Probabilistic Model for Microgrids Optimal Energy Management Considering AC Network Constraints

Mahshid Javidsharifi, *Student Member, IEEE*, Taher Niknam , *Member, IEEE*,
Jamshid Aghaei , *Senior Member, IEEE*, Miadreza Shafie-khah , *Senior Member, IEEE*,
and João P. S. Catalão , *Senior Member, IEEE*

Abstract—A new probabilistic approach for microgrids (MGs) optimal energy management considering ac network constraints is proposed in this paper. The economic model of an energy storage system (ESS) is considered in the problem. The reduced unscented transformation (RUT) is applied in order to deal with the uncertainties related to the forecasted values of load demand, market price, and available outputs of renewable energy sources (RESs). Moreover, the correlation between market price and load demand is taken into account. Besides, the impact of the correlated wind turbines (WT) on MGs' energy management is studied. An enhanced JAYA (EJAYA) algorithm is suggested to achieve the best solution of the considered problem. The effective performance of the presented approach is verified by applying the suggested strategy on a modified IEEE 33-bus system. It can be observed that for dealing with probabilistic problems, the suggested RUT-EJAYA shows accurate results such as those of Monte Carlo (MC) while the computational burden (time and complexity) is lower.

Index Terms—EJAYA algorithm, microgrid (MG) energy management, reduced unscented transformation (RUT), uncertainty.

NOMENCLATURE

DG	Distributed generator.
MG	Microgrid.
RES	Renewable energy sources.
WT	Wind turbine.
PV	Photovoltaic.
MCS	Monte Carlo simulation.
PHEV	Plug-in hybrid electric vehicle.
CHP	Combined heat and power.
PEM	Point estimate method.
ESS	Energy storage system.
UT	Unscented transformation.
RUT	Reduced unscented transformation.

OC	Operational cost.
FC	Fuel cell.
MT	Microturbine.
DoD	Depth of discharge.
TLBO	Teaching-learning-based optimization.
SD	Standard deviation.
MGCC	MG central controller.
CDF	Cumulative density function.
T	Horizon of energy management problem study.
$P_{\mathrm{MT}}^t, P_{\mathrm{FC}}^t$	Real output powers of MT and FC at time t (kW).
$B_{\mathrm{MT}}^t, B_{\mathrm{FC}}^t$	Bid of MT and FC at hour t (€ /kWh).
SUC	Start-up cost (€).
$P_{\mathrm{PV}}^t, P_{\mathrm{WT}}^t, P_{\mathrm{Batt}}^t$	Real output powers of PV, WT, and battery at hour t (kW).
$B_{\mathrm{WT}}^t, B_{\mathrm{PV}}^t, B_{\mathrm{Batt}}^t$	Bid of WT, PV, and battery at hour t (€ /kWh).
$\mathrm{Cost}_{\mathrm{Deg}}^t$	Battery degradation cost (€).
P_{Grid}^t	Active power of the utility at time t (kW).
price^t	Market price at hour t (€ /kWh).
C_{Batt}	Battery investment cost (€).
E_{Batt}	Usable energy of the battery (kWh).
E_t	Battery current capacity (kWh).
N_{cycle}	Battery cycle life.
$E_{\mathrm{Batt}_{\min}}, E_{\mathrm{Batt}_{\max}}$	Minimum and maximum usable capacity of the battery (kWh).
$P_{\mathrm{ch}}(P_{\mathrm{disch}})$	Permitted rate of charge/discharge (kW).
η_c/η_d	Efficiency of the battery during charge/discharge process.
$P_{\mathrm{ch,\,max}}(P_{\mathrm{disch,\,max}})$	Maximum rate of battery charge/discharge during each time interval Δt (kW).
$P_{\mathrm{MT}_{\min}}^t, P_{\mathrm{MT}_{\max}}^t$	Minimum and maximum active powers of the MT (kW).
$P_{\mathrm{FC}_{\min}}^t, P_{\mathrm{FC}_{\max}}^t$	Minimum and maximum active powers of the FC (kW).
$P_{\mathrm{Batt,\,min}}^t, P_{\mathrm{Batt,\,max}}^t$	Minimum and maximum active powers of the battery (kW).
N_{Bus}	Number of buses.
θ_{ij}	Angle of bus (i, j) element of Y_{bus} admittance matrix.

$\delta_i^t,\ \delta_j^t$	Angle of voltage at bus i and j at hour t.
$V_i^t,\ V_j^t$	Voltage magnitude of bus i and j at hour t (V).
Y_{ij}	Magnitude of $(i,\ j)$ element of Y_{bus} admittance matrix.
P_{LD}	Load demand (kW).
Q_{LD}	Load reactive power (kVar).
P_{ij}^{line}	Active power flow in line ij (kW).
$P_{ij,\max}^{\text{line}}$	Maximum active power flow in line ij (kW).
Q_{ij}^{line}	Reactive power flow in line ij (kVar)
$Q_{ij,\ \max}^{\text{line}}$	Maximum reactive power flow in line ij (kVar).

I. INTRODUCTION

DISTRIBUTED generators as a convenient solution for concerns arisen from fossil fuel energy limitations are aggregated to the power system through MGs. In order to clean energy production, the application of RESs, including WT and PV, has been increasing in new MGs [1]. However, the operation and control of MGs have become complicated due to load demand and market price fluctuations, as well as the inherent uncertainties of RESs [2]. Consequently, numerous approaches have been developed for the sake of probabilistic analysis of MGs' performance.

Different research concentrate on probabilistic MGs' optimal operation management problem [3]–[22]. In this regard, two main categories for consideration of uncertainties, namely simulation (including MCS) and analytical approaches can be applied [23].

In [5]–[13], the uncertainties in modeling RESs using MCS are considered. In [5], uncertainties in modeling PHEVs and RESs using MCS are investigated. In order for determining the capacity of hybrid wind, photovoltaic, and battery generation systems with the uncertainties in wind and photovoltaic power production, the particle swarm optimization (PSO) algorithm has been used, whereas MCS has been applied to capture the uncertainties of wind and PV power generation [6].

A two-stage stochastic program formulation is dealt with in [7] for power scheduling and bidding problem where system uncertainties are considered using the MCS approach. In [8], MCS is employed to handle the uncertainties associated with the daily distance driven of PHEVs, load values and prices. Xiang *et al.* [9] develop a scenario-based energy management method to simultaneously maximize the total exchange cost and minimize the social benefit. The uncertain set of the proposed energy management problem is modeled by MCS. A stochastic day-ahead MG management is proposed in [10], in which the method is employed to maximize MG's benefit considering the load demand and wind power generation uncertainty. For modeling uncertainties, some scenarios are generated according to MCS. A two-stage stochastic optimization algorithm is developed in [11], adopting the MC method for definition of the multiobjective optimization problem of optimal integrated sizing and operation of a CHP system for long-term uncertainty in energy demands. Gu *et al.* [12] conduct a technoeconomic evaluation of a solar photovoltaic/thermal concentrator in Sweden

for the building application. In order to take the integrated uncertainties and risks of various variables into account, an analytical model is developed based on the combinations of MCS techniques and multi energy-balance/financial equations. A two-stage stochastic model for optimizing the profit of a smart MG is proposed in [13] where the uncertainty of loads, electricity market price and renewable generation are modeled by developing stochastic scenarios using the MC method.

Although MCS does not depend on the system dimension, it is a comparatively time-consuming method. In [14]–[22], the probabilistic MG operation management is investigated, where PEM is suggested in order to deal with uncertainties. The optimal operation of smart distribution systems considering demand response is solved in [14] in order to minimize the operation and maintenance costs, power loss cost, and cost of energy not supplied. The uncertainties of load demand and renewable power generation are considered using the PEM approach. To address the uncertainties in the optimal operation of MGs, Gazijahani and Salehi [15] propose Hong's 2m-PEM to minimize the operating costs as well as to reinforce the reliability and resiliency of interconnected MGs. 2m-PEM is also applied in [16] to model the uncertainties in load demand, market prices and the available power of RES to minimize the total operation cost of MG in the presence of ESS. Najibi *et al.* [17] used 2m-PEM for consideration of uncertainties of market price variation, PV and WT output power change and load demand error in MG's energy management. Additionally, 2m-PEM is proposed in [18] to investigate the charging effect of PHEVs on the optimal operation and management of MGs. Hong's PEMs is also suggested in [19] and [20] to optimize the operation management of MGs under uncertainty.

The 2m-PEM is applied in [21] for modeling the wind and solar power uncertainties in MGs optimal energy management. In [22], for analyzing the energy consumption of buildings 2m-PEM is used to model the uncertainties of structural and environmental parameters.

Moreover, wherever the correlation between uncertain input variables is considered, the two above-mentioned approaches may require additional calculations, which in turn leads to computational cost burdens. UT as a new analytical method is proposed in order to overcome this inefficiency, while a good level of accuracy along with reasonable execution time is provided [22], [23]. Furthermore, the statistics of a random variable can be calculated using the UT, which is subjected to a nonlinear transformation and operates based on the fact that it is easier to approximate a probability distribution rather than account for an arbitrary nonlinear function [24].

In this paper, the RUT [25] method is employed, which has all advantages of UT, whereas the computational time is approximately half of that of the UT method. In order to investigate an MG's economic optimization problem, an enhanced JAYA (EJAYA) algorithm is introduced and applied.

The JAYA algorithm, which is modified and enhanced in this paper, was first presented by Rao in 2016 [26] in order for the solution of various optimization problems, which was to well manifest the meaning of the Sanskrit word JAYA whose English equivalent is "victory." The major convenience of JAYA is that there is no need to tune and control the algorithmic parameters.

This superior feature is preserved in the suggested EJAYA while the accuracy and search capability of the algorithm is improved. Consequently, in addition to being independent of controlling the algorithmic parameters, the suggested EJAYA demonstrates accurate convergence and very low computational time, compared to other metaheuristic algorithms. It should be mentioned that since in this paper MG energy management while considering ac network constraints, is solved by the EJAYA metaheuristic algorithm, there is no need for linearization of the problem as is ordinarily done when using mathematical optimization methods [27].

Henceforth, the problem is solved in deterministic and probabilistic frameworks. In deterministic conditions, the robustness and effectiveness of the suggested EJAYA are justified by applying the method on a modified IEEE 33-bus system. Afterward, in order to examine the proposed algorithm in probabilistic conditions, the RUT-EJAYA method is applied to deal with the uncertainties related to the forecasted values of the load demand, market price, and available output of RESs. In order to model the variations of the random input variables, a normal distribution density function is made use of. As is naturally clear, fluctuations of the market price in different hours of a day interact with the load demand. Consequently, the correlation between the load demand and market price along with the correlation between WTs are dealt with. Due to the reduced number of samples in the proposed RUT compared to other probabilistic methods, application of RUT in problems with too many random input variables can reduce the computational cost of the process. Furthermore, in addition to computational time efficiency, RUT provides high accuracy in high data rate problems [25].

The main contributions of this paper can be summarized as follows.

1) In order to solve the nonlinear MG energy management problem a novel and efficient algorithm, namely EJAYA, is presented to eliminate the burdensome process of tuning the control parameters of some other metaheuristic algorithms.
2) The problem is investigated in two different deterministic and probabilistic frameworks using the proposed algorithm. The successful validation of the proposed EJAYA is carried out, and the accuracy of EJAYA along with fast convergence is demonstrated. The optimization model is applied on a modified IEEE 33-bus system in order to consider ac network constraints.
3) For dealing with the uncertainties related to the forecasted values of the load demand, market price and available output of RESs, the RUT-EJAYA method is applied. Additionally, the correlated conditions of the uncertain parameters are investigated.
4) The sensitivity of the parameters is analyzed while the proposed method is applied in a probabilistic framework.

II. PROBLEM FORMULATION

The formulation of the optimization model including the objective function along with constraints to be satisfied are described in this section.

A. Operational Cost (OC)

The following can be considered for minimization of the MG operational cost [29]:

$$
\begin{aligned}
\text{Min} \quad \text{OC} = \sum_{t=1}^{T} \big\{ & [u_{\text{MT}}^t . P_{\text{MT}}^t . B_{\text{MT}}^t + u_{\text{FC}}^t . P_{\text{FC}}^t . B_{\text{FC}}^t \\
& + \text{SUC}_{\text{MT}} . u_{\text{MT}}^t . (1 - u_{\text{MT}}^{t-1}) \\
& + \text{SUC}_{\text{FC}} . u_{\text{FC}}^t . (1 - u_{\text{FC}}^{t-1})] \\
& + P_{\text{WT}}^t . B_{\text{WT}}^t + P_{\text{PV}}^t . B_{\text{PV}}^t \\
& + \max(u_s^t, 0) . P_{\text{Batt}}^t . B_{\text{Batt}}^t \\
& + \text{Cos}\, t_{\text{Deg}}^t + P_{\text{Grid}}^t . \text{price}^t \big\}
\end{aligned}
\tag{1}
$$

where Grid and Batt are the abbreviated forms of the utility grid and the battery, respectively. $u_{\text{MT}}^t = u_{\text{FC}}^t = 1$ when the FC and MT are in the ON state, whereas $u_{\text{MT}}^t = u_{\text{FC}}^t = 0$ when they are in the OFF state. When the battery is charging, $u_s^t = -1$; whereas $u_s^t = 1$ is used for hours that the battery is discharging, and $u_s^t = 0$ for hours that the battery is neither charging nor discharging

$$
\begin{aligned}
&\text{if} \quad u_s^t = -1 \Rightarrow -P_{\text{Batt, min}}^t \leq P_{\text{Batt}}^t < 0 \\
&\text{if} \quad u_s^t = 0 \Rightarrow P_{\text{Batt}}^t = 0 \\
&\text{if} \quad u_s^t = 1 \Rightarrow 0 < P_{\text{Batt}}^t \leq P_{\text{Batt, max}}^t.
\end{aligned}
\tag{2}
$$

$\text{Cost}_{\text{Deg}}^t$ is defined as follows [30]:

$$
\text{Cost}_{\text{Deg}}^t = \frac{C_{\text{Batt}} . \text{DoD} . E_{\text{Batt}}}{N_{\text{cycle}}}.
\tag{3}
$$

DoD indicates an absolute discharge relative to the rated battery capacity. In order to show the DoD the following is applied [30]:

$$
\text{DoD}_t = \frac{E_{\text{Batt}_{\max}} - E_t}{E_{\text{Batt}_{\max}}}.
\tag{4}
$$

The cycle life of the battery is then achieved as follows:

$$
N_{\text{cycle}} = a . \text{DoD}^b
\tag{5}
$$

where a and b are battery-specific parameters, which are considered as 1331 and –1.825, respectively, for a Li-ion battery [30].

