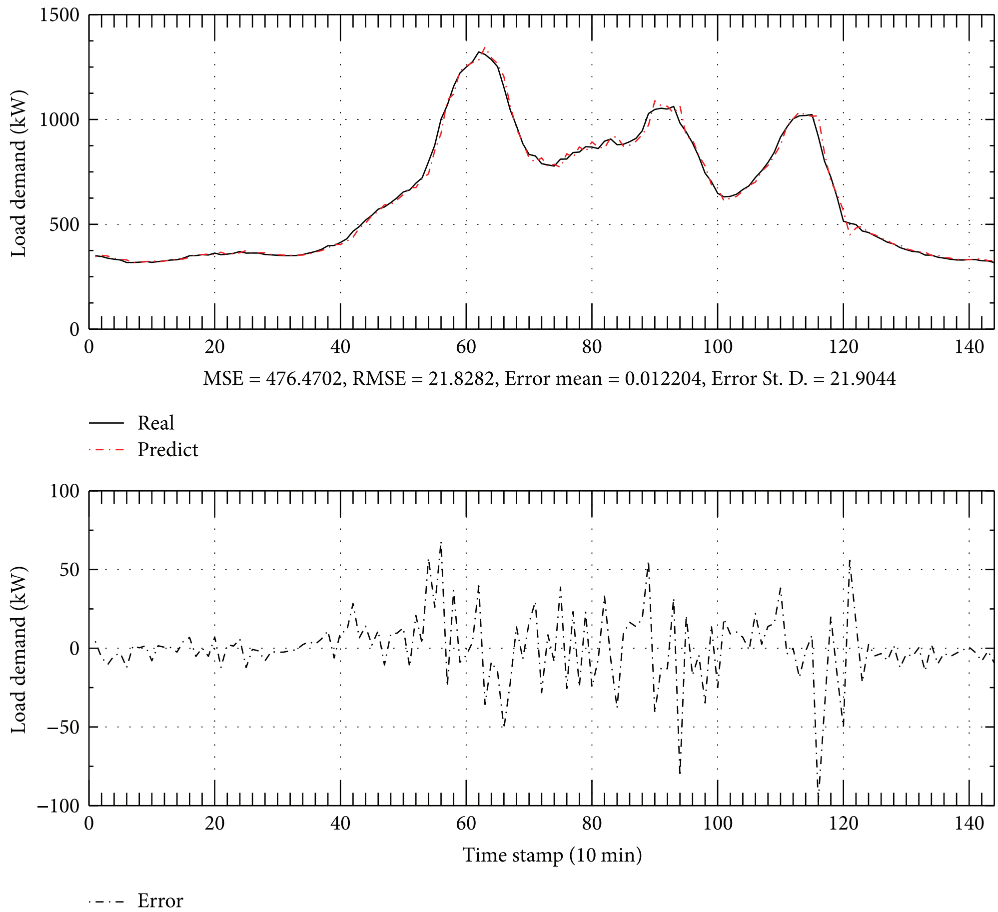

FIGURE 9: One day ahead RMSE value of demand forecast.

balanced out and only start as well as end of time for work are correlated with the demand. Using the identification method, we can safely consider the historical power demand pattern $p_r = p_l$ in order to predict next day ahead power demand $z_r = [p_{r-1}]$ in order to avoid complexity.

$$\hat{\mathbf{z}}_r = P_l(r) = \sum_{i=1}^{n} \beta_i \left(a_0^i + a_1^i p_{r-1} + a_2^i p_{r-2} + \cdots + a_k^i p_{r-k} \right), \quad (15)$$

where $A = [a_0, \ldots, a_{r-144}]^T$ is trained by PSO and similarly considers $P_l^U(r)$ and $P_l^L(r)$ as the lower and upper bounds related to $P_l(r)$ such that $P_l^L(r) \leq P_l(r) \leq P_l^U(r)$ for all r in discrete space. Hence, A^U and A^L are calculated for certain coverage grade and interval band. Weekdays and holiday effects can be integrated with the exogenous variable of the fuzzy interval model for better accuracy, but this job can be done by tuning the model everyday with the past 30-day data point windows in order to refresh the membership parameters of the model.

Figure 9 represents the load power prediction for one day ahead (1–144) data and the RMSE value is recorded as 21.82. It is worth noting that the base load around midnight and evening is accurately captured by the fuzzy model where the small deviations are observed at the peak levels of the predicted demand power, but this issue can be tackled with the rolling horizon type of EMS such as the model predictive controller-based energy manager, because at each time step EMS will trigger for new values and similarly the forecast module also updates its calculation which changes to the new operating points.

In Figure 10, case 1 is shown for the one day ahead load prediction of a weekday using the last day power values as the input. The day starts with the midnight flat load demand around 00–06, then the rise up time starts from 07–10 where the office usually starts, then there have two peaks around 11–13 and 14–16 corresponds to the peak hours pre- and postlunchtimes, after that, a falling edge starts followed by a constant load indicates the off work time. This scenario is accurately predicted by the fuzzy model because the constant pattern in load demand of working days plus the coverage grade C and B contain the majority of the data points with very narrow interval band which shows very low RMSE values. In another load demand scenario shown in Figure 11 as case 2, the pattern is same but the sudden changes at peak time or maximum demand time is very crucial in predicting optimal reserve allocation. As seen here, grade A is successful in capturing more than (95%) of measurement values.

