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Optimal Scheduling of Distributed Energy Resources by Modern Heuristic Optimization Technique

Wenlei Bai, *Student Member*, IEEE
Electrical and Computer Engineering
Baylor University
Waco, Texas 76798, USA

Ibrahim Eke
Electrical and Electronics Engineering
Kirikkale University
Kirikkale 71000, Turkey

Kwang Y. Lee, *Fellow*, IEEE
Electrical and Computer Engineering
Baylor University
Waco, Texas 76798, USA

***Abstract*— The increasing number and types of energy resources and prosumers has complicated the operation in microgrid greatly. Such problem becomes a hard-to-solve or even impossible-to-solve for traditional mathematical algorithms without necessary approximation. However, modern heuristic optimization techniques have proven their efficiency and robustness in complex non-linear, non-convex and large-size problems. In this paper, we propose a comprehensive microgrid which consists of renewables, distributed generators, demand response, marketplace, energy storage system and prosumers, and investigate the behaviors of such system. A novel heuristic method, artificial bee colony, is proposed to solve the day-ahead optimal scheduling of the microgrid. Case studies have shown that such algorithm is able to solve the problem fast, reliable with satisfactory solutions. For the first case, the computational time is 9 minutes compared with 19 hours by a traditional methodical tool which has not taken necessary approximation of the original problem.**

***Index Terms*— Microgrid, Distributed generators (DG), Modern heuristic optimization, Artificial bee colony (ABC).**

I. INTRODUCTION

The concept of microgrid has begun as early as in 2002 defined by the Consortium for Electric Reliability Technology Solutions (CERTS) white paper. Microgrid is an aggregation of loads and distributed generators (DG) which can both operate in islanded and grid-connected mode in a distribution system level [1]. The majority of the microgrid control must be power electronics based to provide the flexibility for reliability and security in local networks [2]. Microgrid not only can exchange power with the main grid, but also provides ancillary services such as voltage stability support, power quality adjustments, etc. [3][4]. Microgrid can make use of additional energy resources and reduce the need for expanding transmission and distribution facilities, which is often very costly [5]. More importantly, a microgrid plays a critical role of improving system reliability by islanding from the main grid during an external outage. Therefore, microgrid has increasingly drawn attentions all over the world.

Microgrid controllers play critical role in optimal scheduling. The goal of optimal scheduling is to optimize specific objective functions (operational cost, power loss, pollutant emission, etc.) by scheduling dispatch of DGs, responsive loads, and power exchanges between the microgrid and the main grid. The whole process needs to be subjected to various technical, reliable, and operating constraints.

Considerable research have been focused on optimal scheduling in microgrid. An optimal scheduling of a renewable micrgrid in an isolated load area by mixed-integer linear programming in proposed in [6]. Such microgrid consists of a wind turbine, PV, fuel cell and an energy storage system (ESS). There are research focusing on grid-connected microgrid optimal dispatch [7][8]. Those work have adopted deterministic models by assuming the perfect forecast of renewables. The work from [9] developed stochastic model which has considered the uncertainty of renewable energy forecast by generating various stochastic scenarios.

In the above literature, the scheduling models are mostly downsized version of the combination of unit commitment (UC) and security constrained economic dispatch (SCED) in the transmission level of power system because the goal of combined UC and SCED is to dispatch the available resources to meet the load demand while satisfying certain constraints [13]. Most of the aforementioned microgrid only contains limited distributed resources and hence is a simple structure. However, the microgrid scheduling problem is considerably different with UC and SCED problem due to the fact that (1) the structure of microgrid can be very complex including a large number of DGs, ESSs and responsive loads, (2) the unbalanced radial distribution network needs a feasible algorithm to solve the AC load flow which is different from that of transmission level network.

It is known that the optimal scheduling of a microgrid is a high dimensional mixed-integer nonlinear programming (MINLP) problem with discontinuous, non

-convex, multi-modal search space. In general, without simplifications (e.g., linearization of the model), it is very computationally costly for MINLP solver. It is also demonstrated that modern heuristic optimization techniques are able to tackle such problem without simplifying the system, and obtain promising results [10][11]. Therefore, in

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this paper, we adopted a novel modern heurist technique, artificial bee colony (ABC), to mitigate the exponentially increasing execution time using traditional mathematical tools. By case studies, it is found that ABC is able to solve the complex MINLP fast, reliable and with satisfactory results. The use of modern heuristic optimization techniques may provide interesting answers and further discussion in the community. In all, the contributions of this paper are:

1) A comprehensive complex microgrid structure is formulated, which includes a considerable number of renewables, dispatchable DGs and ESSs, and involves demand response such as electric vehicles (EV), residential loads, commercial and industrial loads and marketplace. The objective is to maximize profits.
2) Artificial bee colony (ABC) is proposed to solve the day-ahead microgrid optimal scheduling problem. Statistical analysis/evaluation of solutions is conducted as well.

The paper is organized as follows: Section II formulates the optimal scheduling problem in microgrid and Section III describes methodology and the implementation of the ABC. In Section IV the proposed algorithm is evaluated in two case studies. Finally, the conclusion is provided in Section V.

II. PROBLEM FORMATION

In this section the general description of the microgrid is presented first, followed by the formulation of optimal scheduling.

A. *Description of the Microgrid*

The microgrid structure in this paper is adopted from Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), settled in Polytechnic of Porto [12]. The microgrid consists of three major components: *energy resources (ER)*, *energy management system (EMS)*, and *prosumers* as shown in Figure 1. The ER include renewables (wind, solar, etc.), dispatchable DGs (diesel generator, hydropower plant with a reservoir, etc.), demand response program (load demand can be shifted or reduced by selling electricity at a lower price), marketplace (external supplier), and ESS. The EMS is the most essential component, which plays the role of controlling and monitoring the microgrid. Prosumers include electrical vehicles (EV), residential, commercial and industrial demands. It is also worthy to mention that some components are capable of buying/selling electricity from/to micrigrid, such as marketplace, ESS and EVs.

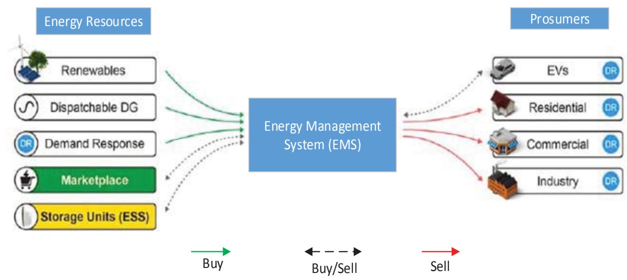

Figure 1. A microgrid Structure.

The EMS is able to buy energy from several resources and marketplace to make revenue by selling energy to customers. In addition, ESS can provide need for load and Vehicle to Grid (V2G) is also allowed to provide need for load. It is also assumed that operational costs and electricity price is fixed for each component. The main objective of the EMS is to perform optimal energy source scheduling of the involved resources for the following 24 hours in order to maximize profits.

B. *Optimal Scheduling of the Microgrid*

The optimal scheduling of the microgrid is a hard combinatorial mixed-integer non-linear programming (MINLP) problem due to a large number of continuous, discrete and binary variables and network non-linear equations. The objective is to maximize profits: income (IN) minus operational cost (OC) as defined as

$$\min \;\; Z = OC - IN \tag{1}$$

Since maximizing profit (IN – OC) is equivalent to minimizing (OC – IN), and thus the goal in (1) is to minimize the objective function Z.

The EMS receives income from four sources: the electricity selling to consumers; the energy selling to the electricity market; the revenue from the ESS by charging electricity; and similarly, from the charging of EVs as following:

$$IN = \sum_{t=1}^{T} \Big\{ \sum_{L=1}^{N_L} P_{Load(L,t)} \cdot MP_{Load(L,t)} + \sum_{M=1}^{N_M} P_{Sell(M,t)} \cdot MP_{Sell(M,t)} + \sum_{E=1}^{N_E} P_{Cha(E,t)} \cdot MP_{Cha(E,t)} + \sum_{V=1}^{N_V} P_{Cha(V,t)} \cdot MP_{Cha(V,t)} \Big\} \tag{2}$$

On the other hand, the OC considers the generation cost of DGs, external suppliers, discharge of ESS and EVs, demand response program, and penalty on non-supplied demand and penalty on DGs' generation curtailment.

$$
\begin{aligned}
OC = & \\
\sum_{t=1}^{T} \Big\{ & \sum_{I=1}^{N_{DG}} P_{DG(I,t)} \cdot C_{DG(I,t)} + \sum_{S=1}^{N_S} P_{Supp(S,t)} \cdot C_{Supp(S,t)} \\
& + \sum_{L=1}^{N_L} P_{LoadDR(L,t)} \cdot C_{LoadDR(L,t)} + \sum_{M=1}^{N_M} P_{Buy(M,t)} \cdot MP_{Buy(M,t)} \\
& + \sum_{V=1}^{N_V} P_{Discha(V,t)} \cdot C_{Discha(V,t)} + \sum_{E=1}^{N_E} P_{Discha(E,t)} \cdot C_{Discha(E,t)} \\
& + \sum_{L=1}^{N_L} P_{NSD(L,t)} \cdot C_{NSD(L,t)} + \sum_{I=1}^{N_I} P_{GCP(I,t)} \cdot C_{GCP(I,t)} \Big\}
\end{aligned} \tag{3}
$$

where E is an index of ESS, I an index of DG units, L an index of loads, M an index of markets, S an index of external suppliers, t an index of time periods and V an index of EVs; N_E is the number of ESS, N_L the number of loads, N_M the number of markets, N_V the number of EVs, N_{DG} the number of DGs, N_S the number of external electricity suppliers; $C_{DG(I,t)}$ is the generation cost (\$) of unit I in t, $C_{Supp(S,t)}$ the energy price of external supplier S in t, $C_{LoadDR(L,t)}$ the load reduction cost of L in t, $C_{Discha(E,t)}$ the discharging cost of ESS E in t, $C_{Discha(V,t)}$ the discharging cost of V in t, $C_{NSD(L,t)}$ the non-supplied demand cost of load L in t, $C_{GCP(I,t)}$ the curtailment cost of DG unit I in t; $MP_{Load(L,t)}$ is the price (\$) of load L in period t, $MP_{Sell(M,t)}$ the price (\$) that market M pays in time period t, $MP_{Charge(E,t)}$ the price (\$) for the charge process of ESS E in period t, and $MP_{Charge(V,t)}$ the price (\$) for the charge process of EV V in period t; $P_{Cha(E,t)}$ is the real power charge (MW) of ESS E in period t, $P_{Load(L,t)}$ the real power demand (MW) of load L in period t, and $P_{Sell(M,t)}$ the real power (MW) sale to market M in period t, $P_{DG(I,t)}$ the real power (MW) generation of DG I in t, $P_{Supp(S,t)}$ the real power generation of external supplier S in t, $P_{LoadDR(L,t)}$ the real power reduction (MW) of L in t, $P_{NSD}(L,t)$ the real power of non-supplied demand (MW) and $P_{GCP(I,t)}$ the generation curtailment power (MW) for load L and DG unit I.

The problem constraints are similar to [13], which is an optimal power flow problem. The equality constraints include the network equations, specifically, the real and reactive power balance equations. Inequality constraints include voltage and angle limits, DG generation and supplier limits in each period, ESS capacity, ESS charge and discharge rate limits, EVs capacity, EVs trips requirements, EVs charge and discharge efficiency and rate limits. Due to the page limit, the authors do not list those constraints explicitly. AC load flow is calculated by a robust algorithm called Backward/Forward Sweep method for distribution radial system.

Inequality constraints are handled in two methods: imposing penalty functions, and direct repair of solutions. Penalty function is introduced as:

$$
p(x_i) = \begin{cases} (x_i - x_{i,\max})^2 & if \quad x_i > x_{i,\max} \\ (x_{i,\min} - x_i)^2 & if \quad x_i < x_{i,\min} \\ 0 & if \quad x_{i,\min} \le x_i \le x_{i,\max} \end{cases} \tag{4}
$$

where p is the penalty function of dependent variable x_i. Penalties will be added to objective functions if dependent variables do not satisfy constraints. The 'direct of solutions' mechanism means that the solutions returned by the function are changed if some constraints are not complied with. Such mechanism can not only handle the constraints, but also provide a fast convergence. For example, control variables such as charge/discharge rates of EVs/ESS are adjusted according to the state of charge and capacity constraints. Therefore, there is no need to impose penalties because the feasible solutions are guaranteed.

III. Methodology

In this section, a modern heuristic optimization technique, the ABC, was introduced to tackle the problem.

In the original ABC algorithm by Karaboga [13], initial artificial bees are spread out randomly in a multidimensional search space. Each artificial bee has the ability to store current information and communicate with neighbours. Inspired by the foraging behaviours of natural honey bee swarms, the ABC has been addressed in various applications [14]

Generally the process of ABC can be summarized as: first, food source positions (feasible solutions) are initialized within the search space randomly. After the initialization the solutions will be improved by the repeated cycles of search process conducted by artificial employed, onlooker and scout bee phases. For the sake of space, the authors only list two fundamental equations used in ABC, and details can be found in the original report [13].

At initialization each vector solution $X_i = \{X_{i,1}, X_{i,2}, \ldots, X_{i,D}\}$ is generated randomly within the limits of the control variables as follows:

$$
X_{i,j} = X_{i,j\_\min} + rand(0,1) \times (X_{i,j\_\max} - X_{i,j\_\min}) \tag{5}
$$

where X_{i,j_min} and X_{i,j_max} are the lower and upper bounds for dimension j; i is from 1 to SN, and j is a random number from 1 to D, and SN is the number of employed bees and onlooker bees, D is the number of control variables (optimization parameters); and $rand(0,1)$ is a uniformly distributed random number in (0,1).

On employed bee phase, each bee searches for rich artificial food sources via updating current solutions based on their neighborhood's information and assess the nectar of new solutions. The search equation that used to update a candidate solution vector V_i is defined as:

$$
V_{i,j} = X_{i,j} + \Phi_{i,j} \times (X_{i,j} - X_{k,j}) \tag{6}
$$

where k is a different integer from i, uniformly chosen from the range [1, SN], $\Phi_{i,j}$ is a random number from [-1,1]. If the updated solution has better nectar than the old one, employed bee will memorize the new solution and discard the old one; otherwise they will keep the old solutions. This particular process is called 'greedy selection'. The structure of ABC is summarized in Figure 2.

Step 1) Initialization:

1.1) Randomly generate *SN* points in the search space as feasible solutions X_i by (5).

1.2) Run Load Flow and evaluate the objective function by (1).

Step 2) From all employed bees ($i = 1, \ldots, SN$):

2.1) Generate a candidate solution V_i by (6).

2.2) Run Load Flow and evaluate the objective function by (1).

2.3) Choose a solution (from X_i and V_i) with better fitness function.

Step 3) For all onlooker bees (only choose 'good' solutions to update. The selection happens under certain probability p):

3.1) Generate a new candidate solution by V_i (6).

3.2) Run Load Flow and evaluate the objective function by (1).

3.3) Choose a solution (from X_i and V_i) with better fitness function.

Step 4) Memorize the best solution so far.

Step 5) For all scout bees (will be executed only after the maximum number of trails):

5.1) Replace X_i with a new randomly produced solution X_i by (5).

5.2) Run Load Flow and evaluate the objective function by (1).

Fig. 2. The overall structure of ABC.

As mentioned earlier, the normal Newton's method for transmission network AC load flow does not fit for solving radial network load flow due to the fact that the system parameters, resistance and reactance ratio R/X, is much higher than that of transmission network. In addition, since the network is unbalanced, distribution network matrices are ill conditioned and thus Newton's method are inefficient in solving such problem. A robust Backward/Forward Sweep method has been developed in [15] for solving load flow of practical three phase distribution system with a large number of nodes and branches. The method has tested for practical systems; therefore we adopted such method in this paper.

IV. Case Studies

In this section, two case studies were conducted to investigate the efficiency of the algorithm and final results were also presented and discussed.

A. 33-bus Scenarios

In this scenario, a 12.66 kV 33-bus distribution network has been considered. As shown in Table I, the system consists of DGs, external suppliers, wind energy, ESS, EVs, market and loads involved in demand response program.

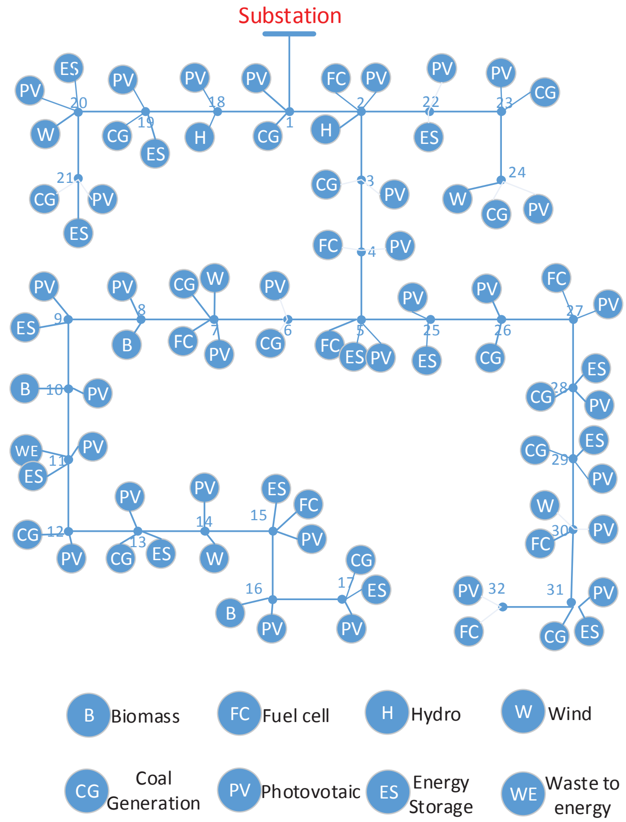

Fig. 3. Schematic of the 33-bus distribution system.

Table I. Scenario I Overview

33-bus 12.66kV distribution network
66 DGs
10 External suppliers
1 Large wind turbine
15 ESS
1800 EVs (V2G allowed)
1 Market
32 various loads involved in demand response

As mentioned previously, the objective of implementing heuristic method to tackle complex optimal scheduling of distributed energy resources is to obtain satisfying results by significantly reducing computational time, because without transformation of the original problem, conventional solver such as mixed integer nonlinear programming (MINLP) will take hours, even days. Table II demonstrates computational time.

Table II. Execution Time

MINLP	ABC
CPU: Intel (R) Xeon (R) @ 2.10GHZ with 16GB RAM	CPU: Intel (R) i7 @ 3.4GHZ with 8GB RAM
19hours	9.01min
280,729 Equations 234,541 Single variables 88,380 Discrete variables	

As shown from Table II, the execution time has been significantly reduced. Figures 4, 5 and 6 show the optimal dispatches of 10th EV, 10th DG, and market. Since there are too many control variables for both cases, and due to the page limit we only present these three as examples.

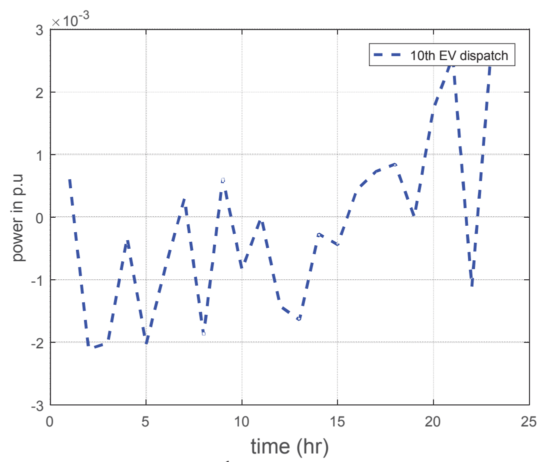

Fig. 4. The 10th EV's optimal dispatch.

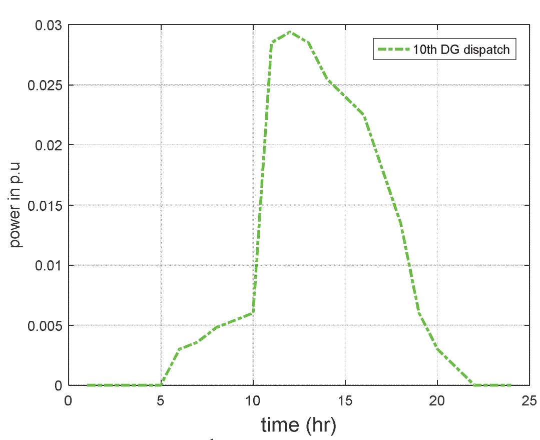

Fig. 5. 10th DG's optimal dispatch.

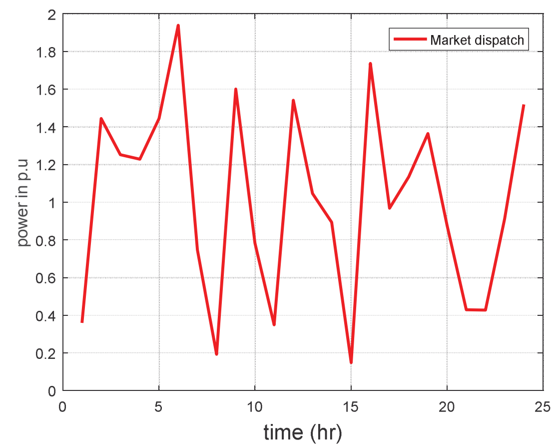

Fig.6. Market's optimal dispatch

B. 180-bus Scenario

In this case, the test system is extended to 180 buses. Similarly, the optimal dispatches of one of EVs, DGs and the market is plotted as examples in Figures 7, 8 and 9. Table III gives the overview of such system. Table IV shows the execution time compared with MINLP.

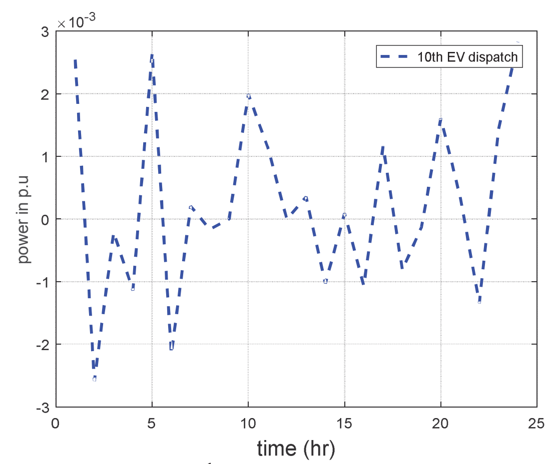

Fig. 7. 10th EV's optimal dispatch.

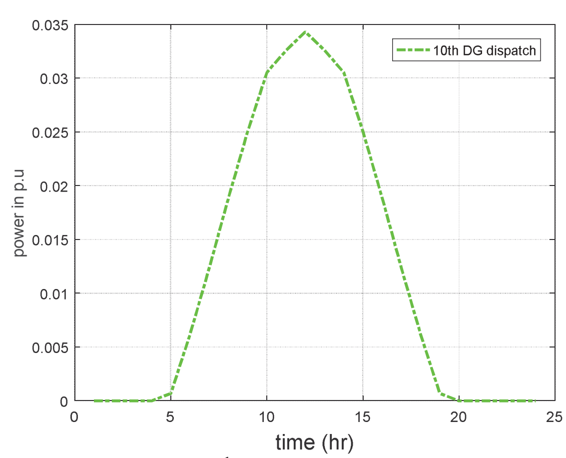

Fig. 8. 10th DG's optimal dispatch.

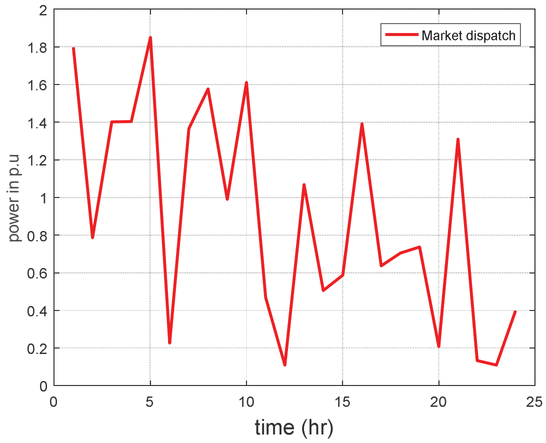

Fig. 9. Market's optimal dispatch.

Table III. Scenario II Overview

180-bus 30kV distribution network
116 DGs
1 External suppliers
7 ESS
6000 EVs (V2G allowed)
1 Market
90 various loads involved in demand response

Table IV. Execution Time

MINLP	ABC
CPU: Intel (R) Xeon (R) @ 2.10GHZ with 16GB RAM	CPU: Intel (R) i7 @ 3.4GHZ with 8GB RAM
168hours	18.12min
910,033 Equations 763,033 Single variables 290,568 Discrete variables	

V. CONCLUSION

In this paper, a microgrid which consists of DGs, ESS, EVs, market, responsive loads, etc. has been adopted for a comprehensive investigation. A novel heuristic algorithm, ABC, is implemented to tackle the optimal scheduling of distributed energy resources. Such problem is a non-linear and non-convex problem, for which it is hard or impossible to use common optimization tools without modification of the system. Thus ABC is proposed to search for the global optimum without simplifying approximation of the system. The ABC has demonstrated its ability to handle complex and large distribution system such as 180 bus system with thousands of equations and variables. By using ABC, successful solutions can be obtained and computational time has been reduced significantly compared with solving the problem by commercial solver without simplifying the problem. ABC is robust in the sense that by running multiple trials, they always converge to successful solutions.

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