Effective Energy Management of Hybrid AC-DC Microgrids with Storage Devices

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Abstract—This paper proposes a stochastic framework for the optimal operation and management of hybrid AC-DC microgrids (MGs) in the presence of renewable energy sources (RESs) and storage devices. Hybrid AC-DC MGs can provide benefit over the traditional AC MGs by elimination of inverting equipment and reducing power losses caused by the AC-DC converters. A stochastic load flow based on an unscented transform is employed to model the uncertainties of active and reactive loads, market power price, wind turbine and photovoltaic output power. Additionally, a new powerful optimizer based on crow search algorithm (CSA) is devised to search the problem space. The proposed method uses a new two stage modification function to increase the search ability of CSA when avoiding premature convergence. The feasibility and performance assessment of the proposed framework are examined on a IEEE standard test system.

Index Terms: Hybrid MG, DC loads and DGs, Uncertainty, Optimization Algorithm.

NOMENCLATURE

\( A_{i,j} \) \( k^{th} \) row or column of matrix \( A \)
\( B_{Gi} \) & \( B_{dj} \) cost of the \( i^{th} \) RES and \( j^{th} \) storage device at hour \( t \)
\( B_{Grid} \) price of utility at hour \( t \)
\( d \) length of the control vector
\( f \) cost objective function
\( f_{Iter}^i \) flight length of crow \( i \) in iteration \( Iter \)
\( Iter \) iteration number in algorithm
\( M_j \) the position of hiding place of crow \( j \)
\( N \) number of crows in the population
\( N_T \) number of scheduling time intervals
\( N_s \) number of storage devices
\( N_g \) number of power units
\( N_{Load} \) number of load levels
\( n \) total number of energy generation sources
\( P_{Gi} \) \( P_j \) \( k^{th} \) active power bought/sold from/to the utility at time \( t \)
\( P_{Grid} \) \( i^{th} \) generator and \( j^{th} \) storage load value in \( k^{th} \) level of \( i^{th} \) hour
\( P_{Load,k} \) \( i^{th} \) active and reactive power injection in -bus \( m \) at time \( t \)
\( P_{Gi,\min} \) \( P_{Gi,\max} \) \( i^{th} \) RES at hour \( t \)
\( P_{j,\min} \) \( P_{j,\max} \) \( i^{th} \) storage device at hour \( t \)
\( P_{grid,\min} \) \( P_{grid,\max} \) \( i^{th} \) control variable (or solution vector in CSA)
\( \Delta t \) control variable (or solution vector in CSA)
\( \beta_{1,..,\beta} \) random number between \([0,1]\)
\( \mu \) A constant value equal to 0.01
\( \eta_{charge, discharge} \) charge (discharge) efficiency of the battery
\( \rho \) weight of the mean value \( \mu \)
\( \sigma \) mean value of random variables

I. INTRODUCTION

Based on the U.S. Department of Energy, a microgrid (MG) is defined as a set of distributed generations (DGs) and interconnected loads with specified electrical boundaries which acts as a single controllable unit with regard to the grid and can decide to either connect or disconnect from the main utility to operate in grid-connected or island modes, respectively [1]. Importance of the MG has drawn significant attention among researchers for benefits such as power loss reduction, power quality improvement, reliability enhancement and higher efficiency [2-5]. Additionally, the development of a MG can help supply remote loads when the transmission and distribution infrastructure are not available. Owing to the islanding capability of MGs, they can restore loads (or at least parts of the loads) in the event of a fault in the main grid; which leads to higher reliability and power quality of electrical services. In terms of voltage, MGs can be classified into three main groups: AC, DC and hybrid.

In AC MGs, loads and DGs are all connected to the AC bus. In these MGs, DC loads are supplied using AC-DC inverters and the DC units are connected to the system using DC-AC converters. In DC MGs, DC buses employ rectifiers and...
inverters for connecting AC power units and DC loads to the system, respectively. The hybrid MG is a system which makes use of the benefits in both AC and DC MGs by incorporating both types of buses and technologies. In hybrid MGs, the AC and DC loads and DGs are connected to the buses with the same technology (DC or AC) which makes the MG cost-effective by avoiding unnecessary inverters or rectifiers. Extensive research has been conducted on different features of the MG for which the majority of them are focused on the AC MGs. In [6], a matrix real-coded genetic algorithm is applied to investigate the optimal schedule of AC MGs. A linear programming approach is proposed in [7] to minimize the cost of a solar-wind AC MG. An optimization method is devised in [8] to find the optimal fuel consumption pattern in a MG supporting the electrical/thermal energy demands. Moreover, in some studies, the interactive power exchange between an AC MG and the main grid are assessed [9-10]. A complete review on the optimal operation of AC MGs can be found in [11].

