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Distributed Control in Hybrid AC-DC Microgrids Based on a Hybrid MCSA-ADMM Algorithm

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ABSTRACT This paper proposes an effective framework for optimal operation management of hybrid AC-DC microgrids incorporating both dispatchable and non-dispatchable energy sources as well as battery storage. The proposed method is constructed based on a fully distributed consensus-based structure making use of a multi-agent mechanism and alternating direction method of multipliers (ADMM). The proposed framework decomposes the microgrid into several agents within which the neighboring agents share the consensus variable (mismatch power flow) with each other. Each agent tries to minimize its own cost based on the consensus variable value received from the other agents. An augmented objective function is then formulated which is nonlinear and needs to be optimized. Due to the high nonlinearity of the objective function, a new optimization method based on crow search algorithm (CSA) is developed to find the optimal local solutions for each agent and drive the ADMM to have a mature convergence. A modified method based on crossover and mutation operators is introduced to increase the search ability of CSA. The performance of the proposed framework is assessed using a typical hybrid AC-DC microgrid with distributed energy resources. The simulation results show the high efficacy of the proposed method in comparison with other methods.

INDEX TERMS Alternating Direction Method of Multipliers, Distributed Control, Emission, Hybrid Micro-grid, Multi-Agent, Optimization Algorithm.

NOMENCLATURE

A. SETS/INDICES

Ω^G/i	Set/index of generators
Ω^T/t	Set/index of operation time horizon
Ω^s/z	Set/index of storage units
Ω^D/k	Set/index of load demand levels
Ω^F/m	Set/index of feeders
$\Omega^N/j, l$	Set/index of neighboring agents
$\Omega^C/n, n'$	Set/index of crow/solutions

B. VARIABLES

E_τ^{ess}	Battery charged energy at time τ
fl_n^{Iter}	Flight length of crow n in iteration $Iter$
f	Objective function value
$Iter$	Iteration number in ADMM
$M_{n'}^{Iter}$	Mean of the crow population in iteration number $Iter$
$P_{i,t}^G$	Output power generation of the ith DG at time t
$P_{i,l,t}^G$	Output power generation of the ith DG in l^{th} agent at time t
P_t^{grid}	Output power generation of the grid at time t
$P_{j,t}^{grid}$	Output power generation of the grid in l^{th} agent at time t
$P_{z,t}^s$	Output power generation of zth storage at time t

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$P^{s}_{z,l,t}$	Output power generation of zth storage in l^{th} agent at time t
$P^{Line}_{m,t}$	Power flow at line m at time t
P_{ij}	Consensus variable
r_n	Random number with uniform distribution in [0, 1]
W^{M}	Crow mean population
X^{Iter}_{n}	Crow n at iteration $Iter$
X	Control variable representing the problem variables
y	Dual variable or Lagrange multiplier
$Z_{j,i,t}$	Consensus variable sending from agent j to agent i
ρ	augmented Lagrangian parameter
Γ^{Iter}_{n}	Crow awareness constant
θ_T	accelerating parameter
ϕ_1, ϕ_2, ϕ_3	Random number in the range (0, 1]

C. PARAMETERS

$B^{s}_{z,t}$	Price of power generation by z[th] storage at time t
$B^{G}_{i,t}$	Price of power generation by i[th] DG at time t
B^{grid}_{t}	Price of power generation by the grid at time t
d	Length of each crow/solution
E^{ini}	Initial battery charge
$E^{ess,\min}/E^{ess,\max}$	Minimum/maximum energy capacity of battery storage
$P^{Line,\max}_{m}$	Maximum allowed power flow at line m
$P^{G,\min}_{i,t}/P^{G,\max}_{i,t}$	Minimum/maximum power capacity of generator
$P^{s,\min}_{z,t}/P^{s,\max}_{z,t}$	Minimum/maximum power charging/discharging rate of storage unit
$P^{grid,\min}_{t}/P^{grid,\max}_{t}$	Minimum/maximum power capacity of main grid
$P^{D}_{k,t}$	Load demand at time t and level k
ρ	Augmented Lagrangian parameter

I. INTRODUCTION

According to the power and energy society, microgrid (MG) is defined as a set of distributed generations (DGs) and interconnected loads with specified electrical borders [1]. Such a system can decide to operate either in islanded or grid-connected mode depending on the situation and operator preferences. The idea of MG helps the power system operator to have a better opportunity for providing the electrical services with higher power quality without the need of high investment for transmission and distribution expansion. In addition, reducing the power losses, operation costs, voltage deviation, increasing reliability and average energy supplied to the consumers are other primary benefits coming out of the MG concept [2], [3]. This has motivated the researchers in recent years to focus on different aspects of microgrid technology. The research works show [3] that a microgrid can help to reduce the high capital costs on the shoulder of the utilities by supporting part of the electric consumers locally. In a technical classification, MGs can be divided into three main groups of AC MG, DC MG and hybrid AC-DC MG. AC MG is the most popular and widely spread type and dominates recent research in the power system society [4]. In AC MGs, AC loads are directly supplied while the DC loads are connected through the converters. On the other hand, DC MGs employ rectifiers and inverters in order to support both AC and DC loads by AC power sources. With respect to AC MGs, DC MGs provide new benefits including but not limited to higher efficiency due to omitting converters, less power losses by avoiding unnecessary power electronic devices and facilitating use of popular DC sources such as fuel cell (FC) and photovoltaic (PV) units. A complete comparison of AC and DC MGs can be found in [5], [6]. In the third group, hybrid MGs exist which bring together the benefits of both AC and DC MGs, called a hybrid AC-DC MG. Omitting the traditional costly devices such as rectifiers and inverters in either AC or DC parts helped the AC-DC MGs to get a more economic option for the current power systems [7]. In comparison with the rich research works done on the AC MGs and DC MGs, the hybrid AC-DC MGs still need more research to clarify their different aspects.