It is worth mentioning that, during charging hours, the battery is considered as load and its cost is added to the load's cost.

B. Constraints

1) Battery Limits: In order to consider the limitation on charge and discharge rates along with limits on the energy stored in the battery, the following equation and constraints are considered for a typical battery [29]:

$$
E_{\text{Batt}_{\min}} \leq E_{\text{Batt}}^t \leq E_{\text{Batt}_{\max}}
\tag{6}
$$

where E_{Batt}^t is associated with the time t as in the following:

$$
E_{\text{Batt}}^t = E_{\text{Batt}}^{t-1} + \eta_c P_{\text{ch}} . \Delta t + \frac{1}{\eta_d} P_{\text{disch}} . \Delta t
$$

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

4

IEEE SYSTEMS JOURNAL

$$P_{\text{ch}}^t \le P_{\text{ch, max}};$$

$$P_{\text{disch}}^t \le P_{\text{disch, max}}$$

$$P_{\text{ch}}^t = \min(u_s^t, 0).P_{\text{Batt}}^t$$

$$P_{\text{disch}}^t = -\max(u_s^t, 0).P_{\text{Batt}}^t. \tag{7}$$

2) Real Power Constraints: Power generations for each dispatchable DG are limited as

$$P_{\text{MT}_{\min}}^t \le P_{\text{MT}}^t \le P_{\text{MT}_{\max}}^t$$

$$P_{\text{FC}_{\min}}^t \le P_{\text{FC}}^t \le P_{\text{FC}_{\max}}^t. \tag{8}$$

Constraints on the rate of charge and discharge of the battery during an hour are considered as follows:

$$P_{\text{Batt}_{\min}}^t \le P_{\text{Batt}}^t \le P_{\text{Batt}_{\max}}^t. \tag{9}$$

3) Power Flow Constraints: The ac network constraint for the modified IEEE 33-bus system is reviewed as follows [28]:

$$\sum_{i=1}^{N_{\text{Bus}}} V_i^t V_j^t Y_{ij} \cos(\theta_{ij} - \delta_i^t + \delta_j^t)$$

$$= u_{\text{MT}}^t.P_{\text{MT}}^t + u_{\text{FC}}^t.P_{\text{FC}}^t + P_{\text{PV}}^t + P_{\text{WT}}^t - P_{\text{LD}}^t - u_s^t.P_{\text{Batt}}$$

$$\sum_{i=1}^{N_{\text{Bus}}} V_i^t V_j^t Y_{ij} \sin\left(\theta_{ij} - \delta_i^t + \delta_j^t\right) = -Q_{\text{LD}}^t. \tag{10}$$

Other constraints are

$$V_i^{\min} \le V_i^t \le V_i^{\max}$$

$$\left|P_{ij}^{\text{line}}\right| \le P_{ij,\text{max}}^{\text{line}}$$

$$\left|Q_{ij}^{\text{line}}\right| \le Q_{ij,\text{max}}^{\text{line}}. \tag{11}$$

III. RUT METHOD

Proper probabilistic methods should be used to deal with the inherent uncertain characteristic of power systems. The RUT approach is a powerful tool to be applied in order to model uncertainty in correlated transformations [25].

To this end, no extra computational time is imposed on the problem when RUT is applied for modeling the uncertainty of the considered nonlinear problem $\vec{Y} = f(\vec{Z})$, where $\vec{Y}$ is the output vector, f is the nonlinear function, and $\vec{Z}$ is the vector of the random input. The length of vector $\vec{Z}$ is equal to the number of uncertain variables, i.e., m. In the UT method, in order to model uncertainty, the problem is solved $2m + 1$ times. This is while in RUT the problem is solved $m + 2$ times [22], which makes the RUT method more proper from the computational time viewpoint. The following steps are carried out in the RUT method to achieve the output variable (operational cost), and its covariance matrix P_{yy} [25]:

Step 1: Choose $0 \le W_0 \le 1$

Step 2: Choose weight sequence

$$W_k = \frac{(1 - W_0)}{(m + 1)}, \ k = 1, \dots, m + 1. \tag{12}$$

Step 3: Initialize vector sequence

$$\xi_0^1 = [0], \ \xi_1^1 = \left[-\frac{1}{\sqrt{2W_1}}\right], \ \xi_2^1 = \left[\frac{1}{\sqrt{2W_1}}\right].$$

Step 4: Expand vector sequence (ξ_k^j) for $j = 2, \dots, m$ according to the following:

$$\left[\begin{matrix} \xi_0^{j-1} \\ 0 \end{matrix}\right]_{k=0}, \ \left[\begin{matrix} \xi_k^{j-1} \\ -\frac{1}{\sqrt{j(j+1)W_1}} \end{matrix}\right]_{k=1,\dots,j},$$

$$\left[\begin{matrix} 0_{j-1} \\ \frac{j}{\sqrt{j(j+1)W_1}} \end{matrix}\right]_{k=j+1}.$$

If a random variable vector $\vec{Z}$ has mean $\vec{\mu}_z$ and covariance matrix P_{zz}, the kth sigma point is

$$Z_k^j = \vec{\mu}_z + \sqrt{P_{zz}} \xi_k^j \tag{13}$$

where $\sqrt{P_{zz}}$ is a matrix square root of P_{zz}. For a positive definite matrix P, the matrix square root means that a matrix $A = \sqrt{P}$ exists such that $P = AA^T$, which should be calculated using numerically efficient and stable methods such as Cholesky decomposition [14]. If there is no correlation between uncertain variables, the elements of P_{zz}'s main diameter will be the square of uncertain variables' standard deviation (σ). However, in correlated conditions, depending on which uncertain variables are correlated, the corresponding rows and columns' elements of P_{zz} have negative or positive values. Accordingly, P_{zz} matrix can be obtained as follows:

$$P_{zz} = [p_{zz}(\alpha, \beta)]_{m \times m} \quad \alpha, \beta = 1, 2, \dots, m$$

$$p_{zz}(\alpha, \alpha) = {\sigma_i}^2 \quad \alpha = \beta$$

$$p_{zz}(\alpha, \beta) = \gamma_{\alpha,\beta}.\sigma_\alpha.\sigma_\beta \quad \alpha \ne \beta \tag{14}$$

where $\gamma_{\alpha,\beta}$ is the correlation coefficient between the αth and βth elements of the covariance matrix P_{zz}.