On the other hand, DC MGs can provide several benefits in comparison with AC MGs: 1) higher efficiency and lower power losses by omitting a number of converters used in AC MGs, 2) ease of usage for DC DGs such as photovoltaic, fuel cell and battery, 3) enabling bus ties to operate without the need to synchronize buses and 4) supplying DC loads such as electric vehicles and LED lights [12]. The increasing number of DC loads such as personal computers, laptops, LED lights, data and telecommunication centers, TVs, radios, etc., support the concept of DC MGs.

The third group belongs to the hybrid MGs which make use of the benefits of both AC and DC MGs. The main idea behind the hybrid AC-DC MGs is to supply both AC and DC loads when using the AC and DC power units in the corresponding parts. Less research has been performed in DC MG than AC MGs. Authors in [13] proposed a mixed integer linear model to provide balance between the generation and electric consumption considering the interconnection of AC and DC components of a hybrid MG. A multi-objective formulation based on NSGA-II is developed in [14] for optimal scheduling of DC MG to take into account the cost of energy circulation in storages. In [15], authors suggest a scheduling approach considering load/generation changes and time of use tariff for a low voltage DC MG incorporating battery energy storage, fuel cell and photovoltaic power generations. A hybrid AC-DC MG is proposed in [16] for better interconnection of DGs to the power grid for both AC and DC MGs.

While each of the above works have addressed significant topics that clarify the major role of hybrid AC-DC MGs, the research in this area is still in its infancy, especially in comparison to the rich literature of AC MGs. This paper aims to investigate the optimal operation and management of hybrid AC-DC MGs considering high penetration of renewable energy sources, traditional DGs and energy storage devices. The proposed hybrid MG considers two power exchanges to get to the optimal scheduling among the power sources. These schemes are: 1) power exchange between the AC and DC parts of the MG and 2) power exchange with the main grid. In order to reach realistic solutions, a stochastic framework based on an unscented transform is developed to model the uncertainties associated with the forecast data of wind turbine, photovoltaic output power, market price and active and reactive power values. The unscented transform is a newly introduced superposition approach which has revealed improved performance in nonlinear transformations and state estimators [17]. As it will be described later, the unscented transform is constructed to model any uncertainty with/without correlation among the uncertain parameters. The proposed approach is a complex nonlinear optimization problem which requires powerful tools for optimal solution. In this way, a new optimization algorithm called crow search algorithm (CSA) is devised which is inspired from the behavior of crows in nature [18]. In addition, a new two stage modification method is proposed to increase the diversity of crow population. The feasibility and performance of the proposed method are examined on practical IEEE 33-bus and typical low voltage test systems as AC and DC MGs, respectively, over a 24 hour horizon.

To the best of authors’ knowledge, this paper is the first work addressing the stochastic operation and management of hybrid AC-DC microgrids. The available research works in the AC-DC microgrids have mainly focused on the planning stage and none of them has focused on the operation and management studies with a deep insight. Therefore, in comparison with the existing literature, the main contributions of this work can be summarized as follows: 1) Developing a sufficient framework to assess the optimal energy management problem in the hybrid AC-DC microgrids. 2) Developing a novel and satisfactory stochastic optimization framework based on CSA and UT to solve the optimal energy management of AC-DC microgrids considering the high uncertainties associated with the prediction error in the wind turbine and photovoltaic output power, market price and consumers load demand. 3) Proposing a new two-stage modification method based on CSA to improve its search ability in the optimization applications.

The rest of this paper is organized as follows: Section II describes the problem formulation for the hybrid AC-DC MG. Section III describes the stochastic load flow based on the unscented transform. Section IV explains the modified CSA (MCSA) as the proposed optimization tool. The solution procedure is explained in Section V. The simulation results on the IEEE test system are devised in Section VI. Section VII explained the main outcomes of the work. Finally, the main concepts and conclusions are given in Section VIII.