A proper research survey on the current technologies of hybrid AC-DC MGs and their structures is provided in [8]. Unfortunately, in comparison with other types of MGs, the number of research efforts on the technology of hybrid MGs is limited. In [9], a mixed integer linear model is formulated for hybrid AC-DC MGs which can provide power balance between generation and consumption sides in both AC and DC parts of the MG. In [10], a multi-objective framework is introduced to optimize both MG costs and emissions using a so-called NSGA-II algorithm. In [11], a tariff price-based management method is proposed to reduce the hybrid MG costs when keeping the adequate balance between the power generation and consumption. Here the DC part of the MG has battery storage, FC and PV units. In [12], a new power management approach based on hybrid energy storage systems is used to investigate the optimal scheduling of a hybrid MG at the grid-connected mode. In [13], a power management method based on three-phase back-to-back converters is proposed to control power dispatch in a hybrid MG.

A complete overview on the hybrid AC-DC MG power management is found in [14]. While each of the above works have provided valuable results in the area of MGs, especially the hybrid type, all of them operate in a centralized framework such that all data needs to be sent to a main center and after analysis the optimal decisions are sent back to the units. In contrast to the centralized control method, another control approach exists which divides the MG into several agents and optimizes the units locally. Such a novel control method can bring many benefits including less computational burden and higher resiliency. In [15], power control and management in a hybrid AC-DC MG is addressed using a decentralized control method based on AC and DC DERs. Such a decentralized architecture will allow different AC or DC loads and sources be flexibly located to decrease the required power conversion stages and system cost and efficiency.

In [16], a community MG with a number of AC and DC MGs is introduced and analyzed. Each MG may have a different frequency and voltage requirement thus requiring a self-controlled entity for the operation. At the same time, it should be able to cooperate with neighboring MGs for increasing its economic gains and reliability. In [17], an independent control mechanism is employed for controlling the interlinking converters in the hybrid MGs. As a result, the hybrid MG operates in the autonomous mode with active power proportionally shared among its DERs. In [18], a decentralized power management and load sharing approach is developed for operation of a hybrid islanded MG integrating PV and battery storage units. The decentralized approach for data transfer between different agents avoids the need for communication links among them. In [19], first a centralized non-convex energy trading formulation is proposed for the optimal energy and demand response management in the distribution grids. It tries to handle the uncertainties associate with the renewable energy sources through a probabilistic power flow. Using convex relaxation techniques and appropriate price signaling, a decentralized energy trading algorithm is devised. While this work has shown great progress in the area of energy management of systems, nevertheless the formulation is not still fully distributed and needs further investigation. A complete review on the different control strategies of hybrid AC-DC MGs can be found in [20].

While each of the above works in the decentralized power/energy control of hybrid MGs could provide valuable improvements, the research in this area is still in its infancy. In other words, there are still considerable gaps in the optimal energy management of hybrid AC-DC MGs in a realistic scenario considering all affective elements in these MGs. To this end, this paper aims to propose a new distributed energy management framework for hybrid AC-DC MGs considering different AC and DC DER technologies such as PVs, wind turbines (WT), micro turbines (MT), FCs and batteries as the storage units. The proposed hybrid MG is decomposed into several agents in which each agent can interact with the neighboring agents to reach consensus. To this end, we introduce a hybrid alternating direction method of multipliers (ADMM) and crow search algorithm (CSA) which can obtain a global optimal solution in very few iterations. The role of CSA is to act as an optimizer for ADMM in order to escape from the many local optima in the problem. In addition, a new two-stage modification method based on crossover and mutation operators is presented to enhance the search ability of CSA and avoiding premature convergence (called modified CSA or shortly MCSA).

Mainly, the biological algorithms based on their non-linearity and non-convexity nature are used on the centralized control scheme to avoid the complexity and guarantee the optimal operation of the system. However, the ever-increasing growth of renewables with their intermittence nature and distributed generations require an integrated control scheme to be able to catch the non-linearity of the system besides the capability of implementation in real-time distributed manner. Thus, mixture of a non-linear optimization approach with the well-known distributed framework such as ADMM can be leveraged to provide a reliable and resilient solution for large scaled network with diverse generations and loads. To summarize, the main contributions of this work are:

- Employing CSA for the first time as a powerful non-linear optimizer to solve the conventional ADMM for obtaining a global solution and mixed integer nature of the proposed optimization problem necessitates the use of a powerful optimization algorithm which can escape from the many local optima while avoiding the premature convergence
- Developing a hybrid ADMM-CSA optimization approach for distributed energy management in hybrid AC-DC MGs
- Developing a two-stage modification method based on crossover and mutation operators to reinforce the CSA for escaping from premature convergence and increasing its search capabilities
- Enhancing number of control parameters of MCSA for tuning the control and energy management system solving both discrete and continuous optimization problems
- Improving the hybrid ADMM-CSA optimization approach balance between the intensification and diversification during the iterative process.

The feasibility and satisfying performance of the proposed method is examined on a notional hybrid AC-DC MG incorporating different DERs such as PV, WT, FC, MT and battery storage as well a connection with the upstream grid for optimal power exchange. The rest of this paper is organized as follows: Section II explains the proposed distributed energy management formulation based on ADMM. Section III describes the new CSA algorithm along with its two-stage modification method. The simulation results are shown and analyzed in Section IV. In Section V, the main outcomes and benefits of the proposed method are discussed. Finally, Section VI reveals the main conclusions and concepts of this work.

