Optimal Sizing of an Islanded Micro-Grid Using Meta-Heuristic Optimization Algorithms Considering Demand-Side Management

Soheil Mohseni, Alan Brent, Daniel Burmester, Abhi Chatterjee
Sustainable Energy Systems, School of Engineering and Computer Science, Faculty of Engineering,
Victoria University of Wellington, PO Box 600, Wellington 6140, New Zealand
Email: soheil.mohseni@ecs.vuw.ac.nz

***Abstract*—This paper proposes a novel modeling approach for optimal sizing of the components of an islanded micro-grid subject to satisfying a reliability index for meeting the loads. The proposed micro-grid incorporates photovoltaic arrays, wind turbines, a battery bank, an inverter, and an electric vehicle (EV) charging station. A demand-side management mechanism based on a deferrable load program is implemented and a model reduction technique is also utilized to mitigate the computational cost. Three different optimization algorithms, namely the whale optimization algorithm (WOA), particle swarm optimization (PSO), and the genetic algorithm (GA) are considered in this study to minimize the total cost of the system. The simulation studies have shown that although the WOA reduces the computational burden and requires much lower iterations compared with PSO and GA, it converges to sub-optimal solutions; therefore, it is not a good option for micro-grid planning purposes. Moreover, the results demonstrate that by charging coordination of EVs and deferring a pre-determined portion of the residential loads, overloading can be avoided and available components can be utilized better, which in turn reduces the sizes of the components and total cost of the system.**

***Index Terms*-- Distributed power generation, Microgrids, Power system planning, Power system reliability, Smart grids.**

I. Introduction

TODAY, due to global warming and climate change issues, limitation of fossil fuels, and energy demand crisis, governments have been urged to expand the share of renewable energy in their energy portfolios. Nevertheless, this objective will not be realized, unless sustainable energy systems, that are able to integrate various distributed energy resources (DER), such as photovoltaic (PV) arrays, wind turbines (WTs), electric vehicles (EVs), etc., are developed [1], [2]. According to the inherent intermittency of renewable energy sources (RES), they have to be integrated into the energy network. One solution for handling the intermittent nature of RES is the micro-grid concept, which can be defined as a discrete and small power grid that provides a platform for the integration of DER and facilitates the implementation of demand-side management (DSM) strategies [3], [4].

Optimal sizing of the micro-grid components is crucial as this guarantees the reliable supply of loads subject to the economic practicality of the system. In this paper, optimal sizing of the components of an islanded micro-grid incorporating PV arrays, WTs, a battery bank, a DC/AC converter, and an EV charging station is considered.

The problem we face is a non-convex and non-linear combinational optimization problem that requires high computational complexity. Therefore, in the way of finding an appropriate optimization algorithm that reduces the computational burden of the considered problem, the whale optimization algorithm (WOA), which is a meta-heuristic optimization algorithm (OA) inspired by the hunting behavior of humpback whales, is tested in this paper and its results are compared with the results obtained by the particle swarm optimization (PSO) and genetic algorithm (GA), which are the two most commonly used OAs in this research topic in the literature, in terms of convergence speed and optimality of the solution obtained.

Most studies have only focused on using simple operating strategies, while calculating the optimal sizes of a renewable energy system components [5], and only a few researchers have considered the effects of DSM techniques in the planning phase of the stand-alone sustainable energy systems [6]–[8], none of which have demonstrated the potential benefits of charging coordination of EVs, while optimally sizing the components of a self-sustainable energy system. In this paper, a DSM strategy under the context of deferrable loads is considered as a means to shave the peak EV charging demand and residential consumption, and flatten the total load curve. The proposed strategy shifts the operation of a percentage of EV charging and residential loads from peak to off-peak consumption hours.

By simulating various model reduction techniques and comparing the results for a hospital's energy system, it has been proved [9] that model reduction through data compression does not have a large effect on the solution accuracy in energy planning problems, but does significantly reduce the computational complexity. Accordingly, because of the large size of the full model, inspired by [9], an appropriate model reduction procedure through compression of the relevant annual data is implemented, which has reduced the computational burden.

This study was undertaken for a conceptual micro-grid in Kish Island in the Persian Gulf. Located approximately 18 kilometers off the southern coast of Iran, the island has a great solar energy potential and an appropriate wind resource for electricity generation.