II. HYBRID AC-DC MG

A. Hybrid AC-DC MG Technology

Hybrid AC-DC MG, presents an innovative way of thinking about design and development of sustainable grids that can easily transition towards smart grids. Technically, instead of having only AC or only DC MGs, hybrid MGs incorporate both AC and DC systems to maximize the efficiency and improve the quality of the electric power grid. Fig. 1 shows the conceptual illustration of hybrid AC-DC MGs in which various AC and DC power units and loads are connected to the corresponding DC and AC networks. The AC and DC links are connected together through converters to form hybrid MGs. Technically, MG control system should insure that 1) DGs and storage can be added or removed from the MG,
seamlessly, 2) equal and stable current sharing among parallel power converters or sources is provided, 3) adequate control on the output voltage fluctuations is available, and 4) desired power flow from/to each MG is satisfied. From the control structure, a microgrid control system is often implemented in a hierarchical manner, with three control loops: 1) the tertiary loop which manages the energy of the system and provides necessary power set points for devices, 2) secondary loop which receives power commands from the tertiary level and thus manages power by stabilizing bus voltages and facilitating current sharing, and 3) primary loop which provides device level control for power converters. There are a fairly high number of methods which will be discussed in the future works.

In terms of the microgrid stability, the widespread and high penetration of renewable energy sources e.g. photovoltaic or wind turbine, followed by disturbances, can be the reason for transient instability. Beyond that, hybrid microgrids can encounter even more challenges, especially in the islanding mode when the microgrid is disconnected from the main grid. In fact, the AC side of the microgrid can no longer be assumed as an infinite bus in the islanded mode which may result in voltage and frequency stability issues. Also, since the balancing control does not exist in a DC microgrid, the DC microgrid cannot maintain stability on its own in the islanded mode and needs to be connected to the AC microgrid. In order to overcome the stability issues in hybrid microgrids, the power balance between the AC and DC parts of the system should be maintained such that the stability is satisfied in both sides. In the AC part of the hybrid microgrid, both active and reactive load demands should be covered fully to keep the frequency and voltage stable. Also, energy storage can serve as ancillary services to maintain the stability of AC and DC parts of the hybrid microgrid for short durations when minimizing the total microgrid total costs during operation and long term analysis.

B. Problem Formulation

The problem formulation begins with the description of the cost objective function and is followed by the relevant constraints. It is worth noting that in this formulation, the $E(.)$ is the expected value of the parameter. The cost objective function incorporates the cost of power production by DGs, storage devices, RESSs and the main grid in the hybrid MG as follows:

$$\min \ E(f(X))= \sum_{i=1}^{N_g} \sum_{j=1}^{N_q} \{ [u_i^t E(p_{Gi}^t) B_{Gi}^t + S_{Gi}^u \max (0, u_i^t - u_i^{t-1}) + S_{Gi}^{off} \max (0, u_i^{t-1} - u_i^t)] + \sum_{j=1}^{N_q} [u_j^t E(p_{Gq}^t) B_{Gq}^t + S_{Gq}^u \max (0, u_j^t - u_j^{t-1}) + S_{Gq}^{off} \max (0, u_j^{t-1} - u_j^t)] + E(p_{Grid}^t) B_{Grid}^t \} \tag{1}$$

It is worth noting that in addition to the cost function alone, power losses and voltage profile are also assessed in the simulation results. In (1), $f(X)$ is the total cost of the hybrid MG. $X$ describes the optimal output power of DGs, storages, utility and their binary status variables as shown in (2):

$$X = [P_g, U_g, G_{(2<\alpha=N_g)}], \quad P_g^t = [P_{G1}^t, P_{S1}^t, P_{Grid}^t]; \quad \forall t \in N_T$$

$$P_{G1}^t = [p_{G11}^t, p_{G12}^t, \ldots, p_{G1N_g}^t], P_{S1}^t = [p_{S11}^t, p_{S12}^t, \ldots, p_{S1N_s}^t], P_{Grid}^t = [p_{Grid}^t]; \quad n = N_g + N_s + 1$$

$$\text{Fig. 1: Conceptual illustration of hybrid AC-DC MGs.}$$

In (3) the value 0 for the vector $U$ indicates OFF status while 1 indicates ON status of the relevant power unit as follows:

$$U_{g} = [u_1^t, \ldots, u_{N_g}^t], u_i^t \in \{0, 1\} \tag{3}$$

The problem constraints include both the constraints in the DC and AC parts of the MG. Power must cover load balance at both DC and AC section of hybrid MG. The demand and generation balance in the DC part of the MG is preserved in (4) as follows:

$$\sum_{i=1}^{N_g} E(p_{G1}^t) + \sum_{j=1}^{N_q} E(p_{Gq}^t) + E(p_{Grid}^t) = \sum_{k=1}^{N_{Load}} E(p_{Load_k}^t) \tag{4}$$

For the AC part, the demand and generation balance on each bus is preserved by the load flow equations as given in (5) and (6):

$$E(F_{mc}^{lin}) = \sum_{n=1}^{N_g} E(V_n^m)^d E(Y_{mn}^{lin}) \cos(\theta_{mn} + E(\delta_m^d) - E(\delta_n^d)) \tag{5}$$

$$E(Q_{mc}^{lin}) = \sum_{n=1}^{N_g} E(V_n^m)^d E(Y_{mn}^{lin}) \sin(\theta_{mn} + E(\delta_m^d) - E(\delta_n^d)) \tag{6}$$

Equations (5) and (6) are nonlinear formulations which are satisfied through the backward-forward ladder load flow.

