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Modelling and Environmental/Economic Power Dispatch of MicroGrid Using MultiObjective Genetic Algorithm Optimization

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1. Introduction

MultiObjective (MO) optimization has a very wide range of successful applications in engineering and economics. Such applications can be found in optimal control systems (Liu et al., 2007), and communication (Elmusrati et al., 2007). The MO optimization can be applied to find the optimal solution which is a compromise between multiple and contradicting objectives.

In MO optimization we are more interested in the Pareto optimal set which contains all non-inferior solutions. The decision maker can then select the most preferred solution out of the Pareto optimal set.

The weighted sum method to handle MO optimization applied in this paper. Furthermore, the weighted sum is simple and straightforward method to handle MO optimization problems.

The need for more flexible electric systems to cope with changing regulatory and economic scenarios, energy savings and environmental impact is providing impetus to the development of MicroGrids (MG), which are predicted to play an increasing role of the future power systems (Hernandez-Aramburo et al., 2005). One of the important applications of the MG units is the utilization of small-modular residential or commercial units for onsite service. The MG units can be chosen so that they satisfy the customer load demand at compromise cost and emissions all the time. Solving the environmental economic problem in the power generation has received considerable attention. An excellent overview on commonly used environmental economic algorithms can be found in (Talaq et al., 1994). The environmental economic problems have been effectively solved by multiobjective evolutionary in (Abido, 2003) and fuzzy satisfaction-maximizing approach (Huang et al., 1997).

Several strategies have been reported in the literature related to the operation costs as well as minimizing emissions of MG. In (Hernandez-Aramburo et al., 2005) the optimization is aimed at reducing the fuel consumption rate of the system while constraining it to fulfil the local energy demand (both electrical and thermal) and provide a certain minimum reserve

power. In (Hernandez-Aramburo et al., 2005) and (Mohamed & Koivo, 2010), the problem is treated as a single objective problem. This formulation, however, has a severe difficulty in finding the best trade-off relations between cost and emission. In (Mohamed & Koivo, 2007) the problem is handled as a multiobjective optimization problem without considering the sold and purchased power.

The algorithm in (Mohamed & Koivo, 2008) is modified in this chapter; the modification is to optimize the MG choices to minimize the total operating cost. Based on sold power produced by Wind turbine and Photovoltaic Cell, then the algorithm determines the optimal selection of power required to meet the electrical load demand in the most economical and environmental fashion.

Furthermore, the algorithm consists of determining at each iteration the optimal use of the natural resources available, such as wind speed, temperature, and irradiation as they are the inputs to windturbine, and photovoltaic cell, respectively. If the produced power from the wind turbine and the photovoltaic cell is less than the load demand then the algorithm goes to the next stage which is the use of the other alternative sources according to the load and the objective function of each one.

This chapter assumes the MG is seeking to minimize total operating costs. MicroGrids could operate independently of the uppergrid, but they are usually assumed to be connected, through power electronics, to the uppergrid. The MG in this paper is assumed to be interconnected to the uppergird, and can purchase some power from utility providers when the production of the MG is insufficient to meet the load demand. There is a daily income to the MG when the generated power exceeds the load demand.

The second objective of this chapter deals with solving an optimization problem using several scenarios to explore the benefits of having optimal management of the MG. The exploration is based on the minimization of running costs and is extended to cover a load demand scenario in the MG. Furthermore, income also considered from sold power of WT and PV. Switching one load is considered in this paper. It will be shown that by developing a good system model, we can use optimization to solve the cost optimization problem accurately and efficiently. The result obtained is compared with the results obtained from (Mohamed & Koivo, 2009).