The rest of this paper is organized as follows: In Section II, the mathematical modeling of the micro-grid components is presented. Section III describes the configuration and power flow of the proposed micro-grid. The procedure of objective function optimization is illustrated in Section IV. Section V presents and analyzes the simulation results. Finally, the conclusion of this study is presented in Section VI.

II. Description of the Micro-grid Components

A. PV Array

The output power of the PV generation system at time step t can be calculated by the following equation [10]:

$$P_{PV}(t) = N_{PV} \times \eta_g \times A_m \times G_t(t), \quad (1)$$

where η_g is the efficiency of PV arrays that is equal to 15.4% [10], A_m is the area of a single array used in the system [m^2] that is equal to 1.9 m^2 [10], $G_t(t)$ is the total solar irradiance incident on the titled plane [W/m^2] at time step t, and N_{PV} is the number of arrays that is calculated at each iteration of the optimal sizing problem. Also, the rated power of each PV array is considered to be 1 kW in this analysis.

B. Wind Turbine

The output power of the wind power generation system at time step t can be described in terms of wind speed by the following equation [11]:

$$P_{WT}(t) = N_{WT} \times \begin{cases} 0 & ; V < V_{cin}, V > V_{coff} \\ P_r \times (\dfrac{V(t) - V_{cin}}{V_r - V_{cin}})^3 & ; V_{cin} \le V < V_r \\ P_r & ; V_r \le V \le V_{coff} \end{cases} \quad (2)$$

where V_{cin}, V_{coff}, and V_r denote the cut-in, cut-off, and nominal wind speeds, respectively that are considered to be 2.5, 25, and 11 m/s, respectively; $V(t)$ is the wind speed at time step t; N_{WT} is the optimal number of wind turbines; and P_r is the nominal power of each wind turbine, which is considered to be 7.5 kW.

C. Battery Bank

The following equation can be used to model the charge quantity of the battery bank at each time step t:

$$E_{bat}(t) = E_{bat}(t-1) + P_{ch}(t) \times \eta_{ch} \times \Delta t - \left(\frac{P_{dch}(t)}{\eta_{dch}}\right) \times \Delta t, \quad (3)$$

where P_{ch} is the transferred power from the renewable energy sources to the battery bank, P_{dch} is the transferred power from the battery bank to the DC/AC converter, and η_{ch} and η_{dch} are the charge and discharge efficiencies of the battery bank, respectively that both of them are considered to be 85% in this study.

At each time step t, the storage capacity of the battery bank is subject to the following constraints:

$$E_{bat,min} \le E_{bat}(t) \le E_{bat,max}, \quad (4)$$

where $E_{bat,min}$ and $E_{bat,max}$ denote the minimum and maximum allowable storage capacities of the battery bank.

In this paper, $E_{bat,max}$ is considered to be the nominal capacity of the battery bank, which is controlled by the optimal capacity of the battery bank (that is calculated at each iteration of the optimal sizing procedure). Furthermore, $E_{bat,min}$ is controlled by the maximum allowable depth of discharge (DOD) of the battery bank that can be described by the following equation [6]:

$$E_{bat,min} = (1 - DOD) \times E_{bat,max}. \quad (5)$$

The maximum allowable depth of discharge of the battery bank is considered to be 0.85. Furthermore, it is assumed that the amount of energy stored in the battery bank at the end of the optimization process should not be less than its amount at the beginning to avoid undersizing due to the presence of charged batteries at the beginning of the simulation.

D. DC/AC Converter

The DC input of the inverter in the proposed micro-grid can be from the DC output of the wind power generation system, PV arrays, and battery bank. In this paper, the efficiency of the inverter is denoted by η_{inv}, which is considered to be 90%.

E. EV Charging Station

In order to charge an EV's battery, the electric vehicle supply equipment (EVSE) is considered in this study, which is an equipment that can communicate with the EV with the goal that charging procedure happens in a protected way. It should be noted that the efficiency of the considered EVSEs is denoted by η_{sta}, which is considered to be 85% in this study [12]. Furthermore, the hourly load profile for the station for a typical year is considered to be available and forecasting this profile based on the historical data falls outside the scope of this paper. It is notable that the considered charging station is in fact a parking lot and the customers benefit from using the parking spaces provided as well. Moreover, the rated power of each EVSE is considered to be 22 kW that can be operated with a three-phase supply voltage of 400 VAC and accepts a maximum current of 32 A.