In order to ensure of operation stability of MG, each power unit can generate within the limited range of its capacity as illustrated by (7):

$$p_{Gi,\min}^t \leq E(p_{Gi}^t) \leq p_{Gi,\max}^t \tag{7}$$

$$p_{Gq,\min}^t \leq E(p_{Gq}^t) \leq p_{Gq,\max}^t$$

$$p_{Grid,\min}^t \leq E(p_{Grid}^t) \leq p_{Grid,\max}^t$$

The amount of stored energy as well as the charge/discharge rate of battery storage is limited as follows:

$$\text{Min} \ E(f(X))= \sum_{i=1}^{N_g} [u_i^t E(p_{Gi}^t) B_{Gi}^t + S_{Gi}^u \max (0, u_i^t - u_i^{t-1}) + S_{Gi}^{off} \max (0, u_i^{t-1} - u_i^t)] + \sum_{j=1}^{N_q} [u_j^t E(p_{Gq}^t) B_{Gq}^t + S_{Gq}^u \max (0, u_j^t - u_j^{t-1}) + S_{Gq}^{off} \max (0, u_j^{t-1} - u_j^t)] + E(p_{Grid}^t) B_{Grid}^t \} \tag{1}$$

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The amount of stored energy as well as the charge/discharge rate of battery storage is limited as follows:
The unscented transform is one of the most well-known and direct approaches for modeling the correlated uncertainty. In 2007, in order to overcome the shortcomings of the above methods, the unscented transform was introduced. The unscented transform method takes advantage of the fact that it is easier to approximate a probability distribution function (PDF) than an arbitrary nonlinear function. With respect to technical classification, there are three different techniques for modeling uncertainty [17]: 1) Monte Carlo Simulation (MCS) 2) analytical methods and 3) approximate methods. The main deficiency of MCS is the large number of runs required for convergence. On the other hand, analytical methods are computationally efficient but work on the basis of some mathematical assumptions for simplifying the problem. In the last group, approximate methods exist that have overcome the above shortcomings and therefore can be more useful. The unscented transform technique is one of the most well-known methods among the approximate methods. The main feature of unscented transform method is its simple concept and direct approach for modeling the correlated uncertainty. In addition, easy coding and simplicity, high ability of capturing uncertainty and low computational burden are special characteristics that make the unscented transform a suitable tool among the other methods in the area. The superiority of this algorithm over the other stochastic methods such as Monte Carlo Simulation and point estimate method is demonstrated in [17]. Considering \( v \) number of uncertain parameters in the problem, unscented transform solves the problem \( 2v+1 \) times to capture the uncertainty effects. In order to describe the unscented transform, it is simpler to consider the nonlinear load flow equations in the form of a nonlinear function as \( S = f(Z) \) wherein \( Z \) and \( S \) are the input and output vectors of the uncertain parameters. In order to model the standard deviation of uncertain parameters, a covariance matrix \( P_z \) is used. In fact, it is the elements of \( P_z \) matrix that determines which parameters are uncertain and which parameters are correlated uncertain. The diagonal elements of matrix \( P_z \) are the variance of the uncertain variables and the non-diagonal elements are the covariance among different uncertain parameters (here correlation is between two WTs which are installed, one in the AC part and one in the DC part of the hybrid microgrid). Using the above equations, the following steps are required to obtain the expected value \( \mu_s \) and variance of output variables \( P_{ss} \):

**Step 1:** Evaluate 2\( v \)+1 concentration points \( s \) from the input random data:

\[
s^0 = \mu \quad (12)
\]

\[
s^k = \mu + \left( \frac{v}{1-W^{0}} P_{zz} \right) ; k = 1,2,\ldots,v
\]

**Step 2:** Evaluate the weighting factor of each sample point using (15), (16) and (17):

\[
W^0 = 1
\]

\[
W^k = \frac{1-W^{0}}{2v} ; k = 1,2,\ldots,v
\]

\[
W^{k+v} = \frac{1-W^{0}}{2v} ; k + v = v+1,\ldots,2v
\]