II. DISTRIBUTED ENERGY MANAGEMENT FORMULATION IN HYBRID AC-DC MG

In this section, distributed energy management problem is explained. To this end, first the conventional energy management problem is explained and then it is reformulated to its distributed form. The conventional energy management problem is a constrained centralized formulation, optimizing the total MG costs, incorporating the cost of power production by DERs, storage devices, renewable energy sources (RESs) and the main grid in the hybrid MG as follows:

$$\text{Min} \quad f(X) = \sum_{t\in\Omega^T} \left\{ \begin{array}{l} \sum\limits_{i\in\Omega^G} P_{i,t}^G B_{i,t}^G + \sum\limits_{z\in\Omega^s} P_{z,t}^s B_{z,t}^s \\ + P_t^{grid} B_t^{grid} \end{array} \right\} \tag{1}$$

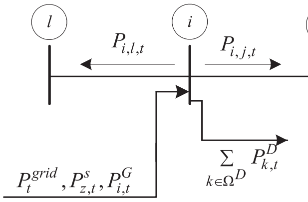

FIGURE 1. Conceptual illustration of converting local variables into their equivalent consensus variables.

The above objective function is optimized (minimized) meeting several equality and inequality constraints as follows:

- Power generation and demand balance should be met using the following equation:

$$P_{i,t}^G + P_{z,t}^s + P_t^{grid} = \sum_{k\in\Omega^D} P_{k,t}^D \tag{2}$$

- The maximum and minimum power capacity of each DER, storage unit or the main grid:

$$\begin{aligned} P_{i,t}^{G,\min} &\le P_{i,t}^G \le P_{i,t}^{G,\max} \\ P_{z,t}^{s,\min} &\le P_{z,t}^s \le P_{z,t}^{s,\max} \\ P_t^{grid,\min} &\le P_t^{grid} \le P_t^{grid,\max} \end{aligned} \tag{3}$$

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

$$E_\tau^{ess} = E^{ini} - \sum_{t=1}^{\tau} P_{z,t}^s \tag{4}$$

$$E^{ess,\min} \le E^{ess} \le E^{ess,\max} \tag{5}$$

- Considering the thermal limits, each feeder is allowed to transfer a specific amount of power as follows:

$$|P_{m,t}^{Line}| < P_m^{Line,\max} \tag{6}$$

In order to make it possible to have a distributed multi-agent formulation for the energy management problem, we need to first change the local variables in each agent into a consensus variable, transferring between different agents. Based on the above formulation, the local variables which are considered to be optimized are the amount of power produced either by DGs $P_{i,t}^G$, storage units $P_{z,t}^s$or the main grid $P_{i,t}^{grid}$. These sources produce or consume power locally depending on their types. In any case, the local variables $P_{i,t}^G$, $P_{z,t}^s$and $P_{i,t}^{grid}$can be represented in the form of consensus variables P_{ij} being exchanged with the neighboring agents as shown in Fig. 1.

According to Fig. 1, the amount of power injected/extracted to/from each agent can be shown as follows:

$$\begin{aligned} P_{i,t}^G &= \sum_{k\in\Omega^D} P_{k,t}^D + P_{i,j,t}^G + P_{i,l,t}^G \\ P_{z,t}^s &= \sum_{k\in\Omega^D} P_{k,t}^D + P_{z,j,t}^s + P_{z,l,t}^s \\ P_t^{grid} &= \sum_{k\in\Omega^D} P_{k,t}^D + P_{j,t}^{grid} + P_{l,t}^{grid} \\ &\forall i \in \Omega^G, \forall t \in \Omega^T, \forall j,l \in \Omega^N, \forall z \in \Omega^s \end{aligned} \tag{7}$$

In the above equation, the term $\sum_{k\in\Omega^D} P_{k,t}^D$ shows the total load demand in the corresponding agent which is assumed to be constant (not a variable). Therefore, the local variables $P_{i,t}^G, P_{z,t}^s, P_t^{grid}$ can be replaced by their equivalent values in (8). Eq. 7 is written specifically for an agent with two neighbors. For an agent with N number of neighboring agents, (7) is expanded as follows:

$$P_{i,t}^G = \sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{i,j,t}^G; \quad \forall i \in \Omega^G, \forall t \in \Omega^T \tag{8-a}$$

$$P_{z,t}^s = \sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{z,j,t}^s; \quad \forall z \in \Omega^s, \forall t \in \Omega^T \tag{8-b}$$

$$P_t^{grid} = \sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{j,t}^{grid}; \quad \forall t \in \Omega^T \tag{8-c}$$

Based on (8), the energy management problem can be reformulated in a new consensus based distributed style. The cost of power production in each agent is calculated as follows:

$$\text{Min} \quad f(P_{i,j,t}^G) = \sum_{t\in\Omega^T} \left\{ \left(\sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{i,j,t}^G \right) B_{i,t}^G \right\} \quad \forall i \in \Omega^G \tag{9}$$

The above equation is provided for agents with DG. For agents with battery storage or main grid, the same equations can be derived as follows:

$$\text{Min} \quad f(P_{z,j,t}^s) = \sum_{t\in\Omega^T} \left\{ \left(\sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{z,j,t}^s \right) B_{z,t}^s \right\} \quad z \in \Omega^s \tag{10}$$

$$Min \quad f(P_{j,t}^{grid}) = \sum_{t\in\Omega^T} \left\{ \left(\sum_{k\in\Omega^D} P_{k,t}^D + \sum_{j\in\Omega^N} P_{j,t}^{grid} \right) B_t^{grid} \right\} \tag{11}$$

On each agent, the corresponding objective function in (9)–(11) is optimized meeting some constraints. For the thermal limitation on each feeder (6), the equivalent constraint is achieved as follows:

$$|P_{i,j,t}^G| < P_{mi}^{Line,\max}; \quad \forall i \in \Omega^G, \forall m \in \Omega^F, \forall t \in \Omega^T \tag{12}$$

$$|P_{z,j,t}^s| < P_z^{Line,\max}; \quad \forall i \in \Omega^s, \forall m \in \Omega^F, \forall t \in \Omega^T \tag{13}$$

$$|P_{j,t}^{grid}| < P_m^{Line,\max}; \quad \forall m \in \Omega^F, \forall t \in \Omega^T \tag{14}$$

Equation (12), (13) and (14) preserve the thermal limit on each feeder connecting agents with a DG, storage device or the main grid, respectively.