III. Configuration and Power Flow of the Micro-grid

A schematic representation of the proposed micro-grid is presented in Fig. 1. The micro-grid consists of three groups of units. The first group includes the energy production units that are PV arrays and WTs. The second group includes the energy consumption units, which are the residential electrical loads and charging demand of the station for charging of EVs. The last group includes the storage unit, which is a typical battery bank. Power flow diagram of the micro-grid is also shown in Fig. 1. According to this diagram, the output power of the photovoltaic unit is P_{PV} [kW] that depends on solar irradiation and the output power of the wind turbines is P_{WT} [kW] that depends on wind speed. Based on the state of generated renewable power at each time step t, three situations can be considered: (i) generation meets demand, (ii) over generation, and (iii) over demand. It is worth mentioning that only supplying the residential loads is considered in the case of over demand and EVs will not be charged by the battery bank to improve the energy efficiency of the micro-grid. In other words, the EVs are only charged by the surplus power generated by PV arrays and wind turbines after meeting the residential loads. Moreover, it should be noted that calculating the optimal size of the EV charging station's three-phase inverter has not been considered in this paper, and therefore the inverter is shown inside the dashed lines in Fig. 1.

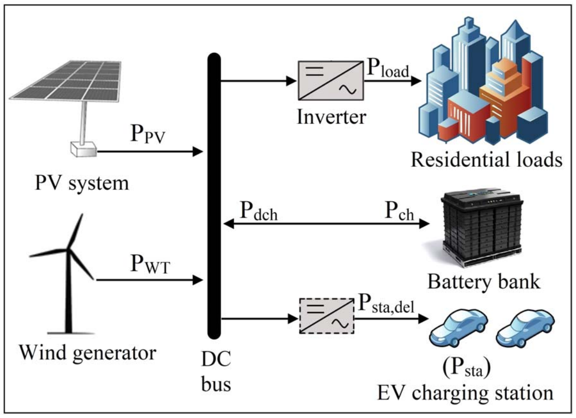

Fig. 1. The schematic diagram of the proposed micro-grid.

A. Operational Strategy

1) Generation Meets Demand

In this situation, the power generated by PV arrays and wind turbines is equal to the sum of residential loads and charging demand of the station; hence,

$$\begin{gathered} P_{PV}(t) + P_{WT}(t) = (P_{load}(t)/\ \eta_{inv}) + (P_{sta}(t)/\eta_{sta}), \\ E_{bat}(t + \Delta t) = E_{bat}(t), \\ P_{sta,del}(t) = P_{sta}(t). \end{gathered} \tag{6}$$

Note that the time steps are taken to be 1 hour in this study.

2) Over Generation

In this situation, in which the renewable power is more than the power requirements of residential loads and charging station, the excess power to the amount of P_{ch} [kW] will be used for charging of battery bank; hence,

$$\begin{gathered} P_{ch}(t) = P_{PV}(t) + P_{WT}(t) - (P_{load}(t)/\ \eta_{inv}) - (P_{sta}(t)/\eta_{sta}), \\ E_{bat}(t + \Delta t) = E_{bat}(t) + P_{ch}(t) \times \eta_{ch} \times \Delta t, \\ P_{sta,del}(t) = P_{sta}(t). \end{gathered} \tag{7}$$

3) Over Demand

In the time steps that there is a shortage of power production for supplying residential loads, the battery bank will be discharged to the amount of P_{dch} [kW] to compensate the shortage of power production; hence,

$$\begin{gathered} P_{dch}(t) = (P_{load}(t)/\eta_{inv}) - P_{PV}(t) - P_{WT}(t), \\ E_{bat}(t + \Delta t) = E_{bat}(t) - (P_{dch}(t)/\eta_{dch}) \times \Delta t, \\ P_{sta,del}(t) = 0. \end{gathered} \tag{8}$$

B. Demand-Side Management

Two types of loads have been considered in this paper: (i) residential and (ii) EV charging loads. It is assumed that at each hour, 25% of the electrical loads are deferrable and supplying them can be deferred by up to 8 hours. The rest of the loads are considered to be critical loads. According to the considered time span for deferring loads, the following residential loads can be considered as deferrable loads: (i) thermostatically controlled loads such as washing machines and clothes dryers, and (ii) the residential loads integrated with energy storage systems, such as electric water and space heaters. Also, the considered charging station is assumed to be a parking lot, which can defer the charging of EVs by up to 8 hours. In order to incorporate this strategy into the model, at each hour, 25% of the total load is added to the load curve over the next 8 hour period. Then, by comparing the resulted values with the current value of the load, the deferrable loads are shifted to the hour at which the accumulated load is minimum if it is lower than the current value of the load. Applying this procedure, the new curve of total electrical load is calculated in advance and fed into the simulation program.