In order to normalize all solutions, the union of weighting factors equals to one:

\[
\sum_{k=0}^{2v} W^k = 1
\]

**Step 3:** Calculate the output function for 2\( v \)+1 input concentration points as follows:

\[
S^k = f(Z^k)
\]

**Step 4:** By the use of (19), calculate the mean \( \mu_s \) and covariance \( P_{ss} \) of the output value:

\[
\mu_s = \sum_{k=0}^{2v} W^k S^k
\]

\[
P_{ss} = \sum_{k=0}^{2v} W^k (S^k - \mu_s)(S^k - \mu_s)^T
\]
being the next victim. In other words, they use their own experience as a thief to predict the same behavior from other crows and find the most secure place to preserve their catches from being stolen. Using these biologically inspired ideas, CSA is created to introduce a powerful heuristic optimizer for solving the nonlinear optimization problems. Each crow in the population indicates a feasible solution for the optimization problem. In fact, each crow is a vector in which each element shows a possible optimal value/status for the corresponding variable. In this problem, the optimal value and status of DGs, storage devices and main grid form the elements of each crow as shown in (2). Additionally, the crow population shows a set of feasible solutions for the proposed optimization problem. CSA is constructed using four main rules [18]: 1) crows live in flocks, 2) crows memorize the position of their hiding places, 3) crows follow each other to do thievery and 4) crows protect their caches from being pilfered by a probability. 

\[ X_{i}^{\text{iter}+1} = X_{i}^{\text{iter}} + r_{i} \times f_{i}^{\text{iter}} \times (M_{j}^{\text{iter}} - X_{j}^{\text{iter}}) \quad i = 1,...,N \quad (22) \]

Where, \( M_{j} \) is the position of the hiding place of the crow, which is the best position that crow \( j \) has obtained so far. Fig. 2 shows the schematic diagram of the above algorithm. According to Fig. 2, small values of \( f_{l} \) guide the CSA toward the local search (in the neighboring of \( X_{i} \)) and large values of \( f_{l} \) lead to the global search (far from \( X_{i} \)). In case the crow \( X_{j} \) knows that a crow \( X_{l} \) is following it, it will change its flight path to fool the crow \( X_{j} \) and protect its nest from attack. Considering a constant value \( \Gamma \) for the awareness of crow \( X_{j} \) about being followed, it will change its flight path using equation below:

\[ X_{i}^{\text{iter}+1} = \begin{cases} 
X_{i}^{\text{iter}} + r_{j} \times f_{j}^{\text{iter}} \times (M_{j}^{\text{iter}} - X_{j}^{\text{iter}}) \quad ; \quad r_{j} \geq 1^{\text{iter}} \\
X_{\text{rand}} \quad ; \quad r_{j} < 1^{\text{iter}} 
\end{cases} \quad (23) \]

In CSA, the parameter \( \Gamma \) is used to provide balance between the intensification and diversification during the optimization process. As the value of \( \Gamma \) is decreased, CSA tends to search in the local area and vice versa.

![Fig. 2: schematic diagram of crow search improvement stage.](image)

Technically, there are some significant features in CSA which can distinguish it from other well-known evolutionary based optimization algorithms such as PSO and GA. First, it should be noted that parameter setting is a significant and influential issue in the optimization algorithms. Owing to the complexity and time-consuming nature of parameter setting, algorithms with a lower number of parameters are more preferable. PSO algorithm perform based on four parameters including the inertia weight, maximum value of velocity, individual learning factor and social learning factor. In GA, selection method, crossover method, crossover probability, mutation method, mutation probability and replacement method are the adjusting parameters which need to be determined, precisely. Nevertheless, CSA includes only two adjusting parameters of flight length and awareness probability. Second, in contrast to the GA and PSO which are greedy algorithms, CSA is considered as a non-greedy algorithm. In fact, CSA will move to the new position generated by a crow even if that new position is not better than its current position. From the mathematic point of view, non-greedy algorithms can increase the population diversity in the new generations more than the greedy algorithms, which can improve the optimization process more effectively. The superiority of CSA over the original and several different versions of PSO and GA is demonstrated in literature [18].