In order to see the maximum and minimum power generation capacity of units in (3), the same way is followed. Therefore, for DGs we will have:

$$\sum_{j\in\Omega^N} P^G_{i,j,t} \le P^{G,\max}_{i,t} - \sum_{k\in\Omega^D} P^D_{k,t}; \qquad \forall i \in \Omega^G, \forall t \in \Omega^T$$
$$\sum_{j\in\Omega^N} P^G_{i,j,t} \ge P^{G,\min}_{i,t} - \sum_{k\in\Omega^D} P^D_{k,t}; \qquad \forall i \in \Omega^G, \forall t \in \Omega^T \tag{15}$$

$$\sum_{j\in\Omega^N} P^s_{z,j,t} \le P^{s,\max}_{z,t} - \sum_{k\in\Omega^D} P^D_{k,t}; \qquad \forall z \in \Omega^s, \forall t \in \Omega^T$$
$$\sum_{j\in\Omega^N} P^s_{z,j,t} \ge P^{s,\min}_{z,t} - \sum_{k\in\Omega^D} P^D_{k,t}; \qquad \forall z \in \Omega^s, \forall t \in \Omega^T \tag{16}$$

$$\sum_{j\in\Omega^N} P^{grid}_{j,t} \le P^{grid,\max}_{t} - \sum_{k\in\Omega^D} P^D_{k,t}; \quad \forall t \in \Omega^T$$
$$\sum_{j\in\Omega^N} P^{grid}_{j,t} \ge P^{grid,\min}_{t} - \sum_{k\in\Omega^D} P^D_{k,t}; \quad \forall t \in \Omega^T \tag{17}$$

Regarding the agents with storage units, one more constraint is required to meet the battery capacity as shown in (4) and (5). By replacing (8.b) in (4) and (5), we will have:

$$\sum_{t=1}^{\tau}\left(\sum_{j\in\Omega^N} P^s_{z,j,t}\right) \ge -E^{ess,\max} + E^{ini} - \sum_{t=1}^{\tau}\left(\sum_{k\in\Omega^D} P^D_{k,t}\right) \quad \forall z \in \Omega^s, \forall t \in \Omega^T \tag{18}$$

$$\sum_{t=1}^{\tau}\left(\sum_{j\in\Omega^N} P^s_{z,j,t}\right) \le -E^{ess,\min} + E^{ini} - \sum_{t=1}^{\tau}\left(\sum_{k\in\Omega^D} P^D_{k,t}\right) \quad \forall z \in \Omega^s, \forall t \in \Omega^T \tag{19}$$

The final constraint is the consensus limit. Any two agents i and j may get into consensus subject to the following limit:

$$P_{i,j,t} - Z_{j,i,t} = 0 \tag{20}$$

In the above formulation, $Z_{j,i,t}$ is a consensus variable introduced to guarantee that node i agrees with its neighbor j in determining the optimal solution for the power flow $P_{i,j,t}$. The same constraint may be considered for agents of other types including storages and main grid. Via the above distributed formulation, the ADMM algorithm is employed to solve the problem. ADMM is an algorithm that is intended to blend the decomposability of dual ascent with the superior convergence properties of the method of multipliers [21]. The ADMM algorithm will solve (9)–(20) and will converge when the consensus condition in (20) is met. As it can be seen from (9)–(20), the objective function is decomposed into several objectives assigned to the agents. Therefore, a general form can be assumed for the objective function as follows:

$$\begin{aligned} &\min\ f(P_{i,j,t}) + g(Z_{j,i,t}) \\ &s.t.\ P_{i,j,t} - Z_{j,i,t} = 0 \\ &\qquad P_{i,j,t} \in (12)\text{–}(16) \end{aligned} \tag{21}$$

Based on the method of multipliers, for each objective function, the augmented Lagrangian is first formed using its objective function and the consensus constraint (20) as follows:

$$L_\rho(P_{i,j,t}, y, Z_{j,i,t}) = f(P_{i,j,t}) + g(Z_{j,i,t}) + y^T(P_{i,j,t} - Z_{j,i,t}) + \frac{\rho}{2}\left\|P_{i,j,t} - Z_{j,i,t}\right\|_2^2 \tag{22}$$

Here y is the dual variable or Lagrange multiplier which will converge to the optimal dual solution after a specific number of iterations. The ADMM method consists of the following iterations to solve the above problem:

$$P^{Iter+1}_{i,j,t} = \underset{P_{i,j,t}}{\operatorname{argmin}} L_\rho\left(P_{i,j,t}, Z^{Iter}_{j,i,t}, y^{Iter}\right) \tag{23-a}$$

$$Z^{Iter+1}_{j,i,t} = \underset{Z_{j,i,t}}{\operatorname{argmin}} L_\rho\left(P^{Iter+1}_{i,j,t}, Z_{j,i,t}, y^{Iter}\right) \tag{23-b}$$

$$y^{Iter+1} = y^{Iter} + \rho\left(P^{Iter+1}_{i,j,t} - Z^{Iter}_{j,i,t}\right) \tag{23-c}$$

where $\rho \succ 0$. According to the above formulation, (23) first optimizes (23-a) to find $P_{i,j,t}$, then a $Z_{j,i,t}$-minimization step is implemented in (23-b) and finally a dual variable update happens in (23-c). It is worth noting that the dual variable update uses a step size equal to the augmented Lagrangian parameter ρ. Each of the three equations in (23) should meet the inequality constraints in (13)–(19). Due to the high nonlinearity and complexity of the above optimization problem, this paper proposes MCSA as a powerful optimizer to solve (23) meeting (13)–(19) which is explained in the next section.