IV. Objective Function Optimization

A. Model Reduction

As optimal sizing is a computationally intensive problem, it is important to simplify the model as far as possible without influencing the optimal solution too much. Accordingly, inspired by [9], a model reduction procedure is selected to alleviate computational cost. In this regard, based on the annual profiles for residential loads, EVs charging demand, solar irradiation, and wind speed (8760 data per item), the monthly averaged daily profiles for the aforementioned parameters are derived and a 12×24 model (288 data per item) is developed for each of them.

B. System Cost

The net present cost (NPC) method is used in this study to calculate the total cost of the system. The NPC of each component can be calculated by the following equation [11]:

$$NPC = N \times \left(CC + RC \times K + O\&M\ \times \frac{1}{CRF(ir, R)}\right), \tag{9}$$

where CC, RC, and $O\&M$ denote the capital, replacement, and operation and maintenance costs, respectively; and CRF and K are the capital recovery factor and single payment present worth, respectively that are defined by Eqs. (10)-(12) [11].

$$CRF(ir, R) = \frac{ir(1 + ir)^R}{(1 + ir)^R - 1}, \tag{10}$$

$$K = \sum_{n=1}^{Y} \frac{1}{(1 + ir)^{L \times n}}, \tag{11}$$

$$Y = \begin{cases} \left[\dfrac{R}{L}\right] - 1 & \text{if } R \text{ is dividable to } L, \\ \left[\dfrac{R}{L}\right] & \text{if } R \text{ is not dividable to } L, \end{cases} \tag{12}$$

where N is the optimal number/capacity of each component, ir is the real interest rate which is considered to be 6%, R is the lifetime of the project [yr] that is considered to be 20 years, and L is the lifetime of each component [yr].

The objective function can be described as

$$NPC = NPC_{PV} + NPC_{WT} + NPC_{bat} + NPC_{inv} + NPC_{EVSE}. \tag{13}$$

C. Reliability

The equivalent loss factor (ELF) reliability index is considered in this study as it holds information about the number and magnitude of the outages that happen in the micro-grid. Accordingly, the ELF indices for the residential and EV charging loads can be calculated by Eqs. (14) and (15), respectively [11].

$$ELF_{load} = \frac{1}{288}\sum_{t=1}^{288}\frac{Q_{load}(t)}{P_{load}(t)}, \tag{14}$$

$$ELF_{sta} = \frac{1}{288}\sum_{t=1}^{288}\frac{Q_{sta}(t)}{P_{sta}(t)}, \tag{15}$$

where $Q_{load}(t)$ and $Q_{sta}(t)$ represent the loss of residential and EV charging loads at time step t [kWh], respectively. In this paper, ELF_{load} and ELF_{sta} are considered to be lower than 0.01 and 0.1, respectively.

D. Optimization Algorithm

As the considered problem is formulated as a constrained nonlinear optimization problem that is not appropriate for mathematical optimization methods, three meta-heuristic OAs, namely WOA, PSO, and GA are used to minimize the objective function and their results are compared with each other in terms of convergence speed and optimality of the solution obtained. These algorithms are briefly introduced in the following. The flowchart of a single-run optimization process embedded in each of the following OAs is shown in Fig. 2. In order to create a fair comparison, the number of search agents and iterations are assumed to be the same for all the aforementioned algorithms and are considered to be 60 and 150, respectively.

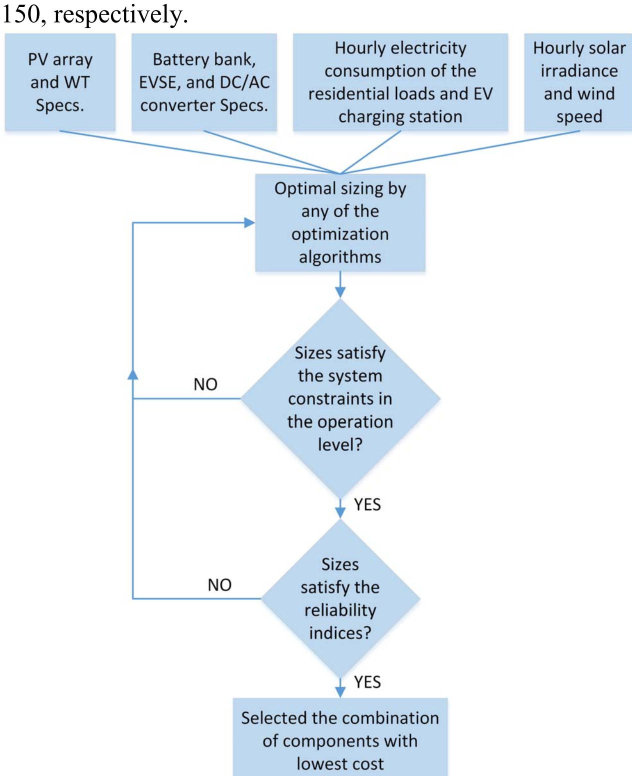

Fig. 2. Flowchart of a single-run optimization process.

1) WOA

WOA is a novel nature-inspired meta-heuristic OA, which is inspired by the hunting behavior of humpback whales and was first introduced by Mirjalili and Lewis in 2016 [13]. The authors in [13] have claimed that it uses a set of rules that improve the candidate solutions in each step of optimization procedure, which makes it superior to the other meta-heuristic OAs. Their claim is checked in the area of energy systems planning in this study.

The following equation describes the main mathematical equation used in this algorithm representing how each whale updates its position:

$$X(t+1) = \begin{cases} X^*(t) - AD, & p < 0.5 \\ D'e^{bl}\cos(2\pi l) + X^*(t), & P \geq 0.5 \end{cases} \tag{16}$$

where $D = |CX^*(t) - X(t)|$, $A = 2ar - a$, $C = 2r$, a is a vector that linearly decreases from 2 to 0 over the course of iterations, p is a random number between 0 and 1, r is a random vector between 0 and 1, $D' = |X^*(t) - X(t)|$, which denotes the distance of i^{th} whale to the prey (best estimation of the solution so far), b is a control constant, l is a random number between -1 and 1, and t shows the current iteration. In this study, b is considered to be 1.

2) PSO

PSO was first introduced by Kennedy and Eberhart in 1995 [14]. Considering a swarm of p particles, the position of each particle X^i in a d-dimensional design space of the problem can be updated as

$$X_{k+1}^i = X_k^i + V_{k+1}^i, \tag{17}$$

with a pseudo-velocity V_{k+1}^i that can be calculated as

$$V_{k+1}^i = w_k V_k^i + c_1 r_1 (P_k^i - X_k^i) + c_2 r_2 (P_k^g - X_k^g), \tag{18}$$

where subscript k denotes a pseudo-time increment; P_k^i and P_k^g are the best position of particle i at time k and the global best position of the swarm at time k in iteration g, respectively; r_1 and r_2 are uniform random numbers between 0 and 1; w is the inertia factor; and c_1 and c_2 are the control coefficients. In this paper, p and w are considered to be 60 and 0.7, respectively. Also, c_1 and c_2 are both considered to be equal to 2 in this study.

3) GA

Genetic algorithm, which is the most frequently encountered type of evolutionary algorithm, starts by assigning a random initial population of chromosomes and evaluating the objective function for each chromosome of the corresponding population. Then, the algorithm implements a selection operation based on the optimality of the chromosomes for reproduction purposes, which is subjected to the crossover (used to merge the genetic information of two parents to produce new off-spring) and mutation (used to keep up genetic diversity from one generation of chromosomes to the next) operations and produces a new generation of chromosomes and determines the best value of the objective function calculated for various generations of chromosomes.

V. Simulation Results and Discussion

The proposed model for optimal sizing of the components of the considered micro-grid is simulated using MATLAB software and the optimal combination of the components is calculated. First, the system is optimized using the WOA, PSO, and GA algorithms and their performance is compared in terms of convergence speed and optimality of the solution obtained. Then, the considered DSM strategy is implemented and the system is optimized using the best algorithm among the above-mentioned algorithms to assess the effects of shifting the residential and EV charging loads from peak to off-peak consumption hours.

The monthly averaged 24-h profile for the entire load demand of the micro-grid, including the residential and EV charging loads before the implementation of the considered DSM strategy, is shown in Fig. 3. Also, the monthly averaged 24-h profiles for the solar irradiance and wind speed are shown in Fig. 4 and Fig. 5, respectively. The aforementioned meteorological data belong to the Kish Island in the Persian Gulf, which is located off the southern coast of Iran that were obtained from the Iran Meteorological Organization. The original data were captured by one sample per hour precision for the year 2016 that are compressed according to the above-mentioned data compression technique.

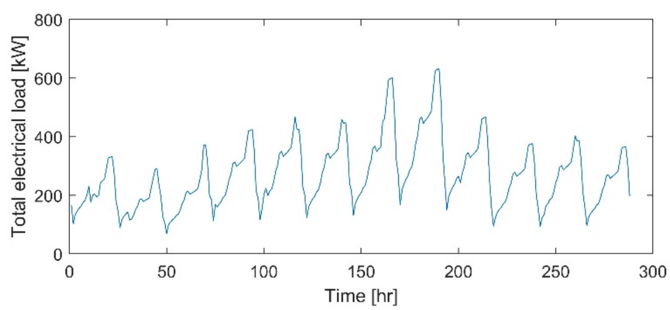

Fig. 3. Monthly averaged daily load of the micro-grid.

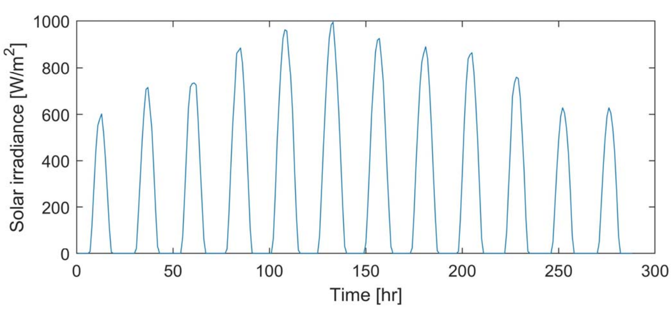

Fig. 4. Monthly averaged daily solar irradiance at the considered location.

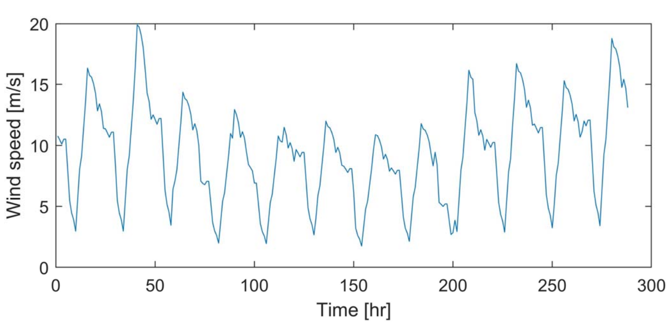

Fig. 5. Monthly averaged daily wind speed at the considered location.

The initial points in the above curves correspond to the monthly averaged values of the considered parameters at 1 o'clock in January 2016.

The specifications of the micro-grid components are shown in Table I [10], [12], [15]. In the table, the "Efficiency" column describes the electric power efficiency and therefore, it is not applicable for the PV array and wind turbine.

TABLE I
Specifications of the proposed micro-grid components [10], [12], [15]

Component	Capital cost	Replace-ment cost	O&M cost	Lifetime [yr]	Efficiency [%]
PV array	$1066 /unit	$902 /unit	$30/ unit/yr	20	N/A
Wind turbine	$11000 /unit	$10000 /unit	$1000/ unit/yr	20	N/A
Battery bank	$264 /kW	$260 /kW	$2.64/ kW/yr	12	85
DC/AC converter	$700 /kW	$650 /kW	$7/ kW/yr	15	90
EVSE	$2000 /unit	$1800 /unit	$20/ unit/yr	20	85

The results obtained by solving the considered optimal sizing problem using WOA, PSO, and GA without considering the DSM strategy are shown in Table II. In this table, the optimal number/capacity of the components have been rounded to the nearest integer. The results show that the GA and WOA have the best and worst performances, respectively. The performance of WOA, although being a state-of-the-art OA, was rather disappointing. This can be justified by the No Free Lunch Theorem [16] that logically proves that there is no meta-heuristic OA properly suitable for solving all optimization problems. Hence, there is evidence to support the hypothesis that the WOA is not an appropriate OA for solving the micro-grid optimal sizing problems.

TABLE II
Comparison of performance of WOA, PSO, and GA

OA	WTs	PV arrays	Battery bank [kW]	Inverter [kW]	EVSEs	Total cost [$]
WOA	64	36	158	491	136	2015560
PSO	66	28	132	358	6	1520888
GA	66	19	133	366	6	1513395

Also, the total cost of the micro-grid in terms of iterations for the aforementioned OAs is shown in Fig. 6. It can be seen that although WOA converges much faster than PSO and GA, it has far less ability to find the optimal solution.

Furthermore, the considered DSM strategy has been incorporated into the micro-grid operation strategy, and the GA is selected, as the OA as it is shown to be superior to WOA and PSO. Table III presents the optimal solution obtained under the considered DSM mechanism using the GA.

The DSM strategy has reduced the peak load from 632.21 kW to 478.38 kW and improved the load factor from 0.4250 to

0.5616, and hence has flattened the load curve. Moreover, the DSM strategy has relatively compensated the low generation flexibility of the renewable energy sources of the micro-grid.

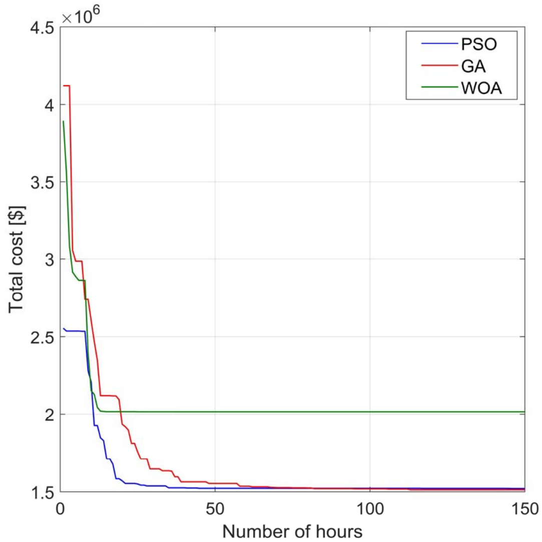

Fig. 6. The total cost of the micro-grid in terms of iterations.

TABLE III
Optimal solution of the problem considering the DSM strategy

OA	WTs	PV arrays	Battery bank [kW]	Inverter [kW]	EVSEs	Total cost [$]
GA	55	22	135	337	5	1257763

It can be observed from Table III that incorporating the DSM strategy into the considered optimal sizing procedure has contributed to enhance the system operation performance, which in turn has reduced the number of WTs and EVSEs as well as the capacity of the inverter, which in turn has reduced the total cost of the micro-grid by 17%.

VI. Conclusion and Future Work

This paper has incorporated a novel operational strategy into the optimal sizing procedure of a micro-grid that takes into account the charging scheduling of EVs, as well as the load deferment potential of residential loads using three OAs. The findings of this study support the idea that implementing the DSM strategies, while optimally sizing the components of the sustainable energy systems, reduces the sizes of some of the components, which in turn reduces the overall cost.

The evidence from this study points toward the idea that compared to the PSO and GA, which are the most commonly used OAs for optimal sizing of renewable energy systems, the WOA is not an appropriate OA in this research topic as it reduces the required number of iterations for convergence at the cost of sacrificing the accuracy of the solution. Also, a data compression-based model reduction technique is applied that has preserved the computational tractability.

This study considered a conceptual self-sustainable micro-grid in Kish Island. Although the meteorological data in this study is specifically associated with the Kish Island, there are many similar regions around the world with this typical weather situation that the proposed micro-grid can be designed and implemented for them, but other than that, the renewable energy technologies used in the proposed micro-grid can also be updated based on the renewable energy potential of other case study locations and the same procedure for optimal sizing of the components can be pursued to consider the effects of charging coordination of EVs and deferring residential loads on the calculated sizes for the components.

To further our research, we intend to consider the effects of the uncertainties associated with renewable generation and load demand, while optimally sizing the components of the micro-grid in the presence of the considered DSM strategy.

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