In addition, CSA algorithm has some special characteristics such as: simple concept, ease of implementation, fast convergence, capability of solving both discrete and continuous optimization problems, proper balance between the local search and global search and having few settings, parameter which make it an appropriate tool for the optimization. Nevertheless, this paper introduces a new two stage modification method to increase the total search ability of CSA. The first part of the proposed modification method makes use of the best current solution \( G_{\text{best}} \) of the crow flock to guide other solutions toward a more optimal position. Considering the velocity \( V_{i} \) for the crow \( X_{i} \), its position is moved toward \( G_{\text{best}} \) using (24) and (25):

\[ X_{i}^{\text{iter}+1} = X_{i}^{\text{iter}} + V_{i}^{\text{iter}+1} \quad (24) \]

\[ V_{i}^{\text{iter}+1} = V_{i}^{\text{iter}} + \beta_{1} (G_{\text{best}} - X_{i}^{\text{iter}}) \quad (25) \]

The second modification method makes use of the crossover and mutation operators from genetic algorithms to increase the diversity of the population. In this way, for each crow \( X_{i} \), three different crows \( X_{m1}, X_{m2} \) and \( X_{m3} \) are chosen such that \( m_{1} \neq m_{2} \neq m_{3} \). Now, by the use of the mutation operator from genetic algorithm, a new mutated solution is produced as follows:

\[ X_{\text{mut}} = X_{m1} + \beta_{2} (X_{m2} - X_{m3}) \quad (26) \]

By the use of \( X_{i}, G_{\text{best}} \) and \( X_{\text{mut}} \), three test solutions are generated using the crossover operator as shown in (27), (28) and (29):

\[ X_{\text{Test1,}i} = \begin{cases} 
x_{\text{mut,}i} 
; \quad \beta_{2} \leq \beta_{3} \\
x_{\text{Best,}i} 
; \quad \text{else}
\end{cases} \quad (27) \]

\[ X_{\text{Test1,d}} = [x_{\text{Test1,}1}, x_{\text{Test1,}2}, ..., x_{\text{Test1,d}}] \quad (28) \]

\[ X_{\text{Test3,i}} = \beta_{3} X_{\text{best}} + \beta_{4} (X_{\text{best}} - X_{i}) \quad (29) \]

The best solution among the above three test solutions is chosen and compared with \( X_{i} \), if it is better than \( X_{i} \), it replaces \( X_{i} \), and otherwise \( X_{i} \) is preserved in its position.

The last part of the modification method deals with updating the value of \( \Gamma \) during the optimization process. At the beginning of the optimization process, it is preferred to have a global search. Thus, \( \Gamma \) should have large values. Similarly, at the end of the optimization process, the \( \Gamma \) parameter should have small values in order to provide the opportunity of local
search. These ideas can be shown in the form of a dynamic formulation as follows:

\[ I_i^{\text{iter+1}} = I_i^0 [1 - e^{-\rho \text{iter}}] \]  

(30)

V. APPLICATION PROCEDURE

This section describes the application of MCSA and the unscented transform to solve for the optimal operation of hybrid AC-DC microgrids.

The sequence of steps for applying MCSA algorithm to minimize total operation cost of MG, are given below:

Step 1: All input data are defined for MG and MCSA algorithm initially. These initial data include the data of MCSA (the initial population size, termination criterion and control vectors), stochastic load flow based on unscented transform (number of uncertain parameters, standard deviation and mean value of uncertain parameters) and the hybrid microgrid data (the data of DGs, renewable energy sources, hourly energy price, storage devices, load demand, network topology and voltage level in both DC and AC sections).

Step 2: By assuming a \( d \)-dimensional search space including \( N \) crows, initialize memory of each crow in which the position of its hiding place is a feasible solution is memorized.

Step 3: Change the constrained optimization problem into an equivalent unconstrained problem using penalty factors.

Step 4: Generate an initial crow population or state matrix \( X \) which consists of: the output power for RESs, DGs, battery energy storage and utility; and status of them within their operations mode. Each crow simulates a feasible solution for the optimization of the MG; therefore, a specific number of crows are generated initially to determine the optimal output power as well as ON or OFF status of the power units in the hybrid microgrid.

Step 5: Evaluate the fitness (objective) function value for each crow in terms of computing the stochastic power flow into the objective function. In order to solve the problem, the stochastic power flow is computed to calculate the expected value of the cost function for each crow in the population. Each time a crow (solution) is generated in the feasible region of the problem space (such that the problem constraints are met), the cost function should be calculated. Using the \( 2n+1 \) sample points generated for problem in (12) - (14), the cost function is calculated \( 2n+1 \) times to model the uncertainty effects.