III. MODIFIED CROW SEARCH ALGORITHM

This section explains a new optimization algorithm called MCSA to solve the consensus based distributed optimization problem explained in the last section.

A. ORIGINAL CSA ALGORITHM

In comparison with other optimization algorithms in the area, CSA has some special features which make it an appropriate method for our problem including simple concept, ease of implementation, fast convergence, providing balance between the local and global searches, few adjusting parameters and ability of solving both continuous and discrete optimization problems. Technically, CSA is a meta-heuristic optimization algorithm mimicking the social behavior of crows for hiding their food and avoiding other birds from stealing from their nests. CSA is originally defined based on four main ideas [22]: 1) crows live in flocks, 2) crows keep in mind their food hiding places, 3) crows chase each other for thievery purposes and 4) crows protect their caches from being pilfered by a probability. Similar to the other meta-heuristic optimization methods, CSA starts with creating a random initial population of crows. Each crow represents an optimal solution for the problem in hand which should meet all constraints. After calculating the objective function for the crow population, the best crow is stored and the position of all the population is moved using the following updating equations:

$$X_n^{Iter+1} = X_n^{Iter} + r_n \times fl_n^{Iter} \times (M_{n'}^{Iter} - X_n^{Iter}); \quad n \in \Omega^C \tag{24}$$

Here *fl* is a parameter balancing the local and global searches such that small values direct toward the local search and large values motivate the algorithm toward the global search. In the case that a crow sees another crow chasing, it will change its path to deceive the attacker. In this way, an awareness constant parameter Γ is defined to update its position as below:

$$X_n^{Iter+1} = \begin{cases} X_n^{Iter} + r_n \times fl_n^{Iter} \times (M_{n'}^{Iter} - X_n^{Iter}); & r_n \geq \Gamma_n^{Iter} \\ X^{rand}; & r_n \prec \Gamma_n^{Iter} \end{cases} \tag{25}$$

The awareness constant Γ balances the intensification and diversification during the optimization process.

B. MODIFIED CSA ALGORITHM (MCSA)

While CSA algorithm reveals outstanding performance in solving many types of complex and nonlinear math problems, it still can be reinforced to show a more robust and powerful performance. To this end, a new two-stage optimization method based on crossover and mutation operators is proposed. Each of these modification methods are implemented in each iteration of the CSA algorithm after solving equations (24)-(25). Each of these methods are explained in the subsequent text:

- *Modification method one*: This modification method tries to move the crow population toward the current best crow in each iteration. Such a mechanism will increase the convergence rate of the algorithm effectively. At the same time, it provides a very good local search for searching around the current best crow in each iteration. First, the mean value of the crow population is calculated, denoted as W^M. Then, each crow X_n in the population is moved toward the current best crow X_{best} using the following math equation:

$$X_n^{new} = X_n^{old} + \theta_T \times (X_n^{old} - W^M) \tag{26}$$

In the above equation, θ_T is an accelerating parameter which can take on values 1 or 2, randomly.

- *Modification method two*: This modification method targets to increase the crow population diversity using the crossover and mutation operators from the genetic algorithm. Therefore, each crow X_n in each iteration is updated by changing its elements (similar to chromosomes in a genetic algorithm) using the following equations:

$$X_n = [x_{n,1}, x_{n,2}, \ldots, x_{n,d}]_{1\times d}$$

$$x_r^{test} = \begin{cases} x_{n,r}; & \phi_1 \leq \phi_2 \\ x_{best,r}; & \phi_1 \succ \phi_2 \end{cases} \tag{27}$$

$$X^{test2} = \phi_2 \times X_{best} + \phi_3 \times (X_{best} - X_n) \tag{28}$$

The best solution between X^{test1} and X^{test2} is compared with X_n, if it is better it replaces X_n, otherwise X_n is kept in its position.

Using the above two-stage modification method, the crow population is updated to provide a higher convergence speed while avoiding possible premature convergence.

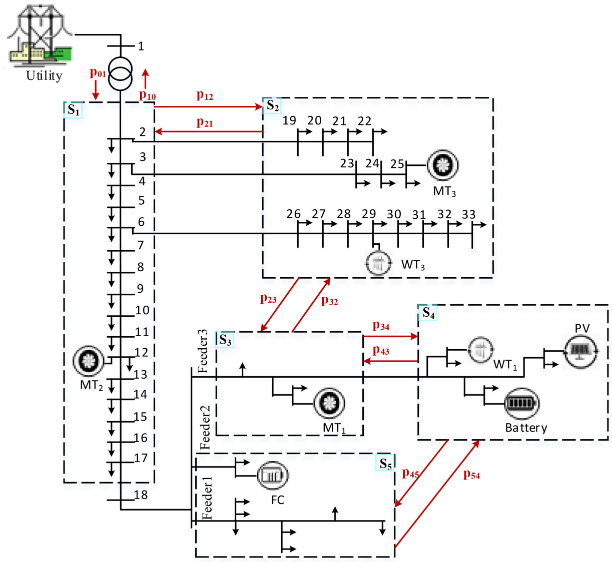

FIGURE 2. Illustration of the hybrid AC-DC test MG.