2. System description

The MG architecture studied is shown in Fig 1. It consists of a group of radial feeders, which could be part of a distribution system. There is a single point of connection to the utility called point of common coupling (PCC). The feeders 1 and 2 have sensitive loads which should be supplied during the events. The feeders also have the microsources consisting of a photovoltaic (PV), a wind turbine (WT), a fuel cell (FC), a microturbine (MT), and a diesel generator (DG). The third feeder has only traditional loads. A static switch (SD) is used to island the feeders 1 and 2 from the utility when events requiring it happen. The fuel input is needed only for the DG, FC, and MT as the fuel for the WT and PV comes from nature. To serve the load demand, electrical power can be produced either directly by PV, WT, DG, MT, or FC. The diesel oil is a fuel input to the DG, whereas natural gas is a fuel input to a fuel processor to produce hydrogen for the FC. The gas is also the input to the MT. Each component of the MG system is modeled separately based on its characteristics and constraints. The characteristics of some equipment like wind turbines and diesel generators are available from manufacturers.
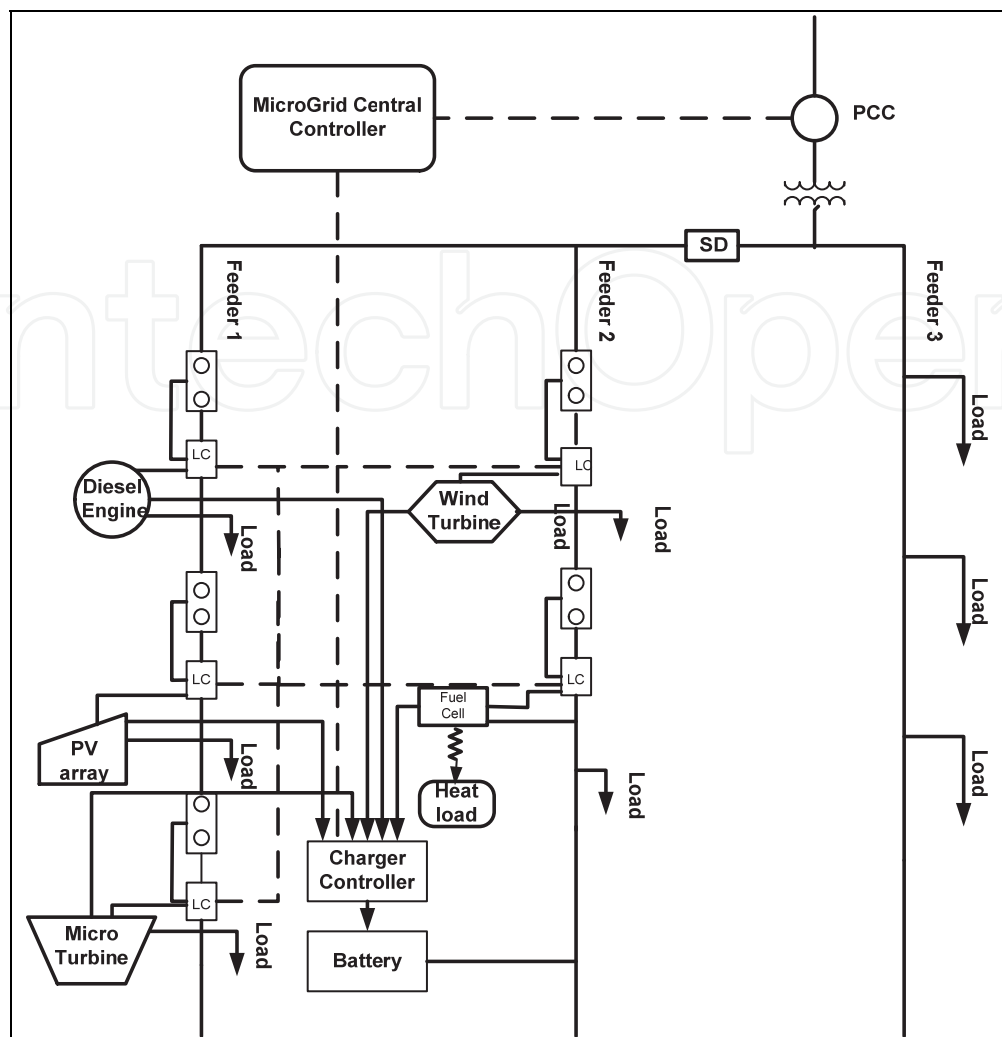
Fig. 1. MicroGrid Architecture.

3. Optimization model

The power optimization model is formulated as follows. The output of this model is the optimal configuration of a MG taking into account the technical performance of supply options, locally available energy resources, load demand characteristics, environmental costs, start up cost, daily purchased-sold power tariffs, and operating and maintenance costs.

Figure 2. illustrates the optimization model, when its inputs are:

• Power demand by the load.
• Data about locally available energy resources: These include wind speed (m/s) Figure 3, temperature (C$^{\circ}$) Figure 4 , solar irradiation data (W/m^2) Figure 5 , as well as cost of fuels ($/liter) for the DG and natural gas price for supplying the FC and MT ($/kW).
• Daily purchased and sold power tariffs in (kWh).
• Start up costs in ($/h).
• Technical and economic performance of supply options: These characteristics include, for example, rated power for PV, power curve for WT, fuel consumption characteristics DG and FC.