Step 6: Choose the best crow in the population \( G_{\text{best}} \). Since the problem is a minimization problem, the crow (solution) with the lowest value of expected cost function is chosen as \( G_{\text{best}} \) and is stored.

Step 7: Generate new position in search space to improve crow population as described in Section IV. The new improved position of the crow is obtained from (22) and (23), respectively. Feasibility of the new position is checked to satisfy all constraint.

Step 8: Apply the proposed modification method to improve the crow population once more. Using (24)-(30), the positions of crows are updated in the population.

Step 9: The crows or feasible solution update. In other words, the position \( G_{\text{best}} \) is updated.

Step 10: Check the maximum number of iterations as the termination criterion, if it is reached finish the optimization process and the best position of the memory in terms of the objective function value (cost) is reported as minimum operation cost, otherwise return to step 7 and repeat the algorithm.

Fig. 3. Block diagram of operation management of MG using MCSA algorithm.
VI. RESULTS

This section is devoted to the simulation results on the IEEE standard test system to clarify the main features of the proposed stochastic framework. The hybrid MG test system includes the IEEE 33-bus test system as the AC network with an interconnection to the DC network at bus 18. Fig. 1 shows the schematic diagram of the hybrid test MG. As can be seen from Fig. 1, the DC and AC parts of the MG are connected to each other through a AC-DC converter. The voltage level of the AC side is 12.66 kV. The complete data for the AC MG can be found in [19-20] and for the DC MG from [21]. In the hybrid MG, two micro turbines (numbers 2 and 3) are installed on buses 12 and 25 as shown in Fig. 1. Also, a wind turbine (number 2), with the same pattern as Fig. 4, is considered on bus 30. The DC MG is connected to the AC MG on bus 18. In order to highlight the power exchange between the AC and DC parts of the hybrid MG, the capacities of DGs in the network are updated. Table I shows the complete data of the hybrid MG.

The analysis is done for 24 hours. Based on costs and benefits, the MG can decide to buy or sell energy from or to the main utility at different hours of the day. Fig. 4 shows the hourly forecast wind turbine and photovoltaic output power, utility energy price and load demand, respectively. It is worth noting that all the initial data of the microgrid in Fig. 4 including the market price are taken from [20]. Nevertheless, in order to have the cost values in $ units, the hourly market price of ref. [20] are transferred from (ct/kWh) currency unit into the $/kW currency unit in this paper. The capacity data and price of power production by each unit are shown in Table I [20]. It is worth noting that in this paper, a set of batteries connected in parallel and series structures are assumed to supply any load with different voltage and current levels. The hourly charge and discharge rate for the set of batteries is assumed to be 150 kW, which is met in all scenarios. It is clear that other charge and discharge rates can be considered and applied on the problem in the similar way. We have reserved adding this future complexity as a future work to be addressed in hybrid AC/DC microgrids [21]. Among these DGs, wind turbine and photovoltaic sources are assumed as non-dispatchable units. Therefore, their hourly power productions are purchased by the DC MG to support the idea of renewable energy sources. Also, it is assumed that WTs on AC and DC parts of the hybrid microgrid are correlated with a correlation coefficient of 0.5. As it can be seen from Table I, the energy production price is different for different types of DGs. Therefore, turning off the more expensive DGs at hours in which the power generation exceeds the load demand is an economical and beneficial decision for reducing the microgrid cost. In other words, it is not economical to preserve all DGs ON when the total load demand can be supplied by some of the cheaper DGs.

In order to evaluate the role of each power unit in the supply, three different scenarios are defined here. In scenario one, all DGs are working (ON mode/in service) and the NiMH-Battery is fully charged. In the second scenario, operators can decide to tradeoff between ON/OFF status of DGs according to the MG requirements and benefits. It is clear that this scenario provides more flexibility for DGs. In this scenario, battery has the same situation as the first scenario. In the third scenario, the initial charge of battery is zero and it has to charge at the beginning of the day to be able to discharge for the rest of the day. DGs can shift between ON and OFF modes depending on the economical preferences.

![Normalized forecasted WT power generation](image)

![Forecasted real-time market price](image)

Fig. 4 Forecast values of load demand, market price and photovoltaic and wind turbine power units [20].

In the first part of the simulations, the effectiveness and reliability of the proposed optimization framework based on MCSA is assessed. Table II depicts the simulation results for three scenarios. The results of energy losses, maximum voltage deviation and total network costs are provided in the table for all scenarios to obtain better understanding. Additionally, for better comparison, the simulation results of particle swarm optimization (PSO), genetic algorithm (GA) and original CSA are provided. According to these result, the proposed MCSA will obtain an optimal solution which is not found by PSO, GA and CSA. In fact, the proposed MCSA shows superior performance for searching the problem space over other algorithms. One significant point is that while the objective function is optimizing the cost of the MG, the energy losses and voltage profile of the system is improved too. This illustrates that the cost function has a strong correlation with the voltage and losses of the network.