Table 3 shows the comparison between PSO-based fuzzy model and other evolutionary-based fuzzy models in terms of RMSE and MAE values for load power forecast. PSO again performs better in terms of RMSE for one day ahead forecast,

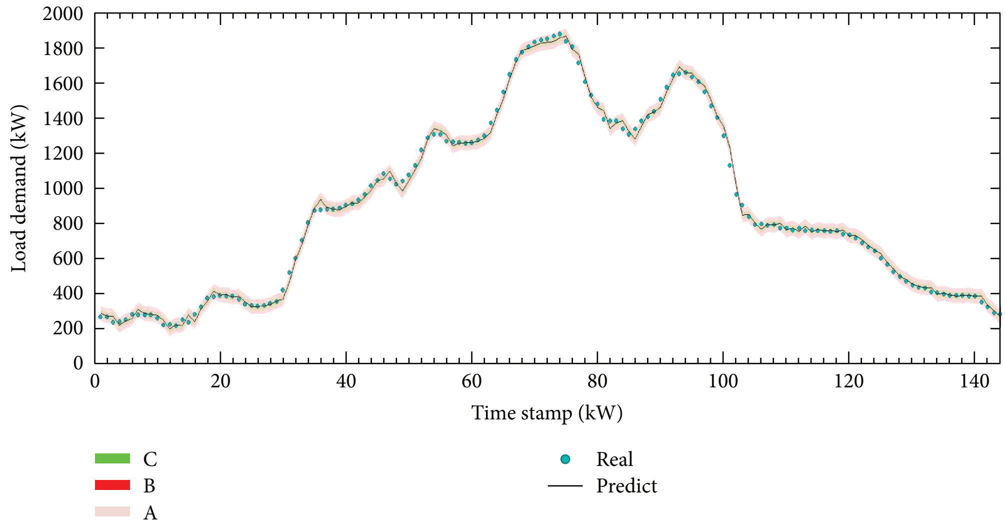

FIGURE 10: Fuzzy Interval prediction for one day ahead (case 1) load power with coverage grades.

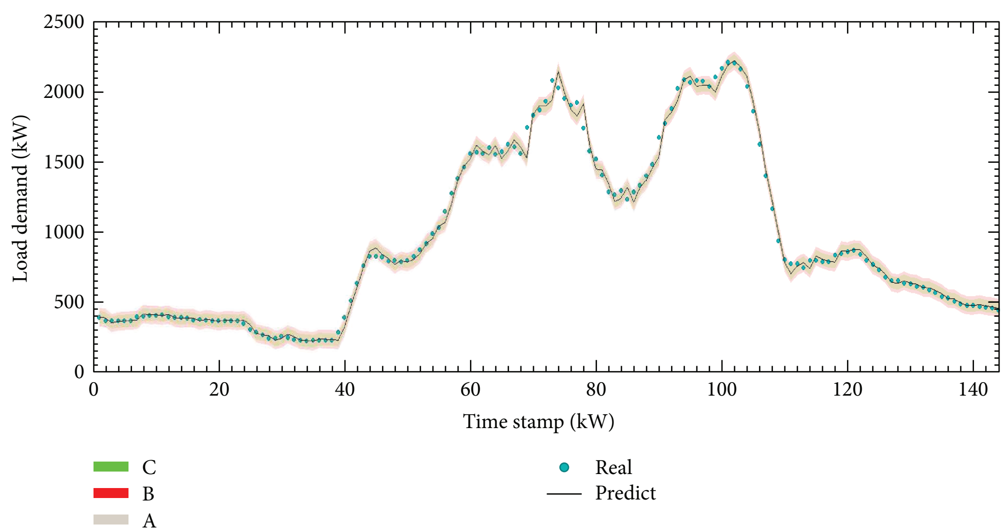

FIGURE 11: Fuzzy interval prediction for one day ahead (case 2) load power with coverage grades.

TABLE 3: Comparison of prediction interval forecast for demand power.

Model	One step ahead RMSE (kW)	One step ahead MAE (kW)	One day ahead RMSE (kW)	One day ahead MAE (kW)	Train time (s)
FR	20.67	18.28	23.38	14.86	20.22
CA	31.11	26.27	51.16	34.59	112.9
FF	16.25	14.10	22.81	15.19	309.8
GA	18.9	17.09	22.47	14.9	153.7
PSO	5.85	46.7	21.83	14.58	115.3

but the training time takes much longer than that of the FR-based training model. Overall, PSO performs well in demand forecast and can be improved more with the additional input of training parameters including time of the day, work, and weekend information.

5. Conclusion

Improved fuzzy interval prediction model trained with meta-heuristic algorithms is proposed in this paper, which is the premise study for energy management system of the micro-grid test bed in Beijing. The fuzzy interval prediction model is helpful in getting close to real results for the uncertainties associated with the nondispatchable renewable generation and consumer demand. Fuzzy prediction intervals are generated for wind, solar, and load for one day ahead prediction using real-time values, and the results are characterized into different coverage grades based on the accuracy of the forecast. Wind and solar showed the higher level of accuracy in the forecast due to the fact that these sources are directly related with their respective input variables whereas load forecast accuracy can be improved with more information and active interaction of the consumer in decision-making. All the results are shown with the traditional fuzzy regression and metaheuristic techniques, where the proposed method showed superior results in terms of lower RMSE and evaluation scores than the other approaches. Furthermore, the error and coverage level information achieved through the proposed scheme will improve the utilization of reserves more robustly in the microgrid. Future work will address the implementation details of energy management system based on the input of this prediction algorithm for the same microgrid test bed.

Conflicts of Interest

The authors declare that there are no conflicts of interests regarding the publication of this paper.

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