IV. SIMULATION RESULTS

This section provides simulation results on a notional hybrid AC-DC MG to show the performance of the proposed distributed consensus-based optimization framework. The hybrid MG test system includes the IEEE 33-bus test system as the AC part which is connected to a DC MG at bus 18. The schematic diagram of the system is plotted in Fig. 2. A converter is employed to connect the AC MG to the DC MG and make it possible for power exchange between the two. The hybrid AC-DC MGs is considered as case study which divided to five sub-systems (S1-S5). The distributed generation spread out among sub-systems to provide a reliable and resilient supply energy for loads. Obviously, the energy exchange between sub-systems is leveraged to improve the resiliency concept of the network in the distribute fashion. The voltage level of the AC MG is 12.66 kV and the data on the grid topology, impedances, load demand, can be found in [23], [24]. The hybrid MG includes two MTs installed on buses 12 and 25 as shown in Fig. 1. There are also two WTs considered in the MG with similar patterns but different capacities, one

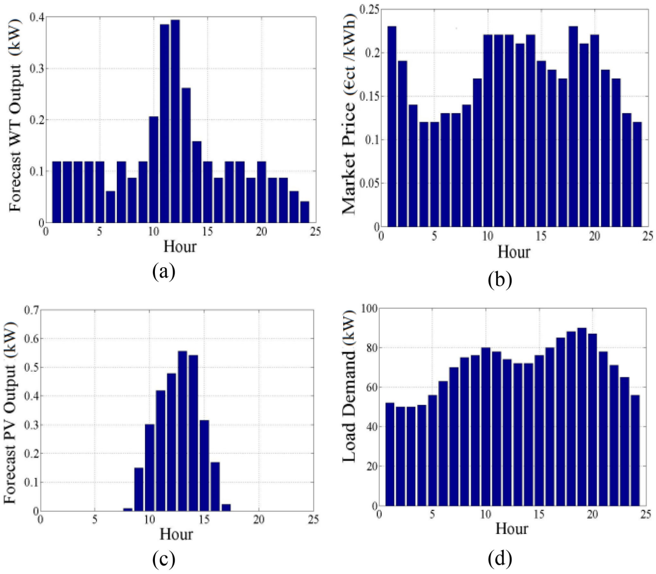

FIGURE 3. Forecast values of (a) wind turbine power units, (b) photovoltaic power units, (c) load demand and (d) market price [21].

TABLE I. Capacity and Bids of the RESs and Distributed Generations

Type	Min Power (kW)	Max Power (kW)	Bid (€ct /kWh)	Start-up/Shut-down cost (€ct)
Micro turbine 3	9	60	0.457	1.65
Photovoltaic	0	55	2.584	0
Wind Turbine 1	0	45	1.073	0
Battery	-80	80	0.38	0
Micro turbine 1	50	250	0.215	1.65
Micro turbine 2	65	250	0.275	1.65
Wind Turbine 2	0	250	2.584	0
PA-Fuel Cell	13	60	0.294	1.65

installed on bus 30 in the AC MG and the other one in the DC MG. Fig. 3(a) shows the forecast output power of WTs for the next 24 hours. All analyses are implemented for 24 hours. One PV is considered in the hybrid AC-DC MG installed in the DC part of the grid with the forecast output power as shown in Fig. 3(b).

The hourly market price and the total load demand for 24 hours of analysis are plotted in Fig. 3(c) and 3(d) all obtained from [25]. The hybrid MG is also connected to the main grid in the AC part which makes it possible to exchange power with the main grid depending on the costs and benefits. A set of battery units are assumed in the hybrid MG installed in the DC part to make it possible for direct charging and discharging of DC power. Batteries have a maximum charging and discharging rate of 150 kW/h. Owing to the incentive policy of the electric grids for supporting renewable DERs, all power produced by WTs and PV are assumed to be purchased by the hybrid MG. The complete data of different DERs are shown in Table I.

Table II shows the optimal power dispatch of units using the proposed hybrid ADMM-MCSA method. As it can be seen from this table, the algorithm has tried to purchase power from cheap units at light-load hours and just at the middle of the day when the load demand expands, the more expensive DGs such PA-FC and MT-2 are utilized. At the same time, the battery is charged at light-load hours at the beginning of the day to be able to discharge at later hours at the middle of the day when the utility electricity prices increase. Such a mechanism helps the hybrid MG to reduce its costs and have a more economic operation.

TABLE II. Optimal Output Power of Units in Hybrid AC/DC MG

Hour	AC Network			DC Network-2				PA-FC
	WT1	MT1	MT2	PV	WT2	MT3	Battery	
1	29.75	65	250	0	5.355	9	0	13
2	29.75	65	50	0	5.355	60	-80	13
3	29.75	65	50	0	5.355	9	-80	13
4	29.75	65	50	0	5.355	9	-80	13
5	29.75	65	50	0	5.355	9	-80	13
6	15.25	65	59.93	0	2.745	9	-40	13
7	29.75	65	250	0	5.355	9	0	13
8	21.75	189.4	250	0.44	3.915	9	0	13
9	29.75	250	250	8.25	5.355	60	0	60
10	51.5	250	250	16.55	9.27	60	80	60
11	146.25	250	250	22.99	26.32	60	80	60
12	173.5	250	250	26.29	31.23	60	80	60
13	65.25	250	250	52.58	11.74	60	-80	60
14	39.5	250	250	46.31	7.11	60	80	60
15	29.75	250	250	17.32	5.355	60	80	60
16	21.75	250	250	9.295	3.915	60	40	60
17	29.75	250	250	1.21	5.355	60	0	60
18	29.75	250	250	0	5.355	9	-80	60
19	21.7	250	250	0	3.906	9	-80	60
20	29.75	250	250	0	5.355	9	0	60
21	21.675	250	250	0	3.901	60	80	60
22	21.675	250	250	0	3.901	60	80	60
23	15.25	250	250	0	2.745	9	0	16.3
24	10.25	65	250	0	1.845	9	0	13

Since the FC is selling energy with a higher price than the other energy sources, the microgrid tends to purchase less power from the FC except at hours that the market price exceeds. Therefore, it is seen that at the beginning of the day (from 1AM to 8 AM), the FC works at its lowest capacity. At later hours (9AM-17PM), the FC price offer is lower than the market price, so it is wise to purchase power from the FC rather than the upper grid. It is clear that PV and WTs as non-dispatchable units are producing power as predicted since we do not need to pay more for their power production after installation. The total MG cost for the 24-hour operation is $1,223,343.10 including both AC and DC parts.

In order to clarify the superiority of the proposed hybrid distributed energy management system for hybrid AC-DC microgrids consists of the five subsystems, the energy exchange between the subsystems are shown in Table III. Each selected distributed generation control by specific controller on each subsystem to maximize the benefits of entire system and minimizes the cost by sharing the energy among the neighbor distributed agents. As it can be seen from the Table III, the dispatchable units (MT2 and MT3) must operate with maximum capacities mostly at the begging of the day to provide better share energy with less cost for DC MG side. On the other sides, the battery in the fourth sub-system charged at the begging of the day to help the neighbor sub-systems by discharging later on the day. In this way, the total cost for the distributed network decreases and resiliency index of the system increases through the distributed control and energy management.

To have a better understanding of the amount of power purchased by the MG from the upstream network, Fig. 4 shows the amount of power exchange between the MG and the main grid. The hourly market bid is plotted in the same image

TABLE III. Optimal Distributed Power/Energy Exchange Among the Sub-Systems

Hour	AC Network		DC Network		
	S_1	S_2	S_3	S_4	S_5
1	231.22	243.74	59.82	-22.96	60.00
2	140.18	143.19	17.98	22.96	60.00
3	216.71	249.98	53.22	-44.06	60.00
4	65.19	237.60	59.91	-58.42	60.00
5	249.01	249.80	52.21	-54.49	60.00
6	214.18	249.82	49.19	-7.147	60.00
7	201.49	250.00	58.82	-53.27	60.00
8	189.47	218.61	32.33	2.319	60.00
9	250.00	250.00	60.00	12.66	60.00
10	237.83	250.00	9.627	-13.02	60.00
11	227.61	211.29	60.00	2.494	60.00
12	77.46	250.00	59.89	-70.82	60.00
13	214.80	250.00	50.50	80.00	60.00
14	248.78	250.00	59.07	0.966	60.00
15	216.34	250.00	59.77	-33.46	60.00
16	240.86	250.00	59.10	-31.46	60.00
17	230.69	201.69	23.20	-71.47	60.00
18	238.99	250.00	58.78	47.31	60.00
19	212.87	250.00	60.00	80.00	60.00
20	250	250.00	60.00	80.00	60.00
21	215.15	250.00	53.86	73.93	60.00
22	191.58	250.00	59.99	-12.38	60.00
23	230.92	250.00	60.00	70.51	60.00
24	248.78	250.00	48.27	-49.50	60.00

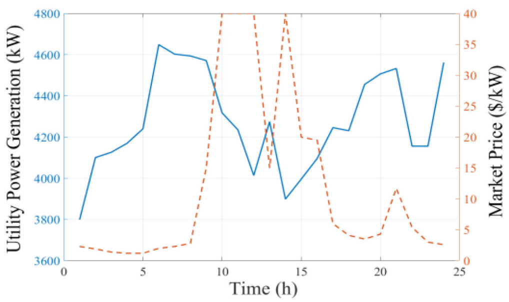

FIGURE 4. Hourly utility power generation and market price in the same frame.

to help better understanding of the MG decisions. According to this figure, from hour 10 AM - 4 PM in which the main grid is offering a high bid electricity, the hybrid MG prefers to reduce its purchases. In this case, by referring to Table II, one can see that the MG prefers to be a customer of its expensive agents including MT2 and PA-FC to still save more money by purchasing less energy from the upstream grid. In contrast, at light load hours, the MG is relying more on the main grid power to reduce its costs and therefore increase its benefit from its connection with the main grid in the AC part.

Fig. 5 shows the convergence characteristics of the objective function for 100 iteration. As can be seen from this figure, the proposed ADMM-MCSA algorithm could converge in the first few iterations, approximately at 12-14. Such a high convergence speed clearly shows the high capability of the proposed method in handling complex operation and scheduling problems in MGs. The initial overshoot seen at the first iterations is due to the consensus process occurring between the neighboring agents to result in a final agreement for the amount of power which each of them should produce. It should also be noted that this result is a significant feature of the proposed distributed framework. In fact, by dividing the whole hybrid MG into five agents, the number of control variables needed to be optimized is reduced as well. Therefore, each agent has to optimize only a few control variables (the consensus variables), thus letting the optimization process proceed much faster.

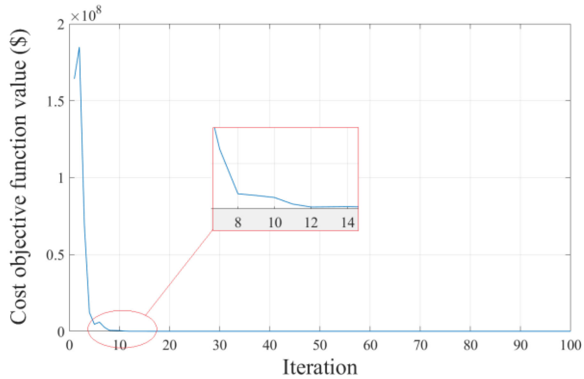

FIGURE 5. Objective function convergence characteristics by the proposed ADMM-MCSA method.

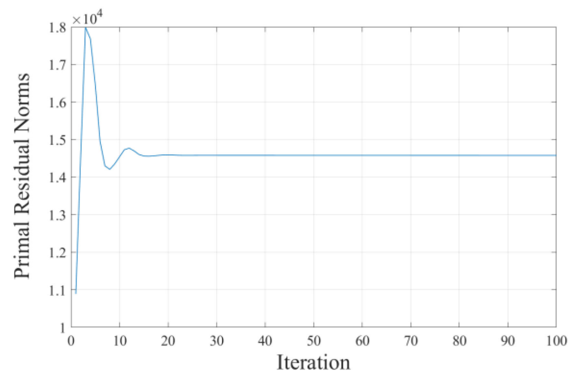

FIGURE 6. Primal residual norms calculated by the proposed ADMM-MCSA method.

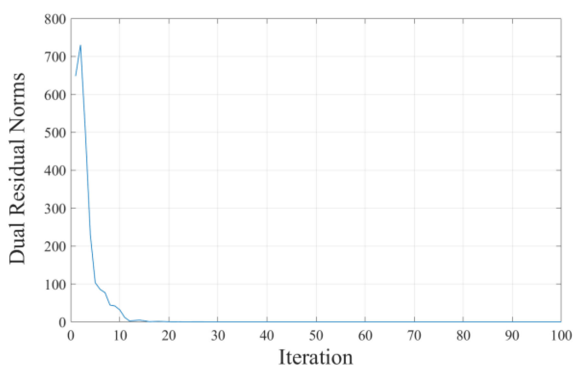

FIGURE 7. Dual residual norms calculated by the proposed ADMM-MCSA method.

Finally, Figs. 6 and 7 show the primal and dual residual norms of the consensus variables during 100 iterations. As it can be seen again, the primal consensus variables form a robust agreement in the first few iterations illustrating the high robustness of the proposed method. The dual residual norm also converges to zero successfully as the ADMM-MCSA

TABLE IV Comparison of the Cost Objective Function Evaluated by Different Algorithms for 20 Trails

Type	Best Value	Worst Value	Standard Deviation Value	CPU Time(s)
GA	$1,223,572	$1,223,852	134.58	24.32
PSO	$1,223,533	$1,223,674	65.94	15.24
MCSA	$1,223,472	$1,223,512	45.27	13.24
Proposed Method	$1,223,343	$1,223,343	0	2.06

proceeds. This means that the neighboring agents consensus increases depending on the norm of the dual residuals. The almost fast convergence of the dual residential norm reveals that a 100% consensus has happened between the agents. This condition in the ADMM guaranties the global optimal solution for the microgrid.

In order to better highlight the main features of the proposed distributed method, Table II reveals a comparison between the genetic algorithm (GA), particle swarm optimization algorithm (PSO), the MCSA and proposed distributed algorithm. All simulations are repeated for 20 trails and the results of the best cost function value, worst cost function value and standard cost of function values are compared. Also, the CPU time needed for this simulation are provided in the Table IV.

According to these results, the proposed method could not only get into more optimal solution, but also shows a much robust response by getting into the same optimal operating point for the hybrid microgrid in all 20 trails. From the computation point of view, the much lower CPU time of the proposed method roots in the distributed structure of the proposed method which divides the total CPU time between all agents (here 5 agents), working in parallel with each other. These results clearly advocate the appropriate performance of the proposed distributed method over other well-known methods in the area.

V. DISCUSSION

A Hybrid AC-DC MG drives MG paradigm to a more mature level by facilitating the support of both AC and DC loads directly via omission of several costly converters in the traditional AC MGs. Nevertheless, high computational burden and security issues present in centralized control of these grids can cause many challenges; not only for the operator but also for the consumers specifically for real-time applications [26]. In response to this issue, this paper proposed a distributed consensus-based method for optimal energy management in hybrid AC-DC MGs incorporating different types of DERs including WT and PV as well as dispatchable units such as FC and MT.

The simulation results on a notional hybrid AC-DC MG show that the proposed hybrid ADMM-MCSA method can converge in the first few iterations, around (approximately 12). The optimal energy dispatch among different agents reveal the economic scheduling of units for reducing the MG costs and increasing its benefits. The MG is motivated to purchase power at light-load hours (like 1 AM to 7 AM) from the main grid, either storing it in the battery storage or using it in time to reduce the power generated by expensive units. Conversely, the MG relies more on its own agents at the middle of the day when the utility electricity price increases, providing a good opportunity for expensive agents to play their role in benefiting the MG. The total CPU time needed to solve the problem is 1.23 (s). The total MG cost for the 24-hour operation is $1,223,343.10. It is also seen that microgrid prefers to purchase more power from internal units at hours 10AM to 4PM when the market price is high. In total, the proposed hybrid distributed ADMM-MCSA method illustrates a high capability and improved features for solving the optimal energy management problem in the hybrid AC-DC MGs.

VI. CONCLUSION

This paper proposed a new distributed consensus-based operation framework for hybrid AC-DC MGs based on ADMM and MCSA. The proposed method made use of ADMM to split the hybrid MG into several agents. In the first step, a distributed formulation for the optimal energy management of hybrid MGs was developed considering RESs, battery as the storage and dispatchable units with different capacities. After forming the augmented Lagrangian, the ADMM will solve it using a three-step iteration. Due to the high nonlinearity, complexity and the constrained nature of the proposed formulation, a new improved meta-heuristic optimization algorithm called MCSA was proposed to aid the ADMM in solving the problem in each agent, optimally. The simulation results on a typical hybrid AC-DC MG incorporating different types of DERs such as WT, PV, MT, FC and battery illustrated the robustness and performance of the proposed method. Also, it was seen that the proposed ADMM-MCSA could help each agent to get into its optimal operating point by minimal data sharing with the other agents. In fact, the data transfer is limited to the neighboring agents which can reduce the big size of data transfer needed in the traditional microgrids. From the economic point of view, the simulated results how that the proposed method provided a suitable balance between the MG and the main grid creating a win-win power exchange with each other. Also, the primal and dual residual norms of the variables showed improved convergence capabilities of the proposed method as ADMM proceeds. The proposed formulation supports the concept of RESs by yielding the incentive policy of maximum purchase of power from these units. In the future, the authors will focus on the possibility of virtual agent formation by the cyber hackers to steal data from the microgrid. Also, the possibility of load shedding is a challenging point which can be addressed in the proposed distributed framework in the future.

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