![Comparing energy losses, voltage deviation and cost functions](image)

**Table II**

<table>
<thead>
<tr>
<th>Case</th>
<th>Energy Losses (kWh)</th>
<th>Voltage Deviation (pu)</th>
<th>Cost Value (€ct)</th>
<th>CPU (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Status</td>
<td>4,065.4</td>
<td>0.0869</td>
<td>105,826.1</td>
<td>-</td>
</tr>
<tr>
<td>First Scenario</td>
<td>GA</td>
<td>3,265.3</td>
<td>0.0856</td>
<td>90,048.3</td>
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<tr>
<td></td>
<td>PSO</td>
<td>3,245.1</td>
<td>0.0846</td>
<td>89,994.6</td>
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<tr>
<td></td>
<td>CSA</td>
<td>3,251.9</td>
<td>0.0839</td>
<td>90,008.8</td>
</tr>
<tr>
<td></td>
<td>MCSA</td>
<td>3,216.2</td>
<td>0.0801</td>
<td>89,710.2</td>
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</tbody>
</table>
In order to better understand the difference between these three scenarios, Tables III, IV and V show the optimal power dispatch of different units for the first, second and third scenario by MCSA, respectively. According to these results, the fuel cell as a cheap DG works at its maximum capacity during most of the scheduling hours. On the other hand, micro turbines due to their high-energy price are preferred to generate power during the peak load hours. The amount of power exchange between the AC and DC parts of the hybrid MG illustrates that during the initial hours of the day in which the electricity price is low, the DC MG extracts energy from the AC part so as to store it in the battery. Therefore, during the peak load hours, this energy exchange reverses and the DC part helps the AC part of the MG by transferring energy to it and reducing the amount of energy required from the main utility. This is an economical policy which can reduce the total cost of the hybrid MG. The simulation results for the second and third scenarios show that letting DGs switch between the ON and OFF status can provide more independence to the MG central control to reduce the operation cost and improve the electrical services.

### Table III

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<thead>
<tr>
<th>Time (hour)</th>
<th>DG Sources (kWh)</th>
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<td>0</td>
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In the second part of the simulation, the voltage profile of the system under different scenarios is investigated to show effectiveness of the hybrid MG. Fig. 5 shows the maximum voltage deviation of the buses from the nominal value during the 24 hours of operation and for different scenarios. According to this figure, the voltage profile of the system is improved in comparison to the initial case wherein there is no DG or storage in the system. Considering these results, the hybrid MG could improve the voltage profile of the system depending on the operation conditions and preferences. Finally, Table VI shows the optimal values of the cost objective function for the three scenarios in the stochastic framework. Here, the uncertainties associated with the forecast error in the active and reactive loads, market price, wind turbines and photovoltaic output power are modeled using the proposed unсertainty transform. For better comparison, the results of the deterministic framework are shown in this table. These results show that considering uncertainty has increased the optimal values of all objectives. This is the cost that we pay to operate the microgrid in a more realistic environment considering different effective probabilities.

### Table V

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<th>Time (hour)</th>
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VIII. CONCLUSION

This paper addresses the optimal operation and management of the hybrid AC-DC MG using a stochastic framework based on unscented transform and MCSA. The proposed stochastic method is employed in three different scenarios to solve the operation problem involving different types of AC and DC DGs and loads in the IEEE test system. In order to execute the search ability of the MCSA, the simulation results in the first part focused on the algorithm performance. The results show the superior performance of MCSA over a number of well-known methods in the area. It is noticed that DC and AC parts of the MG can have a good collaboration by exchanging power and energy during the day to minimize the total cost of the hybrid MG. By comparing different scenarios, it was shown that the scenario with higher flexibility for turning ON and OFF DGs will reduce operation cost, lower energy losses and provide better voltage profile. In a comparison to the initial case of the network, it is deduced that the hybrid MG can benefit the system significantly. Even though the operation cost in the stochastic framework is higher, it provides more a realistic result than the deterministic framework by incorporating the uncertainties of the forecast error in the problem formulation. Future work will focus on the analysis of integrated power and energy management layers and their role on the stability of the hybrid AC-DC microgrids.

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REFERENCES

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References:


