OPTIMUM MANAGEMENT OF HYBRID DISTRIBUTED GENERATIONS IN MICROGRID USING BACTERIAL FORAGING SOLUTION

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ABSTRACT: *This paper presents a method to model the distributed generation (DG) and proposes a novel methodology for managing DG units operation in an isolated microgrid. DG could be utilized in an islanded microgrid; this topology by decreasing the connection of the microgrid to unforeseen networks could improve network reliability and guaranteed securely power supply to the burdens. Security requirement in a specific grid could cause inattention to economic aspects of the network; in this paper to consider costs, first the system has been modeled in an accurate way. Power production, efficiency, fuel consumption and economic characteristics of each DG considered in this model. A number of notable and popular DG technologies such as wind power, photovoltaic, micro turbine, fuel cell and diesel generators are modeled and utilize to model an isolated power system. An optimal network management could be achieved only by considering economic characteristics, a novel evolutionary algorithm known as bacterial foraging algorithm (BFA) has been applied to minimize the defined cost function by considering network and customers (load) limitations. The proposed method has applied to an isolated microgrid. In comparison with pervious works it shows better results in reducing daily power generation and costs.*

Key Words: *Bacterial foraging, DG modeling, Microgrid, Power management*

1. INTRODUCTION

Microgrid is collection of electrical generation and loads. The power generators in the microgrid could be micro turbine, fuel cell, wind turbine, photovoltaic, diesel generator and biomass. Microgrid could appear as special area, such as military zone, industrial park or campus. As a benefit, microgrid could be considered as an electrical load that its demands can be controlled, a load that could be considered constant or could increase in durations of time when electricity is inexpensive, or could act independent like an island during the time in which system is instable.

The purpose of the Power Management System (PMS) in microgrid is to make decision about the best implementation of generators in the microgrid. These decisions are based on quantity of load, price of active power in electric market, cost of fuels, the rate of pollution of generators and many other considerations, in the other hand the microgrid units should be regulated to satisfy customers load demands at the minimum cost for all the time.

To preserve important loads from unforeseen events such as voltage fluctuation which sometimes occur in the networks specially for sensitive areas it seems better to manage microgrid as isolated network to has less contact with upper networks, but this isolated operation can make limitations in providing economic energy for customers, it is operators responsibility in centralized control unit to choose the optimal generators in the microgrid to make energy consumption inexpensive and economical; for this purpose it is necessary to provide various small generators with different performance and economic models.

The management of the microgrid units requires accurate economic model to describe the operating cost which considers generators output power, it also need an optimization program to reduce the operating costs to the lowest level. This goal can be achieved with evolutionary programming.

Some potential economic benefits of microgrid are summarized as in [1]:

- Reducing transmission and distribution cost and energy loss.
- Higher energy efficiency
- The small scale individual investments reduce capital exposure and risk, by closely matching capacity increase to growth in demand.
- The low capital cost potentially enables low cost entry into a competitive market.

Various researches have been done in the area of microgrid. Some model structures have been proposed in [2]. A rational method for optimizing microgrid for cost subject to reliability constraints has been presented in [3]. In [4] the problem of microgrid management has solved without considering the contacts with the other networks [5]. Combinations of one or more resources of renewable energy, hybrid, in which renewable sources can complement each other to improve load factor and reduce maintain and replacement costs is introduced [6]. In spite of high initial investment cost of the hybrid that is the main drawback in adoption of hybrid systems, the need for long lasting, reliable and cost effective system make it possible [7]. Design of a hybrid system would require accurate component selections and select appropriate size for them with suitable operation strategy [8,9]. Optimization and component sizing based on worst initial data such as monthly load scenarios could lead to no optimal design with excess capacity and cost [10]. The author in [11] purposed that the optimal hybrid systems should be determined by minimizing the kilowatt-hour (kWh) cost.

With rapid growth of wind and photovoltaic (PV) in power systems expectances has increased [12]. Fuel cell (FC) also has good work and can be a green source of the future power demand due to its remarkable power quality.

However, because different alternative energy sources can complement each other to some extent, multisource hybrid alternative energy systems (with proper control) have great potential to provide higher power quality and more reliable energy for customers than a system that is based on a solitary source. Because of this characteristic, hybrid energy systems have caught worldwide research attention [13–18].

Alternative energy sources like wind, PV, fuel cell, diesel system, gas turbine, and micro turbine (MT) can be used to build a hybrid energy system [13–18]. Generation of some renewable sources such as PV has no relationship with load demand which can lead to instabilities in the system. A solution to conquer this problem is using intermediate energy storage system, such as battery.

In this paper, microgrid has been modeled precisely based on study of DG performance in terms of accuracy and efficiency. This model includes fuel cost, operation and maintenance cost, and start-up cost as well as the pollution emissions cost so can significantly explains all costs of each generator. However, development of the system model requires minimization of the total system cost. So, it is important that the cost minimizing be done along with considering supplement of microgrid load demands. Considering pollution emissions in dispatching is an attractive alternative in which both penalty cost and emission is considered to be minimized. In recent years, this subject has attracted much attention because it requires making only small modifications in economic dispatch to include emission [19].

The object in this work is to find the most economical generation to satisfy the load demand and generation constraints. The problem is decomposed into several stages; the first stage is modeling of system components, which is important to understand the problem. The next stage is to use an optimization algorithm. This algorithm can make optimum decisions for microgrid operation in order to reduce the total operating cost. The algorithm seeks for the optimal selection of power generators based on input data which includes electrical load demand, technical and cost specifications of microgrid equipment such as wind speed, temperature, and irradiation; also it must provide the electrical load demand in an economical manner.

This paper employs a new integer code optimization algorithm of evolutionary computation, known as bacteria foraging algorithm (BFA) [20], to solve optimal management of microgrid. BFA has been recently introduced [21] and is further applied for: harmonic estimation problem in power systems [22], optimization of both real power losses and voltage stability limit [23], optimization of active power filter design for load compensation [24] and better solution for the unit-commitment problem [20].

To improve certainty of proposed method, results compared with previous work [25], that is, implement Mesh adaptive direct search (MADS) and sequential Quadratic Programming (SQP) for microgrid management, These methods are two popular algorithms in nonlinear optimizations. The results conclude that proposed method (BFA) has better performance in this problem and has reduced generated power and cost more effectively than previous method.

2. MODELING OF THE PROPOSED METHOD

The structure of microgrid that takes into account in this study consists of the micro sources include photovoltaic (PV), wind turbine, fuel cell, micro turbine and a diesel generator.

The fuel input for the diesel generator is diesel oil whereas for micro turbine and fuel cell is natural gas but the fuel for the wind turbine and PV comes from nature. To serve the load demand, electrical power can be produced either directly by PV, wind turbine, diesel generator, micro turbine, or fuel cell. Each component of the microgrid system is modeled separately based on its characteristics and constraints. The characteristics of some equipment like wind turbines and diesel generators are available from their manufacturers.

The optimization model is formulated as follows: The output of this model is the optimal configuration of a microgrid considering the technical performance of generators, load demand characteristics, environmental energy costs, start-up cost, daily electric power price, and operating and maintenance (OM) costs.

Data about locally available energy resources include wind speed (m/s) is depicted in Figure 1, temperature (°C) as in Figure 2, solar irradiation data as shown in Figure 3.

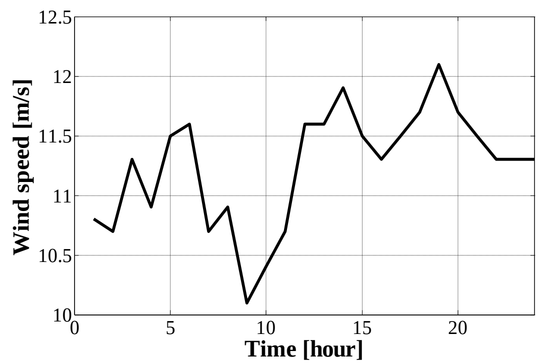


Figure 1 Input wind speed used in this model

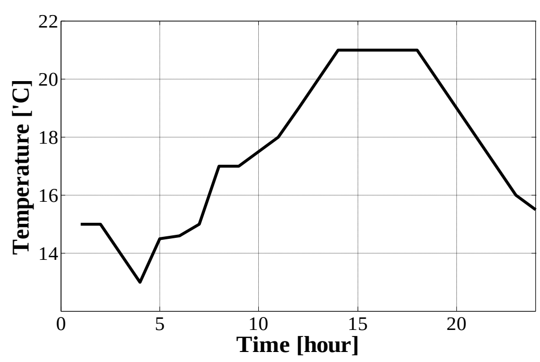


Figure 2 Input temperature used in this model

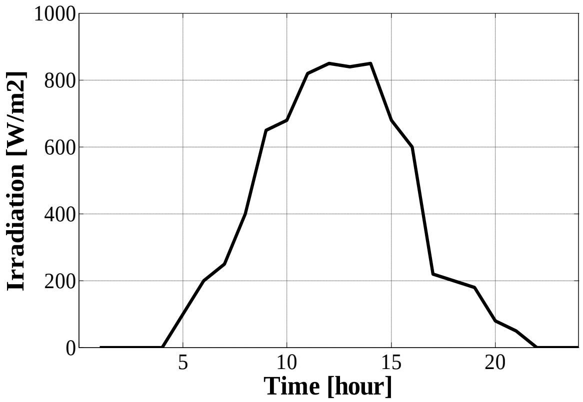


Figure 3 Input irradiation used in this model

3. ENERGY SOURCES

Photovoltaic system, diesel generator, fuel cell and micro turbine models that are used in this paper are based on classical formulations in [25].

To model output power of wind turbine there are three kinds of methods: the linear, quadratic, and cubic models. According to [26] the quadratic model is the most accurate. To compare the results with [25] the same model has been used.

The proposed power model is based on the quadratic model of the turbine power curve as a function of the wind velocity, V, is represented as [26]:

$$P_w = \begin{cases} 0 & V < V_{ci} \ or \ V > V_f \\ P_r \dfrac{V^2 - V_{ci}^2}{V_r^2 - V_{ci}^2} & V_{ci} \le V < V_r \\ P_r & V_r < V \le V_f \end{cases} \quad (1)$$

where

P_w	is output power
P_r	rated power
V_{ci}	cut-in wind speed
V_r	rated wind speed
V_f	cut-out wind speed

We use AIR403 wind turbine model in this work. According to the data from the manufacturer, the turbine rated output P_r is 400W at the velocity of 12.5 m/s (28 mi/h) [27].

Based on with the actual power curve obtained from the owner's manual the parameters which have used to model the power curve in (1) are as follows:

P_r = 400 W; V_{ci} = 3.5 m/s; V_f = 18 m/s; V_r =12.5 m/s.

3.1 Battery Storage Devices

Battery devices, charged during low load demand, usually combined DGs to supply the required peak load demand [29], it could help the microgrid to keep its isolation nature. These batteries are called "deep cycle" that unlike car batteries, which might damage if they have deep discharging for several times, deep cycle batteries can be charged and discharged for a large number of times without any failure. These batteries have a charging controller for protection from overcharge and over discharge that disconnect the battery from the charging process when the battery is fully charged.

When you determining the state of charge for a storage device two charge constraints must be satisfied, the constraints that represent that the maximum allowable charge and discharge current must be less than 10% of battery AH capacity as shown in the following equations, respectively [25]:

$$\begin{aligned} P_{charge} &\le 0.1 \times V_{sys} \times U_{batt} / \Delta t \\ P_{discharge} &\le 0.1 \times V_{sys} \times U_{batt} / \Delta t \end{aligned} \quad (2)$$

Where, V_{sys} is the system voltage at the DC bus, Δt is the time period in hours, and U_{batt} is the battery capacity in Ah (ampere-hour).

4. PROBLEM FORMULATION

In utilizing microgrid sources in power network, it is important to select of suitable DGs that not only economically satisfying the load demand, but also taking into account the environmental externality costs by minimizing the emissions of nitrogen oxides (NO_x), sulfur oxides (SO_2), and carbon oxides (CO_2). The proposed cost function for microgrid that satisfies load demand considered as the following form [25]:

$$\begin{aligned} CF(P) = \sum_{i=1}^{N} & C_i \times F_i \ P_i \ + OM_i \ P_i \ + DCPE_i - IPSE_i \\ & + \sum_{i=1}^{N} \sum_{k=1}^{M} \alpha_k \ EF_{ij} P_i \end{aligned} \quad (3)$$

where

C_i fuel costs of generating unit i ($×h/L for the diesel and $/kWh for the natural gas)

$F(P_i)$ Energy consumption rate of generator unit i (kWh) of natural gas and fuel consumption of diesel generator (L/h)

$OM(P_i)$ operation and maintenance cost of generating unit i ($)

Pi decision variables, representing the power output of generating unit i

$P = (P_1; P_2; \ldots ; P_N)$ decision variable vector α_k externality costs of emission type k ($/lb)

EF_{ik} emission factor of generating unit i and emission type k (lb/MWh)

N number of generating units

M emission types (NO_x or CO_2 or SO_2)

$DCPE$ daily cost of purchased electricity power ($/h)

$IPSE$ daily income for sold electricity power ($/h)

The generator startup cost depends on the time the unit has been off before the start up [25]. The operating and maintenance costs, OM, of generators are supposed to be proportional with the produced energy, where the proportional constant is $K_{OM,}$ for each generator:

$$OM = \sum K_{OM} P \quad (4)$$

The values of K_{OM} for different generation units, diesel engine (DE), FC, MT are as follows [28]:

K_{OM}(DE) = 0.01258 \$/kWh.
K_{OM}(FC) = 0.00419 \$/kWh.
K_{OM}(MT)= 0.00587 \$/kWh.

In microgrid management, the main goal is to balance the differences between the load demand and the generated output power of micro sources in microgrid. Therefore sometimes money should be paid for the purchased power when the generated power is not sufficient to cover the load demand. On the other hand, maybe sometimes there is income when the generated power is higher than the load demand and the power has been generated in lower price than the market. Therefore, to model the purchased and sold power, two different conditions are considered. The following equations define these conditions [30]:

$$\begin{aligned} DCPE &= C_p \times \max\ P_L - P_i, 0 \\ IPSE &= C_S \times \max\ P_i - P_L, 0 \end{aligned} \quad (5)$$

where C_p and C_s are the price of the purchased and sold power respectively in (\$/kWh), P_L is the load demand in microgird in (kWh) and P_i is generated power in microgrid. C_p and C_s are determined with electric market.

To satisfy the active power balance, an equality constraint is:

$$\sum_{i=1}^{N} P_T - P_L + P_{PV} + P_{WT} + P_{batt} \quad (6)$$

where

P_L the total power demanded in kW
P_{PV} the output power of the photovoltaic cell in kW
P_{WT} the output power of the wind turbine in kW
P_{batt} the output power of the battery storage kW
P_T contains sold or purchased power exchange from the electric power network.

Real power output of each generator *Pi* is limited by lower and upper boundaries as follows:

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1, \ldots, N \quad (7)$$

where

P_{min} Minimum operating power of unit i
P_{max} Maximum operating power of unit i

Externality costs and emission factors of the diesel generator, fuel cell, and micro turbine used are stated in [30]. When planning for microgrid, various goals could be set like reduction in emissions and generation costs. To obtain this goal, it is important to highlight all factors influencing the main goal. The following items present the ideas of the implemented algorithm [25]:

Power output of wind turbine is calculated according to Eq. (1) with measured wind speed data.

- Power output of PV is calculated with measured temperature and solar radiation data.
- We consider that wind turbine and PV deliver free cost power (in terms of running as well green power), and suppose that their output powers as negative loads.
- Serving the load demand by other sources (fuel cell or micro turbine or diesel generator) is chosen according to the cost function of each one.
- If the load demand is more than power generation of distributed sources, extra needed power will be purchased from electric power network and its cost will be added to total generation cost, in this contract we don't consider any emission penalty and transmission loss for purchased power. The amount of purchased electric power shouldn't be more than need, because it could indemnify the isolation nature of our microgrid.

5. BACTERIAL FORAGING OPTIMIZATION

The idea of BFA is based on the fact that natural selection tends to eliminate animals with poor foraging strategies and favor those having successful foraging strategies. After many generations, poor foraging strategies are either eliminated or reshaped into good ones. The *E. coli* bacteria that are present in our intestines have a foraging strategy governed by four processes, namely, chemotaxis, swarming, reproduction, and elimination and dispersal [20].

5.1 Process of BFA

Chemotaxis could achieved through swimming and tumbling. Depending upon the rotation of the flagella, the bacterium decides what direction it should move (tumbling) and if the new location of bacterium after moving is better, the bacterium will begin to swim in the same previous direction (swimming).

Suppose that we want to find the minimum of $J(\theta), \theta \in R^P$. Assume that θ is the position of a bacterium and represents the amount of the food at θ the position $J(\theta) < 0$, $J(\theta) = 0$ and $J(\theta) > 0$ representing that the bacterium at location θ is in nutrient-rich, neutral, and noxious environments, respectively.

To represent a tumble, a unit length random direction, say $\phi(i)$, is generated. This will be used to define the direction of movement after a tumble. In particular

$$\theta^i\ j+1, k, l = \theta^i\ j, k, l + C\ i\ \phi\ i \quad (8)$$

where $\theta^i(j,k,l)$ represents the i^{th} bacterium at j^{th} chemotactic, k^{th} reproductive, and l^{th} elimination and dispersal step. *C(i)* is the size of the step taken in the random direction specified by the tumble. If at $\theta^i(j+1,k,l)$, the cost of $J(i,j,k,l)$ is lower than at $\theta^i(j,k,l)$, then another step of size *C(i)* in the direction $\phi(i)$ will be taken and bacterium will begin to swim in the direction $\phi(i)$. This swim is continued as long as it continues to reduce the cost, but only up to a maximum number of steps N_s. This represents that the cell will tend to keep moving if it is headed in the direction of increasingly favorable environments.

It is always desired that the bacterium that has searched the optimum path of food should try to attract other bacteria so that they reach the desired place more rapidly. Swarming makes the bacteria congregate into groups and hence move as concentric patterns of groups with high bacterial density. Let

$$P(j,k,l)=\{\theta^i(j,k,l)|i=1,2,...,S\}$$

Mathematically, swarming can be presented by:

$$J_{CC}(\theta,P(i,j,k))=\sum_{i=1}^{S}J_{CC}^{i}(\theta,\theta^{i}(j,k,l))$$

$$=\sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{P}(\theta_m-\theta_m^i)^2\right)\right] \quad (9)$$

$$+\sum_{i=1}^{S}\left[-h_{repelent}\exp\left(-\omega_{repelent}\sum_{m=1}^{P}(\theta_m-\theta_m^i)^2\right)\right]$$

where $J_{CC}(\theta,P(i,j,k))$, due to the movement of all the cells, is a time varying cost function that is added to $J(i,j,k,l)$ so that the cells will try to find nutrients, avoid noxious substances, and at the same time try to move toward other cells, but not too close to them.

S is the total number of bacteria. *p* is the number of parameters to be optimized which are present in each bacterium position. $d_{attract}$, $\omega_{attract}$, $h_{repelent}$ and $\omega_{repelent}$ are different coefficients that are to be chosen judiciously.

The $S_r=S/2$ least healthy bacteria die and the other healthiest bacteria each split into two bacteria, which are placed in the same location. This makes the population of bacteria constant. This step is called reproduction.

It is necessary that we consider elimination and dispersal in BFA because it is possible in the local environment that the life of a population of bacteria changes either gradually by consumption of nutrients or suddenly due to some other influence. Events can kill or disperse all the bacteria in a region. They have the effect of possibly destroying the chemotactic progress, but they also have the effect of assisting in chemotaxis, since dispersal may place bacteria at better locations. Elimination and dispersal prevents bacteria from being trapped in local optima. For each elimination dispersal event each bacterium in the population is subjected to elimination-dispersal with probability P_{ed}. To keep the number of bacteria constant, if we eliminate a bacterium, simply disperse one to a random location on the optimization domain.

6. IMPROVED BACTERIAL FORAGING OPTIMIZATION ALGORITHM

Some modifications are applied to the BF algorithm suggested in [21] in order to expedite the convergence. The modifications are discussed in the following.

1) In [21] the health of bacterium *i*, j^i_{health} is defined as the sum of bacterium costs in the chemotactic steps.

If health of bacteria is defined by this method, it may not retain the best bacterium for the next generation. In this study, as suggested in [23], the minimum value of all the bacterium chemotactic costs is used for evaluating the bacterium health. This speeds up the convergence, in reproduction stage. The least healthy bacteria die and the other healthiest bacteria first are moved to their minimum cost value locations found in their chemotactic life time and then each split into two bacteria which are placed at the same location.

2) For swarming, the distances of all the bacteria in a new chemotactic stage is evaluated from the global optimum bacterium until that point and not the distances of each bacterium from the rest of the others, as suggested in [23]. The algorithm is discussed here in brief [20].

Step 1:

Initialization: First following variables must be chosen.

- *S* Number of bacteria to be used in the search
- *P* Number of parameters to be optimized
- N_s Swimming length
- N_c Number of chemotactic steps
- N_{re} Number of reproduction steps
- N_{ed} Number of elimination and dispersal events
- P_{ed} Probability of elimination and dispersal
- *C(i)* Unit length runs for every bacterium.
- The values of $d_{attract}$, $\omega_{attract}$, $h_{repelent}$ and $\omega_{repelent}$
- Initialize values for $\theta^i, i=1,...,S$.

Step 2:

Iterative algorithm for optimization:

1) Elimination-dispersal loop: *l=l+1*
2) Reproduction loop: *k=k+1*
3) Chemotaxis loop: *j=j+1*

3.1 For *i=1,..,S* take a chemotactic step for bacterium as follows.

3.2 Compute $J(i,j,k,l)$.

Let

$J(i,j,k,l)=J_{sw}(i,j,k,l)+J_{cc}(\theta^i(j,k,l),P(j,k,l))$ (i.e., add on the cell-to-cell attractant effect for swarming behavior).

3.3 Let $J_{last}=J_{sw}(i,j,k,l)$ to save this value since we may find a better cost via a run.

3.4 Tumble: Generate a random vector with each element $\Delta_m(i)$, $m=1,2,...,p$ a random number on [-1 1].

3.5 Move

Let $\phi(i)=\dfrac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$,

$$\theta^i(i,j,k,l)=\theta^i(j,k,l)+C(i)\phi(i)$$

This results in a step of size $C(i)$ in the direction of the tumble for bacterium i.

3.6 Compute $J(i, j+1, k, l)$ and then let

$$J_{sw}(i, j+1, k, l) = J(i, j+1, k, l) + J_{CC}(\theta^i(j+1, k, l), P(j+1, k, l))$$

3.7 Swim:

3.7.1 Let m=0 (counter for swim length).

3.7.2 While $m < N_s$

- Let m=m+1
- If $J_{sw}(i, j+1, k, l) < J_{last}$ (if doing better), let $J_{last} = J(i, j+1, k, l)$ and then let $J_{sw}(i, j, k, l) = \theta^i(j, k, l) + C(i)\phi(i)$ and use this $\theta^i(j+1, k, l)$ to compute the new $J(i, j+1, k, l)$ as did in 3.7.
- Else, let $m=N_s$. This is the end of the while statement.

3.8 Go to the next bacterium ($i+1$) if $i \neq S$ (i.e., go to b) to process the next bacterium.

4) If $j<N_c$, go to step 3. In this case, continue chemotaxis, since the life of the bacteria is not over.

5) Reproduction:

5.1 For the given k and l and for each $i=1,\ldots,S$, let $J^i_{health} = \min_{j \in 1,\ldots,N_c+1} J_{sw}(i, j, k, l)$ be the health of bacterium i. Sort bacteria in order of ascending cost (higher cost means lower health).

5.2 The S_r bacteria with the highest J_{health} values die and the other S_r bacteria are moved to the location with cost equal to $J^i_{healtth}$ and then split (the copies that are made are placed at the same location as their parent).

6) If $k<N_{re}$, go to step 2. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotactic loop.

7) Elimination-dispersal: For $i=1,\ldots,S$ with probability P_{ed}, eliminate and disperse each bacterium. To do this, if you eliminate a bacterium, simply disperse one to a random location on the optimization domain.

8) If $l<N_{ed}$, then go to step 1; otherwise end.

6.1 Bacterial Foraging algorithm parameters

One of challenges in using of BF algorithm is the appropriate selection of its parameters including S, N_c, N_s, N_{re} and N_{ed}. The speed of convergence differs for different combinations of above parameters. So to achieve the fastest convergence the algorithm should be run for number of times for different values of S, N_c, N_s, N_{re} and Ned. Improper values for these parameters may cause excessive attraction or repellent of bacteria. So these parameters will also affect the convergence of the algorithm. It was found that the fastest convergence occurs when S=50, N_c=20, N_s=4, N_{re}=4 and N_{ed}=2. It is found that the proposed BFA converges is fast enough to find solution and locates a significantly better solution.

7. RESULTS

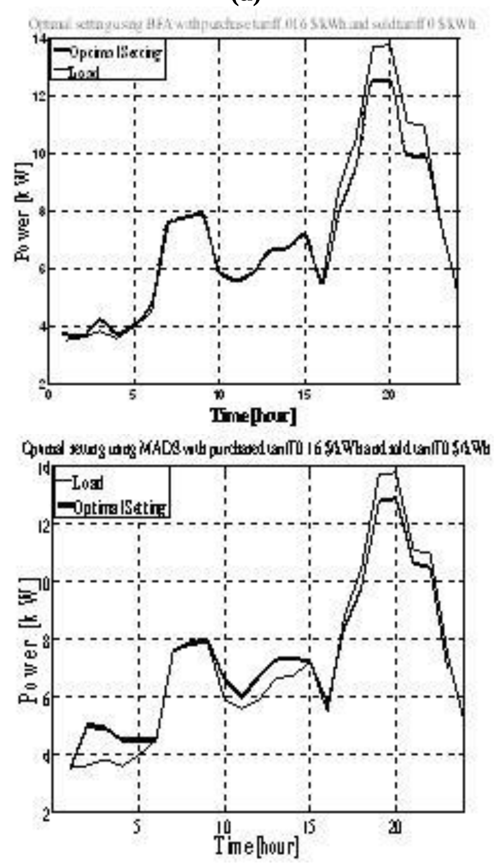
The described optimization model is applied to a load varying between 4 kW and 14 kW. The obtained results show that the battery capacity was not enough for supplying the load for the duration of time so the value of the battery when it is charging, is added to the power demand. Then the algorithm estimates the needed power to charge the battery and serve the load with considering financial aspects.

To evaluate the effect of varying the prices on the optimal settings, some comparisons with the results of mesh adaptive direct search method (MADS) for microgrid management [25] are given in Figure 4 to Figure 7 for load curve.

In each step one price is change, while the other is keeps constant. Figure 4 and Figure 5 show the effect of varying the sold price 0.0 $/ kWh in first case and 0.12 $/kWh in second case, while purchased price is kept constant at 0.16$/kWh by using BFA method and MADS method. Figure 6 and Figure 7 depict the effect of varying the sold price for the same load curve and same using BFA method and MADS method.

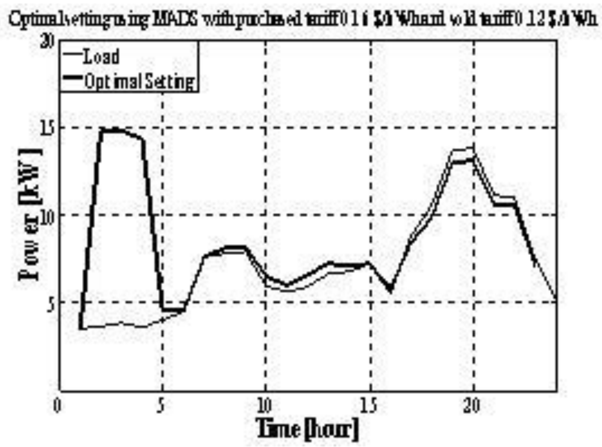
The BFA has better output for minimizing the total cost, also in finding a compromise between sold and purchased power.

(a)



(b)

Figure 4 Effect of sold price on microgrid optimal operation



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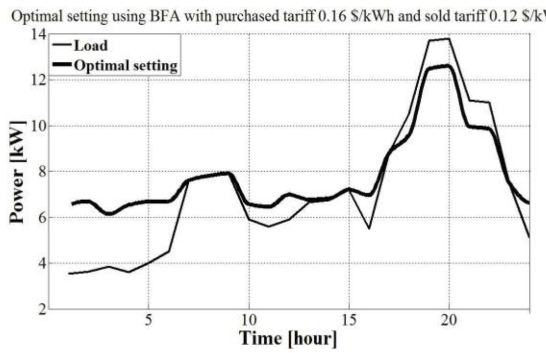
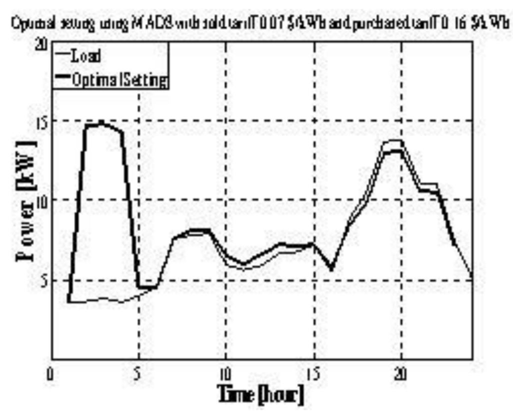


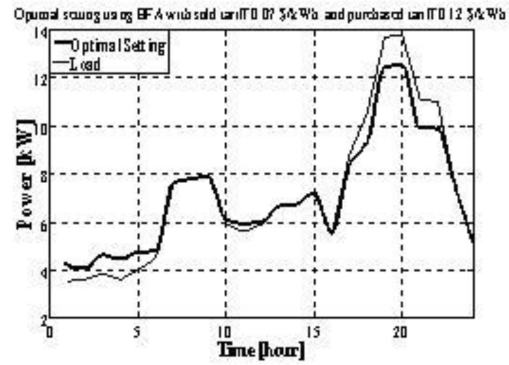
(b)

Figure 5 Effect of sold price on microgrid optimal operation

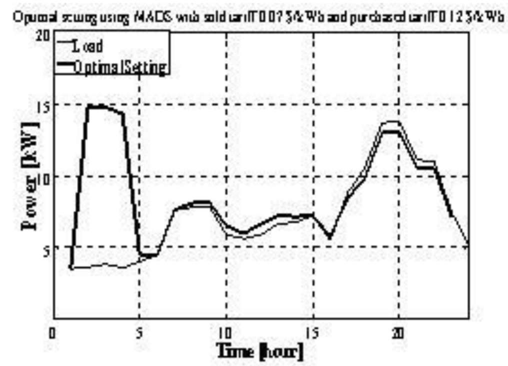


(a)

Figure 6 Effect of purchased price on microgrid optimal .



(a)



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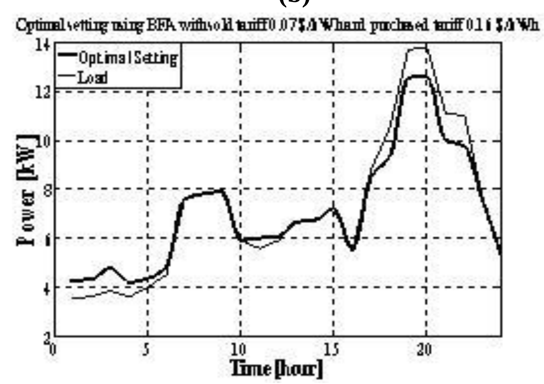


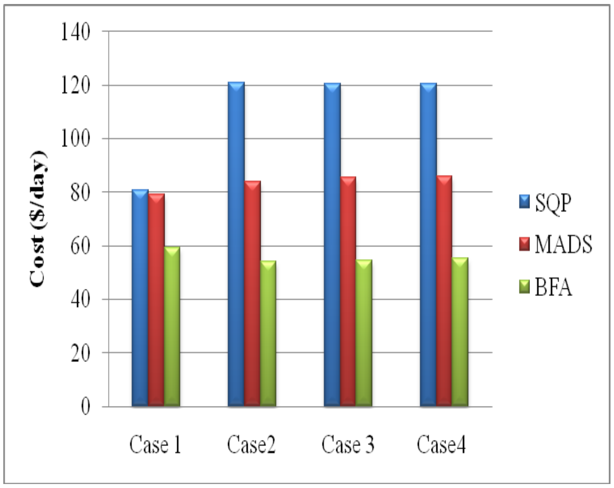
operation

Figure 7 Effect of purchased price on the microgrid optimal operation

Table I summarizes the four applied cases [25]. Unlike MADS method that could not find optimal value in the last two cases when make changes in the purchase prices by keeping the sold prices at a constant value, BFA can recognize the optimal setting of the microgrid in all situations. However, using BFA leads to better cost compared to MADS method. The effectiveness of the approach has been show through different scenarios.

The total electrical output power of the three micro sources with MADS is similar in the three last cases but BFA could find the best choice with different value in total cost and also for each load amount, operating prices and operating cost. In some cases, one or two units are not used for a long time, in other cases, one unit is used only for short peak-load periods based on financial benefits, as shown in Figure 4 to Figure 7.

Switching on one or two units will cause increment in the total operating cost due to the start-up costs. In addition,



the Figure 8 Comparison of optimal generation with different method

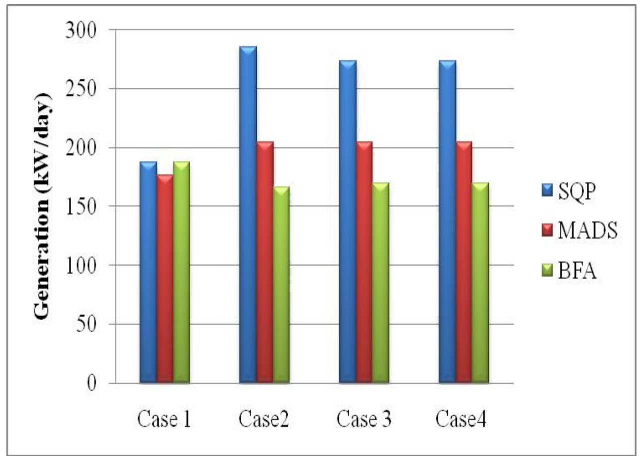


Figure 9 Total Cost of optimal generation as different method

utilization of the three units in parallel results in operating the units at lower efficiencies compared to a single unit since they generate a higher percentage of power based on their ratings. The result from BFA shows the high accuracy of finding the minimum and proves the high capability of the BFA to extract the features of the optimal performance its performance compare in Figure 8 and Figure 9.

From result in Table I the average optimal daily operating cost using MADS is about *83.5920* $/day that is average of four cases. This value increases to *110.6832* $/day if the SQP method is used to find optimal values, but BFA by its good performance reduce average cost to *55.765* $/day that show *33.2%* cost decrement in comparison to MADS and *49.6%* decrement in cost in comparison to SQP algorithm as shown in Figure 8 and Figure 9. The reduction achieved using the BFA technique represents a minor decrease in the daily operating cost.

From Table I and Figure 8 and Figure 9, it is clearly evident that the SQP algorithm failed to meet reducing the cost as the selection of the power was at maximum. The total cost was 80.8576 $ in case 1 and 120.8424 $ in case 2, The effect of changing purchase prices on the operation of the microgrid with purchase price 0.12 $/kWh in case 3 and 0.16$/kWh in case 4, while the sold prices is kept constant at 0.07$/kWh for both cases [25], but BFA has good performance in all four cases in comparison either MADS or SQP.

These results show the success of the BFA to capture the optimal behavior of the microgrid with high accuracy for four different cases. Table I compares the total daily operating costs when the BFA is used to minimize the total cost of the microgrid with the SQP and MADS considering the optimal settings for the four investigated cases.

Generally, the BFA approach can be applied to provide simple and effective optimized decisions for microgrid.

8. CONCLUSION

A model to determine the optimal operation of a microgrid with considering both load demand and environmental requirement has been presented in this paper. The proposed optimization problem includes a variety of energy sources that usually used in microgrid: a fuel cell, a wind generator, a diesel generator, a micro turbine and a photovoltaic cell. Constraints are considered in the optimization problem to reflect some of the limitations which found in a small scale generation systems and also environmental externality costs have been considered. From the results, it is clear that the optimization method works very well and assigns optimal power to the best generators after taking into account the cost function for each of DG. Responses are affected by several variables including sun irradiation, wind, emission, operation and maintenance cost, sold and purchased price, and the variable power demand.

The results reflect the capability of the proposed method to obtain both reduction in the operating costs and providing the load demand. The proposed procedure can be executed with different loads and for periods more than one day for variable electrical market price. From the obtained results it is remarkable that the effect of changing the sold prices results in different optimal settings of the microgrid depending on the optimization technique. It is clear that the sold prices have more effect on the method. The total network cost per day is the lowest in all cases when the BFA method is utilized.

TABLE I
OPTIMAL GENERATION AND TOTAL COST OF MICROGRID

Different method	PL (kW/Day)	Cp ($/kWh)	Cs ($/kWh)	Total cost ($/Day)			Optimal Generation (kW/Day)		
				SQP	MADS	BFA	SQP	MADS	BFA
Case 1	171.4	0.16	0.00	80.86	79.08	59.108	187.65	176.10	187.67
Case 2	171.4	0.16	0.12	120.84	83.91	54.08	285.0	204.28	166.23
Case 3	171.4	0.07	0.07	120.51	85.61	54.65	273.12	204.28	169.54
Case 4	171.4	0.07	0.007	120.52	85.78	55.22	273.12	204.28	169.81

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