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Syed Furqan Rafique
the Department of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, China.

Jianhua Zhang
the Department of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, China.

Muhammad Hanan
the Department of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, China.

Waseem Aslam
the Department of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, China.

Atiq Ur Rehman
the Department of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, China.

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Authors
Syed Furqan Rafique, Jianhua Zhang, Muhammad Hanan, Waseem Aslam, Atiq Ur Rehman, and Zmarrak Wali Khan

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Energy Management System Design and Testing for Smart Buildings Under Uncertain Generation (Wind/Photovoltaic) and Demand

Syed Furqan Rafique*, Jianhua Zhang, Muhammad Hanan, Waseem Aslam, Atiq Ur Rehman, and Zmarrak Wali Khan

Abstract: This study provides details of the energy management architecture used in the Goldwind microgrid test bed. A complete mathematical model, including all constraints and objectives, for microgrid operational management is first described using a modified prediction interval scheme. Forecasting results are then achieved every 10 min using the modified fuzzy prediction interval model, which is trained by particle swarm optimization. A scenario set is also generated using an unserved power profile and coverage grades of forecasting to compare the feasibility of the proposed method with that of the deterministic approach. The worst case operating points are achieved by the scenario with the maximum transaction cost. In summary, selection of the maximum transaction operating point from all the scenarios provides a cushion against uncertainties in renewable generation and load demand.

Key words: microgrid economic optimization; generation forecast; load forecast; energy management system; fuzzy prediction interval; heuristic optimization

1 Introduction

Smart MicroGrid (MG) energy dispatch systems can perform real-time optimization, forecast intermittent sources, manage energy storage, control loads, and schedule optimum resources to minimize the operational cost of MGs[1, 2]. Various techniques to achieve these goals have been reported in the literature based on the utilization and infrastructure of Energy Management Systems (EMS). These techniques mainly focus on minimization of operating costs, namely, capital, maintenance, startup and shutdown, fuel, and energy purchase costs from the main grid, as well as emission, penalty, and load shedding costs, among others.

Demands for power and enhancements in the power system infrastructure have increased, and future power systems must cope with the demand/supply issue with the help of energy-saving schemes, and economical and environment-friendly infrastructure. Such requirements have led to the development of a concept of distributed power systems in which renewable sources are interconnected, unlike in traditionally centralized power plants. As this type of infrastructure is challenging to construct, researchers around the world have focused on improvements in the microgrid infrastructure to effectively manage reliable and economical operations in the network.

MGs operate in two modes, i.e., grid-connected and isolated, making them very difficult to control. At the distribution side of low-voltage systems, MGs connect all distributed energy sources, such as wind turbines, solar panels, storage type resources, and local loads (controllable/uncontrollable). Electric loads may either be critical or non-critical. Wind and solar power also creates fundamental problems in terms of dispatching because...
of their unpredictable behavior and fluctuation based on weather variations.

Energy Storage Systems (ESS) and conventional generators are extremely important in renewable MGs because they provide support as backup power when Renewable Generation (RG) is unavailable. This requirement has led to a conflict of interest between reducing carbon emission to promote a green environment and maintaining the reliability of the system. Various studies\(^3\)\(-\)\(^5\) have been carried out to control and manage ESS and conventional generators to minimize the operational and emission costs of these types of systems. This section will provide the objectives and constraints to solve the Economic Dispatch (ED) problem in renewable MG systems.

EMS issues are described in Refs. \([3, 4]\) for isolated MGs with Renewable Energy (RE) sources, and Mixed-Integer Linear Programming (MILP) is used to minimize operating costs and penalties when serving power demand. In Ref. \([5]\), the smart usage of PhotoVoltaic (PV) panels and high penetration of electric vehicles, as well as their charging and discharging strategies, was discussed to realize a smart grid-type infrastructure. The stochastic based approach in Ref. \([6]\), describes a probability degree interval-based optimization technique to address the ED issue in multiple MGs; here, the Probability Distribution (PD) is utilized to convert intervals into a deterministic problem, which is effectively solved by quadratic programming. The method involves an interval of uncertain variables rather than the Probability Distribution Function (PDF) or fuzzy membership function. The Takagi OA method\(^7\) has been used to generate scenarios in grid-connected MGs by adding error PD values into point forecasting; this method reduces forecasting errors in RG and load. The same authors also developed a robust EMS with two-step relaxation and the Benders algorithm to maximize the exchange cost between the MG grid and utility. This system was tested by Monte-Carlo simulation in a feasibility study. The authors in Ref. \([8]\) created an excellent approach to solve the RE and load uncertainty issue by using a Fuzzy Prediction Interval (FPI) scheme.