Step 5: Input $m + 2$ sigma points to the function to find the output samples

$$\vec{Y}_k = f(\vec{Z}_k). \tag{15}$$

Step 6: Calculate the mean $\vec{\mu}_y$ and covariance matrix P_{yy} of the output $\vec{Y}$ as follows:

$$E(y) = \vec{\mu}_y = \sum_{k=0}^{m+1} W_k Y_k \tag{16}$$

$$P_{yy} = \sum_{k=0}^{m+1} W_k (Y_k - \vec{\mu}_y)(Y_k - \vec{\mu}_y)^T. \tag{17}$$

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

JAVIDSHARIFI *et al.*: PROBABILISTIC MODEL FOR MGs OPTIMAL ENERGY MANAGEMENT CONSIDERING AC NETWORK CONSTRAINTS 5

IV. EJAYA ALGORITHM

A. Brief Overview on Original JAYA

The JAYA algorithm that was proposed by R. Venkata Rao is enhanced and applied in this paper. As the methodology is demonstrated in the following, due to the simplicity and rapidity of the algorithm and since no need exists to have any information about control parameters, JAYA becomes more advantageous compared to other metaheuristic algorithms [27]. The goal is to minimize the MG operational cost as the objective function. Let us assume that the best solution "*best*," and the worst solution "*worst*" obtain the best and the worst values of OC in the entire candidate solutions, respectively. Let $\vec{X}_{i,\text{iter}}^{\text{new}}$ be the ith candidate during the *iter*th iteration. Then, to modify the decision variables, the individuals could be changed according to the following [27]:

$$\vec{X}_{i,\text{iter}}^{\text{new}} = \vec{X}_{i,\text{iter}} + r_{1,i,\text{iter}}(\vec{X}_{\text{best}} - \vec{X}_{i,\text{iter}})$$
$$- r_{2,i,\text{iter}}(\vec{X}_{\text{worst}} - \vec{X}_{i,\text{iter}}) \tag{18}$$

where r_1 and r_2 are random variables in [0, 1]. $\vec{X}_{\text{best}}$ is the best solution in each iteration, whereas $\vec{X}_{\text{worst}}$ is the worst solution in the population. $\vec{X}_{i,\text{iter}}^{\text{new}}$ will be accepted if its objective function value is better than that of $\vec{X}_{i,\text{iter}}$.

B. Enhanced JAYA (EJAYA)

When the dimensions of the problem increase, the original JAYA suffers from getting trapped in local optima. Consequently, in order to achieve the global best solution, three modifications as in [30] are applied to improve the convergence ability and accuracy of the algorithm. The major convenience of JAYA which is its independence from tuning and controlling the algorithmic parameters is preserved in EYAYA while the accuracy and search capability of the algorithm are improved.

1) First Modification: To increase the accuracy of the algorithm, the size of population is considered variable and changes as follows:

$$N = \text{round}\left(\frac{(N_{\max} - N_{\min}) \times \text{iter}}{\text{iter}_{\max}} + N_{\min}\right) \tag{19}$$

where $N_{\min}$ and $N_{\max}$ are, respectively, the minimum and maximum populations, and $\text{iter}_{\max}$ is the maximum number of iterations. To avoid being trapped in local optima, a variable population size is considered in each iteration. As a result, the accuracy of the algorithm will improve.

2) Second Modification: The second modification is applied to improve the accuracy of the proposed approach. Five constants $k_1 \neq k_2 \neq k_3 \neq k_4 \neq k_5$, all unequal to i, are chosen randomly from the population. Three mutations ($\vec{X}_{\text{mut}_l}, l = 1, 2, 3$) are defined as

$$\vec{X}_{\text{mut1}} = \vec{X}_{k_1} + \text{rand1}(.) \times (\vec{X}_{k_2} - \vec{X}_{k_3}) \tag{20a}$$

$$\vec{X}_{\text{mut2}} = \vec{X}_{\text{mut1}} + \text{rand2}(.) \times (\vec{X}_{\text{best}} - \vec{X}_{\text{worst}}) \tag{20b}$$

$$\vec{X}_{\text{mut3}} = \vec{X}_{k_4} + \text{rand3}(.) \times (\vec{X}_{\text{best}} - \vec{X}_{k_5}). \tag{20c}$$

TABLE I
PSEUDOCODE OF THE THIRD MODIFICATION

iter=1
while $\text{iter} \leq \text{iter}_{\max}$
for i=1 to N

  if $1 \leq \text{iter} \leq \frac{1}{3}\text{iter}_{\max}$

select one of the mutations of (20) randomly, namely $\vec{X}_{\text{mod1}}$, *and apply it to the ith member*

  if $\vec{X}_{\text{mod1}}$ *is better than* $\vec{X}_{i,\text{iter}}$,

    set $\vec{X}_{i,\text{iter}} = \vec{X}_{\text{mod1}}$

  end

else if $\frac{1}{3}\text{iter}_{\max} + 1 \leq \text{iter} \leq \frac{2}{3}\text{iter}_{\max}$

select two of the mutations of (20) randomly ($\vec{X}_{\text{mod1}}$ *and* $\vec{X}_{\text{mod2}}$), *and apply them to the ith member*
  determine the best solution among $\vec{x}_{\text{mod}\ 1}$, $\vec{x}_{\text{mod}\ 2}$ *and* $\vec{x}_{i,\text{iter}}$

    set $\vec{x}_{i,\text{iter}} = \vec{x}_{\text{mod},\ s}$ *(s=1 or 2)*

  end
else if $\frac{2}{3}\text{iter}_{\max} + 1 \leq \text{iter} \leq \text{iter}_{\max}$
  apply all three mutations
determine the best solution among $\vec{x}_{\text{mod}\ 1}$, $\vec{x}_{\text{mod}\ 2}$, $\vec{x}_{\text{mod}\ 3}$ *and*
$\vec{x}_{i,\text{iter}}$

    set $\vec{x}_{i,\text{iter}} = \vec{x}_{\text{mod},\ s}$ *(s=1or 2 or 3)*

  end
 end
end
iter=iter+1
end

3) Third Modification: In order to increase the convergence speed of the algorithm, the third modification is applied according to the pseudocode of Table I. This modification can increase the search ability of the algorithm. Applying this modification helps the algorithm to better investigate the search space, and also it prevents the algorithm to be trapped in the local optima. In Table I, *N* and iter are, respectively, the representatives of the size of the population and number of iterations.

V. APPLICATION OF THE PROPOSED METHOD

The specification of the DG's produced powers in the MG as a function of the input variables is the major purpose of the MG's optimal operation management. In the considered problem, the vector of the input random variables, $\vec{Z}$, is as follows, whereas the output vector, $\vec{Y}$, is the MG operational cost:

$$\vec{Z} = \begin{bmatrix} \vec{P}_{\text{WT}} & \vec{P}_{\text{PV}} & \vec{P}_{\text{LD}} & \vec{\text{price}} \end{bmatrix}^T. \tag{21}$$

The following procedure is carried out in order to solve the MG energy management problem.

Step 1: Initialize the population size, number of variables and termination criterion. Problem information including MG properties, beside bids and power information of DGs, storages and utility, hourly WT and PV power forecasts are specified. The initial battery charge is also defined in this step.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

6

IEEE SYSTEMS JOURNAL

Step 2: Generate $m + 2$ sigma points for random input variables based on (13), and calculate the weight associated with each $\vec{Z}$ using (12).

Step 3: Set $k = 1$.

Step 4: Choose the kth sigma point.

Step 5: Initialize the value of decision variables, u_{MT}^t, P_{MT}^t u_{FC}^t, P_{FC}^t, u_s^t, and P_{Batt}^t according to their admissible limits.

Step 6: Check the battery constraint according to (6) and (7) and the ac network constraints according to (10) and (11). If the constraints are not satisfied, a high value will be attributed to the objective function of that member of population such that it will be ignored or eliminated.

Step 7: Calculate the objective function for the initial population.

Step 8: Choose $\vec{X}_{\mathrm{best}}$ and $\vec{X}_{\mathrm{worst}}$ as described in Section IV.

Step 9: Set iter $= 1$.

Step 10: Set $i = 1$.

Step 11: In order to achieve new solutions, apply the JAYA algorithm based on (18), and modifications as described in Section V, to the ith individual of the population.

Step 12: For each new solution, check the battery constraint according to (6) and (7) and the ac network constraints (10) and (11). Calculate the objective function for each new solution.

Step 13: If $i < N$, set $i = i + 1$ and go to Step 11; otherwise go to Step 14.

Step 14: Update N according to (19).

Step 15: Determine the best solution in the new population.

Step 16: Sort the generated population in an ascending manner based on their objective function values. Select the first N individuals as the population of the next iteration of the algorithm. Accordingly, the first individual in the population is $\vec{X}_{\mathrm{best}}$, whereas the last individual is selected as $\vec{X}_{\mathrm{worst}}$.

Step 17: Control the termination criterion, and if satisfied, terminate the algorithm and go to Step 18; otherwise, set iter $=$ iter $+ 1$ and return to Step 10.

Step 18: Save the best solution.

Step 19: If $k + 1 > m + 1$, go to Step 20, otherwise go to Step 4.

Step 20: Using $m + 2$ output sigma points (best solutions), calculate the expected value and covariance of each random variable according to (16) and (17).

Fig. 1. Single-line diagram of the simulated distribution system.

TABLE II
DATA OF THE DG UNITS

Unit	$P_{\min}$ (kW)	$P_{\max}$ (kW)	Bid (€/kWh)
MT	300	1500	0.457
FC	200	1500	0.294
ESS	-500	500	0.38
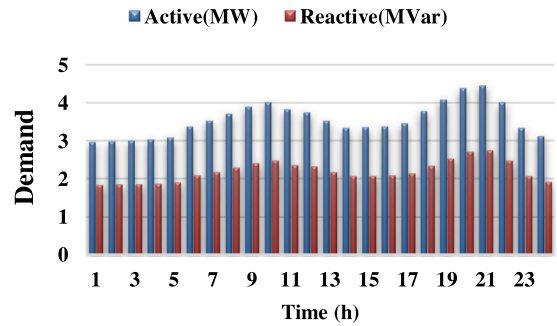
Fig. 2. Active and reactive load profiles during the scheduling horizon.

VI. SIMULATION RESULTS

In order to verify the effectiveness of the proposed approach, the approach is applied on two deterministic and probabilistic frameworks on the modified IEEE 33-bus system of Fig. 1. The technical data of the DG units are given in Table II. Two WTs with a total capacity of 1.3 MW, along with a PV unit with a capacity of 0.5 MW, are installed at buses 14, 32, and 24, respectively. For the sake of clarity of the performance of each power unit, a 24-h scheduling scheme is assumed for the analysis of the simulated system. Th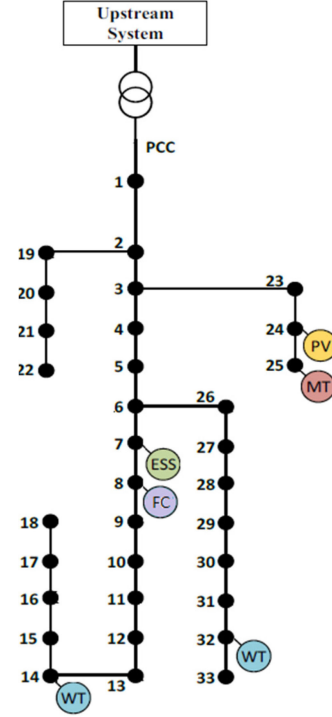e load profile and market price are illustrated in Figs. 2 and 3, respectively [16]–[19]. The proposed method was implemented in MATLAB 8.1 and solved with a personal computer with Core i7 CPU and 32 GB RAM.

A. Deterministic Framework

In the deterministic framework, the random input variables are considered constant and equal to their forecasted values.

As is observed in Table III, when the number of the population is more than 40, the results remain constant, which can serve as a
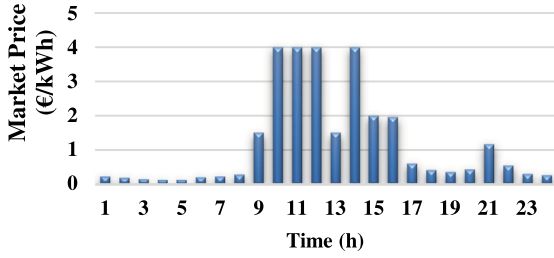
Fig. 3.   Real-time market price [16]–[19].

TABLE III
INFLUENCE OF CHANGING THE NUMBER OF POPULATION ON
RESULTS OF THE PROPOSED ALGORITHM

Number of population	Solutions			
	Best (€)	Worst (€)	Ave (€)	SD (€)
20	37076.3	38176.5	37528.6	22.6
40	36614.7	37083.3	36845.3	14.3
60	36614.7	37077.6	36844.8	14.2
80	36614.7	37069.1	36844.2	14.2
100	36614.7	37052.6	36843.7	14.1

TABLE IV
COMPARISON OF THE TOTAL COST AND SIMULATION TIME FOR DIFFERENT
ALGORITHMS IN THE DETERMINISTIC FRAMEWORK

METHOD	Best (€)	SD (€)	NUMBER OFES	SIMULATION TIME (S)
PSO	37280.9	30.4	2000	361.84
TLBO	36780.4	28.7	2000	448.31
JAYA	36681.6	23.8	2000	220.01
EJAYA	36614.7	14.1	2000	110.14

proof of the robustness of the proposed algorithm. Consequently, the number of population is considered equal to 40 for the subsequent simulations.

For the sake of briefness, the ON–OFF conditions of the generation units are not shown in the tables, but it can be concluded that during the hours when the output power of the generators is equal to zero, $u_i = 0$ holds. This is while during other hours $u_i = 1$. Furthermore, for the battery in hours where the power is negative, which means that the battery is charging, $u_s^t = -1$. However, for positive powers which are during the discharging hours of the battery, $u_s^t = 1$. In hours when the battery is not charging nor discharging, $u_s^t = 0$.

In Table IV, a comparison is performed among the four different algorithms PSO, TLBO, JAYA, and the proposed EJAYA. The comparison proves the best performance of the suggested algorithm from total operational cost and computational time points of view.

The proposed algorithm's convergence characteristic is illustrated in Fig. 4. As is noticed, approximately from the 150th iteration the algorithm converges to the best solution. Consequently, favorably fast convergence, which is a positive aspect, is well obtained by the proposed EJAYA.

The values of the total cost, SD and simulation time of the suggested EJAYA and those of some other algorithms, including PSO, TLBO, and JAYA, are compared and presented in Table IV.

Additionally, in Table V the same comparison is performed among EJAYA, the original JAYA as well as other modified versions, namely MJAYA I, II, and III, in order to justify the
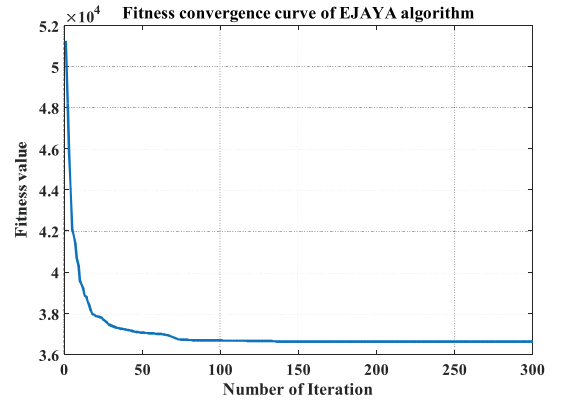

Fig. 4.   Convergence characteristic of the proposed EJAYA.

TABLE V
COMPARISON OF THE OBJECTIVE FUNCTION VALUE
ACHIEVED FOR 50 TRIALS

Method	Best (€)	SD (€)	NUMBER OFES	SIMULATION TIME (S)
JAYA	36681.6	23.8	2000	220.01
MJAYA I	36654.4	21.6	2000	218.57
MJAYA II	36638.1	19.4	2000	218.63
MJAYA III	36622.5	17.7	2000	156.20
EJAYA	36614.7	14.1	2000	110.14

influence of each of the applied modifications. Each MJAYA algorithm is obtained by applying one separate modification of Section IV-B. In MJAYA I, the first, in MJAYA II the second, and in MJAYA III the third modification is applied. The priority of the proposed EJAYA in which all modifications are applied simultaneously (see Section V), is obviously observed.

B. Probabilistic Framework

Being robust and efficient, the proposed algorithm is suggested to be applied in the probabilistic framework. Some papers such as [22], [31], and [32] carried out comparisons between the UT and other probabilistic methods including MCS and PEM in different subjects and problems such as probabilistic load flow [22], stochastic system reconfiguration [31], and MG's operation management [32]; hence, the advantages of the UT method is proved. Consequently, in this section, the comparison is performed among the proposed RUT, the UT method, and MCS. It is worth mentioning that in the MC approach, 20 scenarios are considered for each random variable, consequently, the number of iterations for MCS equals $96 \times 20 = 1920$. In this paper, uncertain variables follow a normal distribution function whose mean values equal the base values in the deterministic framework, and SDs equal a specific percentage of its mean values [22]. In order to interrogate the probabilistic situation, two scenarios are examined. In the first scenario, the uncertainties in load demand, market price and available output of RESs without any correlation are considered. In the second, the correlation between the load demand and market price along with the correlation between WTs are inspected while the uncertainties are considered similar to the first probabilistic scenario.

1) First Scenario (Uncorrelated Variables): In this case, the random input variables have a normal distribution with mean
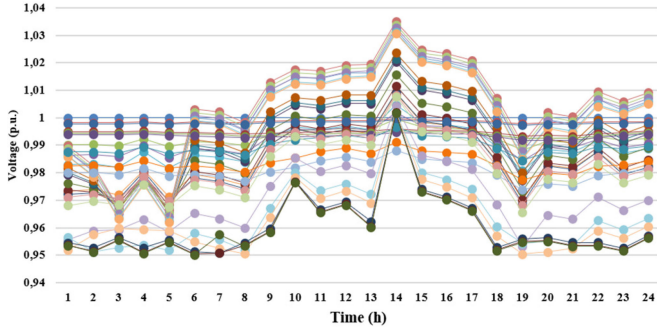
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

8   IEEE SYSTEMS JOURNAL

Fig. 5.   Bus voltages during the scheduling horizon.

TABLE VI
BEST SOLUTION FOR THE PROPOSED RUT METHOD (FIRST SCENARIO:
UNCORRELATED VARIABLES)

	MT		FC		Battery	
Hour	M.V	SD	M.V	SD	M.V	SD
1	331.2	6.7	1185.9	18.4	-408.6	9.3
2	300.6	1.8	1326.4	17.3	-360.6	10.2
3	522.5	35.4	1211.1	18.3	-212.4	11.2
4	574.3	34.6	1128.8	22.6	-243.8	10.7
5	598.4	38.7	907.5	16.2	-26.1	3.7
6	652.1	19.4	1383.7	12.9	-11.7	3.1
7	741.7	20.8	1443.8	8.1	9.3	2.3
8	842.1	2.4	1485.9	2.7	-10.5	2.9
9	1500	0.0	1500	0.0	161.7	10.4
10	1499.9	0.1	1500	0.0	114.2	9.8
11	1499	0.5	1500	0.0	158.9	11.2
12	1499.3	0.2	1499.5	0.2	-342.2	19.7
13	1499.4	0.2	1499.7	0.1	-377.5	20.1
14	1500	0.0	1500	0.0	0.0	0.0
15	1499.6	0.8	1499.8	0.1	0.0	0.0
16	1499.6	0.7	1499.6	0.2	0.0	0.0
17	1428.9	9.1	1500	0.0	-174.3	9.2
18	1019.5	17.6	1499.9	0.1	-64.3	4.2
19	1363.1	8.7	1498.2	0.4	-52.2	3.8
20	1293.7	12.3	1487.9	1.3	0.0	0.0
21	1500	0.0	1500	0.0	78.1	5.1
22	1488.6	11.3	1499.7	0.2	44.1	4.3
23	702.2	26.5	1499.8	0.1	6.4	1.3
24	742.7	23.4	1193.3	12.4	-16.8	2.1

TABLE VII
COMPARISON OF THE PROPOSED RUT AND OTHER METHODS (FIRST
SCENARIO: UNCORRELATED VARIABLES)

	MCS	UT	RUT
TOTAL COST (€)	36600.8	36780.3	36610.4
SD (€)	112.7	148.3	115.1
RUN TIME (HOUR)	61.1	5.7	2.9

TABLE VIII
COMPARISON OF THE PROPOSED RUT AND OTHER METHODS (SECOND
SCENARIO: CORRELATED VARIABLES)

	MCS	UT	RUT
TOTAL COST (€)	36118.5	36167.4	36120.0
SD (€)	95.3	102.4	98.6
RUN TIME (HOUR)	64.7	6.1	3.2

TABLE IX
THE BEST SOLUTION FOR THE PROPOSED RUT METHOD (SECOND SCENARIO:
CORRELATED VARIABLES)

	MT		FC		Battery	
Hour	M.V	SD	M.V	SD	M.V	SD
1	403.6	14.3	1091.1	14.8	-208.4	7.9
2	381.8	11.3	1370.6	7.8	-376.9	4.3
3	307.5	2.1	1151.1	9.1	-188.2	8.6
4	505.5	19.4	1176.2	9.4	-368.9	4.9
5	322.9	5.1	1124.4	9.8	-120.7	8.4
6	457.2	13.6	1382.1	7.2	10.3	2.1
7	781.2	18.7	1440.6	8.1	10.4	3.2
8	939.7	16.4	1480.2	1.3	-22.7	3.1
9	1497.6	0.4	1499.7	0.2	0.0	0.0
10	1500	0.0	1500	0.0	155.8	8.1
11	1498.8	0.2	1499.9	0.1	152.2	8.2
12	1500	0.0	1500	0.0	79.1	5.4
13	1387.5	14.7	1483.3	2.4	-371.8	6.7
14	1500	0.0	1500	0.0	447.2	7.1
15	1499.7	0.1	1499.9	0.1	0.0	0.0
16	1500	0.0	1500	0.0	10.5	1.6
17	1492.2	2.8	1499.9	0.1	-123.7	2.1
18	1290.1	8.8	1497.7	1.1	-172.8	2.3
19	1172.9	10.2	1492.6	1.3	13.5	1.9
20	1450.4	5.9	1500	0.0	-71.4	2.9
21	1492.3	1.7	1498.9	0.7	85.7	2.7
22	1499.5	0.2	1499.9	0.1	55.5	2.1
23	580.5	19.6	1486.3	1.8	10.1	1.7
24	464.2	11.8	1304.2	8.9	-10.4	1.8

values equal to the ones expressed in [33], and SD equal to 10% of the mean values. Fig. 5 shows the bus voltages during the scheduling horizon. It is obvious that the voltages are kept within permissible ranges. The best solution for the proposed RUT method, including the mean values and SDs of the dispatchable units, is shown in Table VI. Since FC has the lowest bid, in most hours the maximum electrical energy is purchased from FC. Thus, the SD of FC in most hours is approximately zero. During the hours when the market price is high (from hour 9 to hour 16, and in hour 21), or when the load demand is low, it is decided to purchase electrical energy from the MT in the maximum value. In these situations, the SD values for MT are about zero. A comparison between the results of the proposed RUT method with those of UT and MCS is presented in Table VII. According to Table VII, when the proposed RUT method is applied, the total cost is approximately equal to that of MCS, whereas the simulation time is considerably lower. Besides, in comparison with the UT method, since the number of sigma points in RUT is about half of UT, the runtime is less than half while the accuracy of RUT is significantly more. It can be

concluded that for problems with high random input variables, since the accuracy of the proposed method is comparable with MCS, the proposed RUT is preferable.

2) Second Scenario (Correlated Variables): In addition to consideration of uncertainties, the correlation between load demand and market price (negative correlation coefficient equal to 0.2) and the correlation between WTs (it is supposed that there exist two WTs in the considered MG with a positive correlation coefficient equal to 0.7) are considered according to (14), in order to show the ability of the proposed approach in solving problems with correlated variables. The above-mentioned correlation coefficients' values are taken from [34]. A comparison between the results of the proposed RUT method with those of UT and MCS is shown in Table VIII. The best solution, including mean values and SDs of the dispatchable units, for the RUT method is shown in Table IX. Similar to the first scenario, SD is near zero for FC in most hours, since FC is the least expensive unit, which sells its maximum power value almost during all hours. When the market price is high and the load demand is
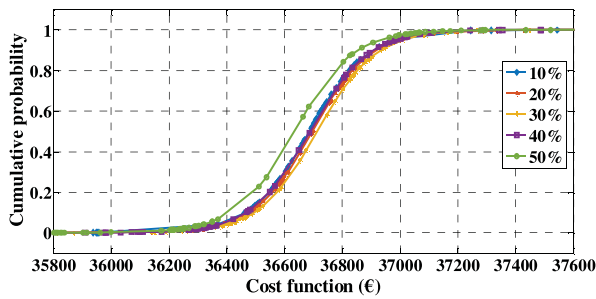
Fig. 6. Sensitivity analysis of the SD value of random variables on the cost function value.

low, the MGCC decides to purchase from MT, which leads to a lower SD, which is about zero.

C. Sensitivity Analysis

In order to have a better perception of the effects of SD variations on the objective function, a sensitivity analysis was performed. The effect of changing the SD values of random variables on the cost function is investigated by simultaneously changing the SD values of all variables, and the probabilistic scheme is run for each case. The values of SD parameters alter from 0.1 to 0.5 times their initial values in discrete steps of 0.1. It is assumed that the cost function follows the normal distribution function and the concept of CDF is utilized. As expected, according to Fig. 6, the increase of the random variables' SD leads to the increase of the SD value of the cost function.

VII. CONCLUSION

The novel RUT-EJAYA approach was suggested for optimal operation of renewable-based MGs. Probabilistic and deterministic frameworks were explored in order to investigate the effectiveness of the proposed approach on the modified IEEE 33-bus system. In order to study the probabilistic framework, the RUT method was proposed. The approach can efficiently find the minimum solution for the total operation cost of MG while considering the ac network constraints. The uncertainties were considered in the output power of WT and PV units, along with the load demand and market price. Additionally, the correlation between the load demand and market price, along with the correlation between WTs were taken into account. Results were compared with the MCS and the original UT methods. It was demonstrated that not only is the accuracy of RUT no less than that of UT, but also this method surpasses UT from the computational efficiency point of view. Moreover, in comparison with the MCS, the results were significantly close to those of MCS, whereas the computational time was considerably lower. Finally, the sensitivity of the parameters was analyzed in the probabilistic framework. Since the inherent uncertainties in the parameters were taken into account, the probabilistic solution was more accurate and real. It can be concluded that probabilistic scheduling tools are the essential requirements of economic and reliable optimal operation of systems, especially MGs, due to

the presence of RESs. According to the results and the comparison with MCS, for dealing with other probabilistic problems, RUT shows accurate results such as those of MCS while the computational burden/time is less. Furthermore, since in EJAYA the algorithmic parameters are less than other metaheuristics, and comparatively there is less need to tune the parameters, the suggested approach can be more convenient in real applications. Future works can include investigation of stochastic MG energy management while other objective functions, including emission and reliability, can be added to the problem formulation.

REFERENCES

[1] S. A. Pourmousavi, M. H. Nehrir, C. M. Colson, and C. Wang, "Real-time energy management of a stand-alone hybrid wind-microturbine energy system using particle swarm optimization," *IEEE Trans. Sustain. Energy*, vol. 1, no. 3, pp. 193–201, Oct. 2010.

[2] M. Nehrir *et al.*, "A review of hybrid renewable/alternative energy systems for electric power generation: Configurations, control, and applications," *IEEE Trans. Sustain. Energy*, vol. 2, no. 4, pp. 392–403, Oct. 2011.

[3] Y. Zhang, N. Gatsis, and G. B. Giannakis, "Robust energy management for microgrids with high-penetration renewables," *IEEE Trans. Sustain. Energy*, vol. 4, no. 4, pp. 944–953, Oct. 2013.

[4] B. Zhao, X. Zhang, J. Chen, C. Wang, and L. Guo, "Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system," *IEEE Trans. Sustain. Energy*, vol. 4, no. 4, pp. 934–943, Oct. 2013.

[5] H. Kamankesh, V. G. Agelidis, and A. Kavousi-Fard, "Optimal scheduling of renewable micro-grids considering plug-in hybrid electric vehicle charging demand," *Energy*, vol. 100, pp. 285–297, 2016.

[6] M. Bashir and J. Sadeh, "Optimal sizing of hybrid wind/ photovoltaic/battery considering the uncertainty of wind and photovoltaic power using Monte Carlo," in *Proc. 11th Int. Conf. Environ. Elect. Eng.*, 2012, pp. 1081–1086.

[7] D. T. Nguyen and L. B. Le, "Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1608–1620, Jul. 2014.

[8] C. Chen and S. Duan, "Optimal integration of plug-in hybrid electric vehicles in microgrids," *IEEE Trans. Ind. Inform.*, vol. 10, no. 3, pp. 1917–1926, Aug. 2014.

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

[10] R. Jabbari-Sabet, S.-M. Moghaddas-Tafreshi, and S.-S. Mirhoseini, "Microgrid operation and management using probabilistic reconfiguration and unit commitment," *Int. J. Elect. Power Energy Syst.*, vol. 75, pp. 328–336, 2016.

[11] L. Urbanucci and D. Testi, "Optimal integrated sizing and operation of a CHP system with Monte Carlo risk analysis for long-term uncertainty in energy demands," *Energy Convers. Manage.*, vol. 157, pp. 307–316, 2018.

[12] Y. Gu, X. Zhang, J. A. Myhren, M. Han, X. Chen, and Y. Yuan, "Techno-economic analysis of a solar photovoltaic/thermal (PV/T) concentrator for building application in Sweden using Monte Carlo method," *Energy Convers. Manage.*, vol. 165, pp. 8–24, 2018.

[13] M. J. Salehpour and S. M. M. Tafreshi, "A two-stage stochastic optimization based-on Monte Carlo simulation for maximizing the profitability of a smart microgrid," *J. Hyperstructures*, vol. 6, no. 2, pp. 52–67, 2017.

[14] F. S. Gazijahani, H. Hosseinzadeh, N. Tagizadeghan, and J. Salehi, "A new point estimate method for stochastic optimal operation of smart distribution systems considering demand response programs," in *Proc. Elect. Power Distrib. Netw. Conf.*, 2017, pp. 39–44.

[15] F. S. Gazijahani and J. Salehi, "Integrated DR and reconfiguration scheduling for optimal operation of microgrids using Hong's point estimate method," *Int. J. Elect. Power Energy Syst.*, vol. 99, pp. 481–492, 2018.

[16] S. Sharma, S. Bhattacharjee, and A. Bhattacharya, "Probabilistic operation cost minimization of micro-grid," *Energy*, vol. 148, pp. 1116–1139, 2018.

[17] F. Najibi, T. Niknam, and A. Kavousi-Fard, "Optimal stochastic management of renewable MG (micro-grids) considering electro-thermal model of PV (photovoltaic)," *Energy*, vol. 97, pp. 444–459, 2016.

[18] A. Kavousi-Fard, A. Abunasri, A. Zare, and R. Hoseinzadeh, "Impact of plug-in hybrid electric vehicles charging demand on the optimal energy management of renewable micro-grids," *Energy*, vol. 78, pp. 904–915, 2014.

[19] S. Mohammadi, B. Mozafari, S. Solimani, and T. Niknam, "An adaptive modified firefly optimisation algorithm based on Hong's point estimate method to optimal operation management in a microgrid with consideration of uncertainties," *Energy*, vol. 51, pp. 339–348, 2013.

[20] S. A. Alavi, A. Ahmadian, and M. Aliakbar-Golkar, "Optimal probabilistic energy management in a typical micro-grid based-on robust optimization and point estimate method," *Energy Convers. Manage.*, vol. 95, pp. 314–325, 2015.

[21] A. Baziar and A. Kavousi-Fard, "Considering uncertainty in the optimal energy management of renewable micro-grids including storage devices," *Renewable Energy*, vol. 59, pp. 158–166, 2013.

[22] M. J. Bordbari, A. R. Seifi, and M. Rastegar, "Probabilistic energy consumption analysis in buildings using point estimate method," *Energy*, vol. 142, pp. 716–722, 2018.

[23] M. Aien, M. Fotuhi-Firuzabad, and F. Aminifar, "Probabilistic load flow in correlated uncertain environment using unscented transformation," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2233–2241, Nov. 2012.

[24] S. J. Julier and J. K. Uhlmann, "Unscented filtering and nonlinear estimation," *Proc. IEEE*, vol. 92, no. 3, pp. 401–422, Mar. 2004.

[25] H. R. Baghaee, M. Mirsalim, G. Gharehpetian, and H. Talebi, "Application of RBF neural networks and unscented transformation in probabilistic power-flow of microgrids including correlated wind/PV units and plug-in hybrid electric vehicles," *Simul. Model. Pract. Theory*, vol. 72, pp. 51–68, 2017.

[26] S. J. Julier and J. K. Uhlmann, "Reduced sigma point filters for the propagation of means and covariances through nonlinear transformations," in *Proc. Amer. Control Conf.*, 2002, pp. 887–892.

[27] R. Rao, "Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems," *Int. J. Ind. Eng. Comput.*, vol. 7, pp. 19–34, 2016.

[28] A. Gholami, T. Shekari, F. Aminifar, and M. Shahidehpour, "Microgrid scheduling with uncertainty: The quest for resilience," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2849–2858, Nov. 2016.

[29] A. Deihimi, B. K. Zahed, and R. Iravani, "An interactive operation management of a micro-grid with multiple distributed generations using multi-objective uniform water cycle algorithm," *Energy*, vol. 106, pp. 482–509, 2016.

[30] M. Javidsharifi, T. Niknam, J. Aghaei, and G. Mokryani, "Multi-objective short-term scheduling of a renewable-based microgrid in the presence of tidal resources and storage devices," *Appl. Energy*, vol. 216, pp. 367–381, 2018.

[31] A. Kavousi-Fard, T. Niknam, and M. Fotuhi-Firuzabad, "Stochastic reconfiguration and optimal coordination of V2G plug-in electric vehicles considering correlated wind power generation," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 822–830, Jul. 2015.

[32] S. Tabatabaee, S. S. Mortazavi, and T. Niknam, "Stochastic energy management of renewable micro-grids in the correlated environment using unscented transformation," *Energy*, vol. 109, pp. 365–377, 2016.

[33] T. Niknam, F. Golestaneh, and A. Malekpour, "Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm," *Energy*, vol. 43, pp. 427–437, 2012.

[34] A. Feijóo, D. Villanueva, J. L. Pazos, and R. Sobolewski, "Simulation of correlated wind speeds: A review," *Renewable Sustain. Energy Rev.*, vol. 15, pp. 2826–2832, 2011.

Mahshid Javidsharifi (S'17) is currently working toward the Ph.D. degree at Shiraz University of Technology, Shiraz, Iran.

Taher Niknam (M'14) is a Professor with Shiraz University of Technology, Shiraz, Iran. His research interests include power system restructuring and impacts of distributed generations on power systems.

Jamshid Aghaei (M'12–SM'15) is a Professor with Shiraz University of Technology, Shiraz, Iran. His research interests include renewable energy systems, smart grids, electricity markets, and power systems optimization.

Miadreza Shafie-khah (M'13–SM'17) is an Assistant Professor with the University of Vaasa, Vaasa, Finland. His research interests include power market simulation, market power monitoring, power system optimization, demand response, electric vehicles, price forecasting, and smart grids.

João P. S. Catalão (M'04–SM'12) is a Professor with the Faculty of Engineering, University of Porto, Porto, Portugal, and a Research Coordinator with INESC TEC, Porto, Portugal. His research interests include power system operations and planning, hydro and thermal scheduling, wind and price forecasting, distributed renewable generation, demand response, and smart grids.