Authors have proposed a fuzzy interval prediction algorithm using the Takagi and Sugeno (T&S) model; in this algorithm, the variance of residuals between the observed data and local model generate upper and lower bounds of renewable and load expected power\(^8\). This method showed significant results and performance in terms of Root-Mean-Square Error (RMSE) reduction in the Hutaconda MG facility in Chile. Robust EMS using two parallel model predictive controllers, each of which calculated the optimal dispatch signals and then used convex sums to obtain the final robust dispatch within 95% confidence intervals, has also been developed. A double-layer coordinate control approach for MG energy management was proposed in Ref. \([10]\), thus proving that the priority of the MG (wind, PV, battery storage system, MicroTurbine (MT), and diesel engine) differs in the grid-connected and isolated modes. The EMS of an MG consists of two layers, i.e., the scheduling layer and the dispatch layer. The scheduling layer gathers forecasting data, while the dispatch layer controls all of the units on the basis of real-time data; error residuals between the two layers are compensated using reserve power. This method has shown promising results in both modes of MG operation, where the grid mode is used to maximize economic benefits. The most important job of the isolated mode is to maintain power quality. Interested readers can check\(^11\) for an in-depth review of state-of-the-art forecasting and EMS development techniques.

The primary objective of MGs is to reduce energy costs via efficient use of generation resources to power demands. An MG with a wind turbine, solar panels, a Vanadium Redox Battery (VRB), and MT is considered in this study for optimization, and the proposed model can be scaled up with extra battery packs and generation resources. From the MG security and stability point of view, the energy management task should provide enough active/reactive power in the system so that required regulation tasks, for instance, regulation of voltage and frequency when considering the uncertainty due to renewables or demand fluctuations, can be easily performed. Consequently, the objective should consider the uncertain actions of RG and account for these in the formulas in term of cost functions. The total cost includes the purchase cost of the grid and operational and maintenance costs for the generators and battery. The following points describe the main differences of this study from Refs. \([7, 9]\). First, the proposed scheme for predicting renewable and load considering a fuzzy prediction interval, which is trained via the particle swarm approach rather than Ref. \([9]\) for fast convergence, eliminates the likelihood of falling into local minima. Moreover, intervals are formed with certain interval widths based on historical data and the error co-variance. Second, Convergence Grades (CGs) are introduced as performance indicators in the forecasting system, thereby allowing the decision-maker to choose and set the required uncertain band width for future forecasting with a certain level of conservation. In addition, a comparison is carried out
against other approaches to check the feasibility of the forecast. Third, the ED problem is solved via a scenario-based robust formula of MILP objections and constraints using Particle Swarm Optimization (PSO) rather than Ref. [7]. This scenario-based approach enables the EMS to hedge against uncertainties in forecasting and reduce computational times for real-time implementation. Finally, a comparative analysis is presented and discussed for using scenario-based robust dispatching versus the deterministic case in a grid-connected MG test bed. The method reduces the economic cost of the system and proves the adequacy of the proposed system against uncertainties.

2 Modified Fuzzy Prediction Interval

FPI modeling has been utilized in several studies in the past, and it is used to forecast power output for non-dispatchable sources. FPI is useful for approximation of non-linear dynamic systems and facilitates the development of a robust EMS formulation, which is the ultimate goal of this study. The number of rules are minimized in this study which makes the partition of output variable space that is projected onto the input variable space to obtain the optimal solution for fuzzy sets and rules. The fuzzy clustering approach is used to create this partition and achieve the premise parameters. Fuzzy c-mean clustering is applied to develop initial clusters, minimize intra-cluster variance, and assign initial weights that will be adjusted in later stages to avoid local minima. The T&S-based fuzzy model is helpful in achieving consequence parameters based on the least-squares method.

In Ref. [8], the co-variance of error vector was used to develop a Fuzzy Regression (FR) model without describing the training method, thus deeply affecting the accuracy of the system. By contrast, in this paper, an evolutionary-based training method for linear regressors in the fuzzy interval is described to improve the accuracy of the proposed approach in comparison with the existing Back Propagation (BP)-based methods; performance indicators, such as the CG, and interval bands for lower and upper intervals are also introduced to check the quality of forecast. To approximate function families for various sets of intervals using fuzzy prediction interval, the authors calculate forecasting intervals with a certain interval bandwidth $\sigma$ and a fuzzy co-variance model of error because the deterministic solution is not reliable in renewable/load predictions\cite{12},

$$\hat{z}_t^U = f^{TS}(x_{t-1}, y_{t-1}, w_{t-1})$$

$$\hat{z}_t^L = f^{TS}(x_{t-1}, y_{t-1}, w_{t-1}) +$$

$$\sigma^2 Cov^TS(x_{t-1}, y_{t-1}, w_{t-1})$$

where $\hat{z}$ is the predicted vector that depends on inputs $x$, $y$, and $w$ (control vector). $\sigma$ is the interval width and can be adjusted for the given dataset with certain coverage grade $CG$, and $Cov^{TS}$, the co-variance of the target and predicted data, is modeled as $Cov_e = (y_j - \hat{y}_j)$, similar to the T&S mentioned earlier. Hence, the FR model $T$ parameter in $\hat{z}_t = T^TA + e_j$ is identified by clustering and with Eqs. (1) and (2). $e_j$ is the error vector $e$ for forecasting, and the coefficient $A$ and co-variance matrix $Cov_e$ are trained using evolutionary search algorithms such as Back Propagation (BP), PSO in Table A1 in Appendix.

2.1 Coverage grade

To classify the forecast system based on performance, we introduce a $CG$ system. This performance evaluation method with interval bands gives insights into the accuracy of the predictions. Three $CG$ levels, namely, A, B, and C, are defined.

$$CG = \frac{\sum_{j=1}^{m} \kappa}{m}$$

The $CG$ is calculated to adjust the $\sigma$ value for the interval; here, $\kappa$ is the binary parameter that shows whether the measurement data lie inside of the interval. Lower values of RMSE in the point forecast give the band width for respective grades, i.e., A grade ($90\% < CG \leq 100\%$) coverage, B grade ($70\% < CG \leq 90\%$) coverage, and C grade ($low < CG \leq 60\%$) coverage. Based on the defined parameters, the proposed method will constantly improve the performance of the forecast using interval bands and $CG$ tuning with Eq. (3). For example, in terms of $CG_q$, a forecaster labeled $A_q$ indicates to the operator that the algorithm was running at the best possible performance for the past 30 historical points. Historical wind velocity and turbine power are used to train the model for wind power forecasting, historical solar irradiance and PV panel power output are used to train the model for solar power forecasting, and historical demand and time of the day are inputs used to train the model for load (building) power forecasting.

2.2 Comparative analysis with benchmarks

In this paper, two benchmarks, i.e., FR\cite{9} and radial basis neural network, are used to validate the accuracy of the
proposed scheme based on certain scores. The authors utilized two probabilistic scoring methods: the Pinball score\(^{[13]}\) which penalizes observations that lie outside the lower and upper bounds, and the Winkler score\(^{[13]}\) which additionally accounts for the width of the probability interval. Apart from these two scores, Normalized Average Width (NAW)\(^{[8]}\) is used to evaluate the models, where a lower value corresponds to better accuracy for a given interval forecast. The load forecast is selected for the benchmark test because it performs poorer than wind and solar forecasts.

As shown in Table 1, Pinball, Winkler, and NAW scores are shown correspond to the selected benchmarks for a 144-point-ahead forecast. FR and Genetic Algorithm (GA) are near in this competition with the proposed method. Other approaches, including FireFly (FF) and the Cultural Algorithm (CA), do not perform as well as the previous approaches. This result clearly indicates that the proposed scheme yields the lowest scores among the other benchmarks. The consistent performance of the proposed scheme over the benchmarks shows that the FPI is not only accurate in terms of coverage but also gives a narrower interval than the other schemes. For a more in-depth analysis of the forecast scheme used in this paper, readers can refer to Ref. [12].

### 3 Scenario Based Economic Dispatch

ED in renewable MGs is a way to reduce system costs while satisfying the load demand via short-term dispatching of power generation sources provided the system works under defined constraints, including transmission and operation. The ED problem can be written as

$$\min F = \sum_{i=1}^{N_s} c_i P_i$$

subject to the real power balance between electricity generation and demand. \(\sum_{i=1}^{N_s} P_i = P_{\text{demand}} + P_{\text{networkloss}}\). Here, the limits also act as constraints for generation resources \(P_{\text{lower}} \leq P_i \leq P_{\text{upper}}\), where \(P_{\text{lower}}\) and \(P_{\text{upper}}\) are the limits of \(i\)-th power source in kW; \(N_s\) is the total number of generation units; \(c_i\) is the cost of \(i\)-th generation unit; \(P_{\text{demand}}\) is the total power demand; \(P_{\text{networkloss}}\) is the power loss during operation; \(F_i\) is the total generation cost of unit \(i\).

#### 3.1 Cost function and constraints

Suppose that RG, including wind and solar sources, is prioritized for supplying power to the load demand, and that extra power can be supplied by a VRB (Table A2) and MT (Table A3). Suppose also that the VRB acts as a load and that the charging power and state-of-charge are also known at every time stamp. The prerequisites for the construction of objectives in a renewable MG are forecast points for generation and loads, plus a distributed energy resource cost function, power limits, and parameters. The operating cost, which includes MT generator and transactions cost from the grid, must be minimized in this case. Let \(T\) denote the prediction horizon, which is 24 hours. In short, by minimizing the MT running time and buying grid energy, we are directly reducing operational costs and indirectly reducing carbon emissions. The cost function for MG is defined as

$$\min F = \sum_{i=1}^{T} C_{i}^{\text{gen}} + \sum_{i=1}^{T} C_{i}^{\text{start/shut}} + \sum_{i=1}^{T} C_{i}^{\text{OM}} + \sum_{i=1}^{T} C_{i}^{\text{transact}}$$

subject to:

- \(\sum_{i=1}^{T} C_{i}^{\text{transact}}, \forall s \in S\)
- \(P_{\text{gen}} + P_{w} + P_{b} + P_{u} + P_{\text{transact}} = P_{\text{demand}} + P_{\text{loss}}\)
- \(P_{\text{min}} \leq P_{\text{gen,j}} \leq P_{\text{max}}\)
- \(P_{\text{min}} \leq P_{b,j} \leq P_{\text{max}}\)
- \(\Delta i \leq P_{\text{gen},i+1} - P_{\text{gen},i} \leq \Delta i\)
- \(\Delta i \leq P_{\text{gen},i} - P_{\text{gen},i-1} \leq \Delta i\)

where \(P_{\text{gen}}, C_{i}^{\text{OM}}, C_{i}^{\text{start/shut}}, C_{i}^{\text{transact}}\) denote the MT power, the operation and maintenance cost, the startup and shutdown cost, and the transaction cost for buying or selling power to the grid at the \(i\)-th time stamp, respectively. In the case of an isolated MG, the term \(C_{i}^{\text{transact}}\) can be removed and only generator-related costs

| Table 1 Comparison with benchmarks. |
|---------------------------------|
| Model       | Pinball score | Winkler score (50%) | NAW score |
|------------|--------------|---------------------|-----------|
| Proposed   | 7.33         | 52.2                | 4.50      |
| FR         | 7.46         | 52.7                | 4.62      |
| RBNN       | 10.34        | 99.7                | 8.52      |
| GA         | 7.40         | 54.2                | 4.66      |
| FF         | 10.34        | 99.7                | 8.52      |
| CA         | 29.58        | 800.3               | 43.4      |
remain in Eq. (5). \( \hat{P} \), and \( S \) are the worst transaction cost and scenario set, respectively. \( P_w, P_s \), and \( P_{\text{demand}} \) denote the predicted wind power, solar power, and load demand, respectively, and \( P_b, P_s, \text{SoC}, \) and \( P_{\text{loss}} \) denote the battery reference power, the power from the utility, the state-of-charge of the battery, and the network power dissipated through the inverter and lines, respectively. RU and RD are the ramp-up and ramp-down rates of the generator, respectively. \( n_b \) and \( w_b \) respectively denote the charging/discharging efficiency and energy capacity of the battery. Finally, \( P_{\text{gen}}^{\text{min}}, P_{\text{gen}}^{\text{max}}, \text{SoC}^{\text{min}}, \) and \( P_{\text{u}}^{\text{min}} \) respectively denote the minimum allowable values for the MT, battery, state-of-charge, and utility power, and \( P_{\text{gen}}^{\text{max}}, P_{\text{b}}^{\text{max}}, \text{SoC}^{\text{max}}, \) and \( P_{\text{u}}^{\text{max}} \) denote the maximum allowable power limits for the MT, battery, state-of-charge, and utility power, respectively.

The cost in Eq. (5) related to natural gas consumption is based on the efficiency curve of the generator, which determines the amount of gas required to generate a specific amount of power by simply multiplying the cost per volume with the volume of gas used in the process. The remaining volume of natural gas is also computed, and the start-up and shut-down cost of the generator are taken into account. A charging curve is drawn to estimate the amount of power needed as a function of discharging depth and obtain the state of charge between defined ranges, as shown in Eq. (5). Note that the optimal solution in Eq. (5) relies on two factors, namely, predicted available generation and predicted demand power. The net unserved power is determined based on the difference between formal generation and demand. This unserved power is used in the ED procedure as an unfulfilled demand to be managed. The dependence noted is the ED procedure as an unfulfilled demand to be managed.

The use of the FPI in Section 2 to forecast RG and demand makes the dispatch problem robust in nature. Hence, different solution trajectories for \( P_{\text{gen}} \) and \( P_b \) are obtained using prediction intervals. The prediction intervals also provide the worst and best case scenarios for the available energy. The net load profile is calculated for different scenarios by using lower and upper bounds obtained from the prediction intervals under certain CGs.

### 3.2 Scenario-based EMS

The robust worst-case solution can be obtained by solving the general robust formula:

\[
\min_x \left\{ c_T x + \max_y d^T y(x, s) \right\}
\]

where \( x \) is the solution vector corresponding to the MT and battery power reference values and \( y \) is the exchange cost vector calculated through \( x \) and the stochastic scenario vector \( s \).

(1) Get \( N \) testing scenarios by using the lower and upper bounds of the forecast and generate an \( N \) array of wind, solar, and demand scenarios.

(2) Solve the two-stage minimization problem: First, get the minimum total cost using \( N \) scenarios individually and then select the maximum transaction cost and corresponding \( x \) array from \( N \) cases.

(3) The scenario with the worst-case total cost would give the robust optimization solution corresponding to the maximum grid transaction cost. Note that multiple same transaction cost values correspond to different scenarios due to limiting constraint in the objective in the algorithm as below.

**Require:** Get initial parameters (initial decision \( x_0 \)
including $P_{\text{gen}}$, $P_b$ and $P_u$, SoC, weights, cost function (5), variable count, variable range, max iteration, population size, inertial weight and damping ratio, and personal and global learning coefficient).

Get the lower and upper bounds of wind, solar, and load from the FPI model.

Get the unserved power $P_n$.

Generate the scenario set $S$ from $P_n$ \{scenarios corresponding to different $CG$\}.

for $s = 1$ to $N$ do
  Run the PSO for 5 including constraints.
end for

Ensure: objective cost minimized.

Save $F$, $x$ for each scenario in $S$.

return Transaction cost $T_r$ for all scenarios in $S$

3.3 Fuzzy battery model

A fuzzy battery model is developed based on the time of day and SoC as inputs and $P_{\text{in}}$ and $P_{\text{out}}$ decisions as system outputs. This function is primarily developed to avoid unfavorable levels outside the bounds of SoC and prolong battery life.

4 Test on the Goldwind Microgrid Test Bed

The performance and detailed model of EMS are discussed in Section 3 and illustrated here for 24-hour-ahead operations using the modified Goldwind MG test bed. The results of interval forecasting for renewable and load are used as inputs for operational optimization of the grid-connected MG. All simulations are performed on an Intel i5, 2.53 GHz quadcore processor with 4 GB RAM, running Windows 8.1. All of the data used in this section are available in the appendix of this paper. The actual Goldwind test bed diagram is illustrated in Fig. 1, and the diesel engine and super-capacitor are not included in this study.

4.1 Test system and case studies

The proposed method is implemented on a modified version of the Goldwind MG test bed in Beijing. This MG system has an MT and VRB that degrades over time, hence, the maximum output power could only be limited to half of the original power limit for safe operation. This MG test bed now has a 130 kW MT and a 100 kW VRB system, and the MG is connected to the Beijing development zone grid as a local utility grid (Figs. 2–7). The total installed capacity of the system was modified to 3.18 MW, including the wind turbine and PV system. The parameter tables for all components (Tables A1–A3), including particle swarm coefficients, are given in Appendix.

The load and generation profile for 24-hour-ahead optimization is presented in the last section. The peak load
was considered as 3 MW, and the baseline value for the office building load is around 150 kW. The forecast data are extracted from the forecasting system described earlier. Thus, the sources of uncertainty are the wind, solar, and load forecasts in the system. Coverage intervals, namely A, B, and C, are then divided into nine scenarios, and each individual $CG$ is divided into three more scenarios corresponding to different values of $0 \leq \omega \leq 1$ in linear summation as $S = S_L + \omega S_U$. Hence, three values of $\omega$ are randomly chosen as lower and upper bounds of each $CG$ to generate nine scenarios for rapid computation. Users can choose various combinations from the three $CG$s and select that which best corresponds to worst/best.

To check the effectiveness of the proposed EMS model with prediction intervals to mitigate uncertainties in dispatch, two case studies are considered: one with prediction (0% uncertainty) and the other with interval prediction in nine scenarios.

**Proposed Case**

This case corresponds to nine scenarios with different coverage intervals and is solved using the PSO method discussed in the EMS section. The main agenda of optimization in grid-connected MGs is to determine robust worst-case dispatch points for a 24-hour-ahead window. Therefore, the algorithm is tested with nine different scenarios of RE, and the modified load is shown in Fig. 8. At the peak of demand, only solar with very low wind power output is available; hence, this selected day is very critical for observing effective dispatch.

**Deterministic Case**

This case corresponds to the deterministic formula of EMS with a zero percent error in the predicted and real values, which means the forecasting value is accurate at all-time stamps of the day. The Daxing district grid price is obtained for a commercial customer. The two peaks ($10 – 14, 18 – 20$) have buying rate of $0.14$/kWh, the mid-peak ($7 – 9, 15 – 17, 21 – 22$) buying rate is $0.09$/kWh, and the off-peak ($23 – 06$) price is $0.06$/kWh. The power selling rate is fixed for the entire day at $0.10$/kWh.

**4.2 ED results**

This part of the report discusses the aforementioned ED for the given MG test bed. The dispatch models are based on the following considerations:

- **Cost**, which includes the fuel, transaction, O&M, startup, and emission costs over a 24-hour-ahead operation window.
- **SoC of VRB**, which includes the average change in state-of-charge levels of the battery for a 24-hour-ahead window.

The commitment and scheduling of the micro-turbine and battery unit are of particular interest, as these sources will have a low cost on peak hours of the day with more uncertainties in the load demand. Hence, these units will support the system in a cost-effective manner as the buying price from the grid is higher at peak hours. Considering the non-dispatchable RE and load demand profile mentioned
in Fig. 8, the ED signals corresponding to VRB and MT are illustrated in Figs. 9–11 in an hourly fashion.

The MT and VRB are dispatched in Figs. 9–11. Here the most noticeable difference can be noted at hours 15 and 17, where the proposed method commits more capacity than that provided by the predicted case, thereby utilizing the full potential of low-cost sources at peak hours of the day.

In the energy storage case, the EMS influences the charging and discharging commands based on the SoC level requirement. The initial SoC is set to 0.5% before the start of the simulations. The battery unit noticeably charges at off-peak hours (1–3 and 20–23) and discharges at peak hours (7–8 and 10–18), as expected. The primary difference in this particular net load profile case is that at hour 17, the proposed method (the C3 scenario) commits battery power to reduce large transaction costs from the utility.

SoC chart

The average SoC chart in Fig. 12 shows the resources allocated to tackle possible changes in wind and solar. Here, A3 evidently shows the lowest average SoC, whereas C3 shows a higher value. Thus, the C3 scenario highly utilizes the ESS, and a lower level of SoC can be observed in the predicted case.

Fuel cost and transaction price

The stacked bar graph in Fig. 13 shows the lowest and highest total and transaction costs in the decision-making process. The lowest transaction cost occurs for C3, while the highest cost corresponds to the prediction case. The transaction cost of the best-scenario case, C3, is 3.36%, which is lower than that obtained for the deterministic case. This savings primarily comes from the commitment of ESS and MT on peak hours of the day for the proposed method, so C3 is the best-case scenario to adopt for ED dispatch commands. The worst-case scenario is A1, which presents higher transaction costs. As the total cost, including fuel costs, is practically the same for all cases considered, the ESS cost and utilization at a proper time are the main factors influencing cost reduction.

Emission Cost

The emission cost is presented in Fig. 14. The lowest cost occurred for the A1 net load profile, and C1...
showed a higher emission cost because more capacity is committed from the MT in this case. The robust worst-case result is 2.43% lower than that obtained from the deterministic case. If the main objective of optimization is reduction in emission cost, A1 can be considered an option for ED solution. However, in the present study, the main objective is to minimize the transaction cost; hence, C3 is the best scenario to consider.

Based on two stage optimization theory, the value of total transaction cost calculated for the worst case scenario would remain the best case in most scenarios generated by the wind, solar, and load profiles. Another case to validate involves high-RG days. The same data are used with different wind and solar. Figures 15–17 show the results for different days with higher wind and solar power generation. The difference in both dispatch results occur at hours 7, 12, 16, and 17, where the proposed method reduces the transaction cost by setting higher values for battery commitment. Moreover, the MG sells extra power to the utility throughout the day.

The average SoC chart in Fig. 18 shows the resources allocated to tackle the possible changes in wind and solar. Here, B1 shows the lowest average SoC, while A3 shows a higher value. Thus, the utilization of ESS is high in the A3 scenario.

The transaction cost of C3 is 5% lower than that in the deterministic approach and 5.2% lower than the worst-case scenario A3 in Fig. 19. Similarly, the total cost of C3 is $31 lower than that in the deterministic case and $29 lower than in A3. The emission costs of C3 and B3 are the same, but the lowest emission cost is observed in case A1 in Fig. 20. The emission cost of A3 is 1.8% higher than that in the predicted case. The difference between the predicted and proposed solutions is that the latter uses spinning reserves to counteract variations in wind, solar, and load demands, whereas, the former uses just the utility grid to provide power.
4.3 Computational performance of EMS

Computational flexibility is a fundamental issue in EMS that must be solved to enable its use in real-time operations. The performance calculation time (s) based on the proposed scheme is 86.29 for A1, 89.18 for A2, 93.43 for A3, 87.82 for B1, 88.37 for B2, 87.05 for B3, 83.54 for C1, 84.85 for C2, 87.05 for C3; by comparison, this time is 87.05 for deterministic case. Note that for all cases, the average time is around 1.2 min, which is highly acceptable, considering that the forecasting data are fetched from the database, which also takes time to calculate. In this study, a separate processor is used in parallel to perform forecasting and save results in the database every 10 min. Therefore, the actual operation time required for the dispatch decision in EMS is reduced drastically.

5 Conclusion

The main objective of this paper is to formulate an EMS for grids connected in an MG using an uncertainty-aware scheme. The ED problem is solved based on the forecasting results obtained through a modified FPI. CGs were divided into several scenarios to obtain the lowest operational cost and maximize the transaction cost to achieve robust results. Furthermore, a scenario-based EMS was proposed to account for the uncertainty associated with the forecast. A scenario set was generated using the unserved power profile and CG to compare the feasibility of the method with that of the deterministic approach. Simulation studies were then carried out on a modified test bed of the Goldwind MG system. Selection of a proper operating point improves the performance and reliability of the system, which indicates that proper selection of uncertain policies improves the economic benefits of EMS. In summary, fuel and total costs showed lower variations, but ESS management improved considerably compared with the deterministic case. Overall, without considering the PD, the proposed method hedged unit commitment results against the forecast uncertainty with fair computational time.

Appendix

### Table A1 PSO parameters for economic dispatch.

| S.no | Value          |
|------|----------------|
| No. of Var | 3              |
| Min Var  | 0              |
| Max Var  | 1              |
| Personal learning | 1.49    |
| Global learning  | 1.49            |
| Damping coefficient | 1              |
| Population size | 100             |
| Initial weight | 0.729          |
| Iteration | 200             |

### Table A2 VRB parameters for economic dispatch.

| S.no | Value          |
|------|----------------|
| Min power | 0 (kW)        |
| Max power output | 100 (kW)    |
| Capacity  | 800 (kWh)     |
| Initial SoC | 50 (%)        |
| O/M cost  | 0.00419 ($/kWh) |
| Input efficiency | 0.95      |
| Output efficiency | 0.95      |
| Power cost | 0.10 ($/kW)   |
| Voltage range | DC 250-388 (V) |
| Rated current | DC 640 (A)  |
| Ambient temperature | 5-35 (Celsius) |

### Table A3 MT parameters for economic dispatch.

| S.no | Value          |
|------|----------------|
| a    | 80 ($/h)       |
| b    | 0.25 ($/kWh)   |
| Upramp rate | 85 (kWh) |
| Downramp rate | 85 (kWh) |
| Min power | 0 (kW)        |
| Max power | 130 (kW)      |
| Startup cost | 10 ($)        |
| O/M cost  | 0.00587 ($/kWh) |
| NOx  | 0.6188 (g/kWh) |
| SO2  | 0.000928 (g/kWh) |
| CO2  | 184.08 (g/kWh) |
| Initial status | OFF       |

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References

[1] Q. Fu, A. Nasiri, V. Bhavaraju, A. Solanki, T. Abdallah, and D. C. Yu, Transition management of microgrids with high penetration of renewable energy, *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 539–549, 2014.

[2] D. Tran and A. M. Khambadkone, Energy management for lifetime extension of energy storage system in micro-grid applications, *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1289–1296, 2013.

[3] S. Mazzola, M. Astolli, and E. Macchi, A detailed model for the optimal management of a multigood microgrid, *Appl. Energy*, vol. 154, pp. 862–873, 2015.

[4] J. Silvente, G. M. Kopanos, E. N. Pistikopoulos, and A. Espuña, A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids, *Appl. Energy*, vol. 155, pp. 485–501, 2015.

[5] M. van der Kam and W. van Sark, Smart charging of electric vehicles with photovoltaic power and vehicle-to-grid technology in a microgrid: A case study, *Appl. Energy*, vol. 152, pp. 20–30, 2015.

[6] C. X. Huang, D. Yue, J. Xie, Y. P. Li, and K. Wang, Economic dispatch of power systems with virtual power plant based interval optimization method, *CSEE J. Power Energy Syst.*, vol. 2, no. 1, pp. 74–80, 2016.

[7] Y. Xiang, J. Y. Liu, and Y. L. Liu, Robust energy management of microgrid with uncertain renewable generation and load, *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1034–1043, 2016.

[8] D. Sáez, F. Ávila, D. Olivares, C. Cañizares, and L. Marín, Fuzzy prediction interval models for forecasting renewable resources and loads in microgrids, *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 548–556, 2015.

[9] F. Valencia, J. Collado, D. Sáez, and L. G. Marín, Robust energy management system for a microgrid based on a fuzzy prediction interval model, *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1486–1494, 2016.

[10] Q. Y. Jiang, M. D. Xue, and G. C. Geng, Energy management of microgrid in grid-connected and stand-alone modes, *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3380–3389, 2013.

Jianhua Zhang was born in Beijing, China, in 1952. He received the M.S. degree in electrical engineering from North China Electric Power University, Beijing, China, in 1984. He was a Visiting Scholar with the Queen’s University, Belfast, U.K., from 1991 to 1992, and was a Multimedia Engineer of Electric Power Training with CORYS T.E.S.S., France, from 1997 to 1998. Currently, he is a Professor and Head of the Transmission and Distribution Research Institute, North China Electric Power University, Beijing. He is also the Consultant Expert of National “973” Planning of the Ministry of Science and Technology. His research interests are in power system security assessment, operation and planning, and micro-grid. Prof. Zhang is an IET Fellow and a member of several technical committees.

Syed Furqan Rafique is a PhD scholar in School of Electrical and Electronics Engineering at North China Electric Power University (NCEPU), Beijing. He completed his Bachelor in Electronics Engineering from National University of Science and Technology (NUST), Pakistan in 2012 and MS in Power system Protection at NCEPU in 2014. He was working in Goldwind Technology, Beijing as an R&D Engineer for 2 years. Nowadays, he is working on the formulation of Standard documents for Global Renewable energy Interconnection at China State Grid Cooperation, Beijing. He published over 13 research papers. His research interest lies in energy management system, smartgrid, power electronics control, and power system protection.
Muhammad Hanan is pursuing the PhD degree in Electrical Engineering in School of Electrical and Electronics Engineering at North China Electric Power University (NCEPU), Beijing, China. He got B.S. degree in Electrical Engineering from University of Central Punjab (UCP), Lahore, Pakistan. He received his Master degree (M.Eng.) in Power Electronics and Power Drives from Northwestern Polytechnical University (NPU), Xi’an, China. He worked for Technical Innovation Standard Division at GEIDCO in State Grid Cooperation of China (SGCC), Beijing. His research areas are power electronics and power drives, power system, automation and renewable energy, power markets, and smart grid.

Waseem Aslam received the B.S. and M.S. degrees from UCET, Islamia University of Bahawalpur, Punjab, Pakistan in 2011 and 2013, respectively, all in electrical engineering (Power). Currently, he is pursuing the PhD degree at North China Electric Power University, Beijing, China. He was working as an Electrical Engineer in a Govt. Engineering Institute. His research interests include smart grids, reliability, and power quality improvement.

Atiq Ur Rehman received the BS and MS degrees from University of Engineering and Technology (UET), Peshawar, Pakistan, in 2009 and 2013, respectively. Currently, he is pursuing PhD degree in power system and automation from North China Electric Power University (NCEPU), Beijing, China. His research interests include smart grid, HVDC, and FACTS devices.

Zmarrak Wali Khan received the B.S. degree in Electrical Engineering in 2013 from COMSATS Institute of Information Technology (CIIT), Abbottabad, Pakistan. He received the M.S. degree in Electrical Engineering from CECOS University, Peshawar, Pakistan. He is currently pursuing PhD degree in the field of Power System and Automation in School of Electrical and Electronic Engineering, North China Electric Power University (NCEPU), Beijing, China. His research interests lie in the renewable energy, smart grids, MMC, and DC-Grids.