- Operating and maintenance costs and emission factors: Operating and maintenance costs must be given ($/h) for all generators; emission factors must be given in kg/h for DG, FC, and MT.
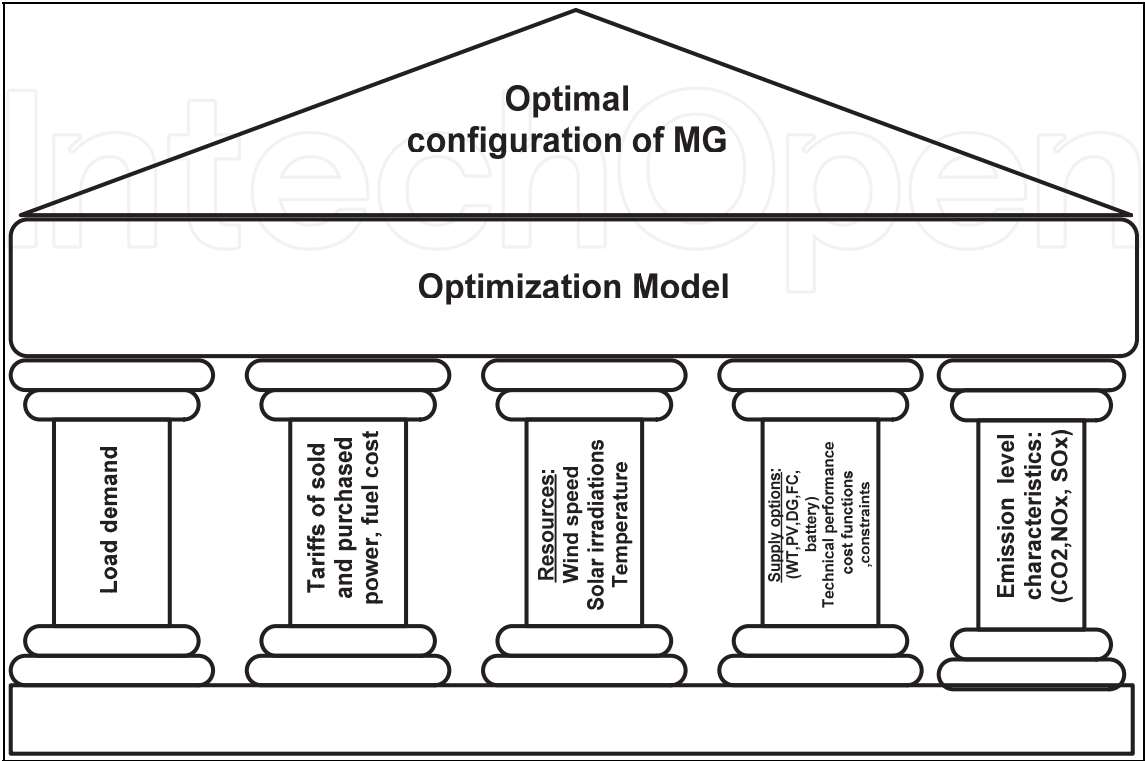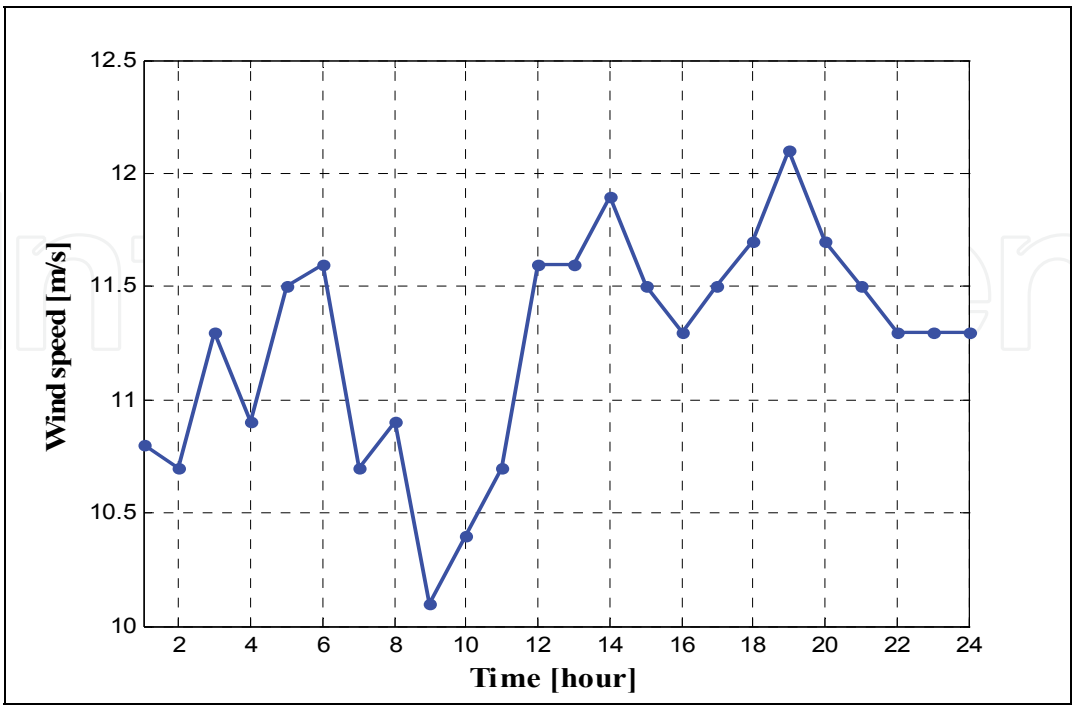

Fig. 2. The Optimization Model.

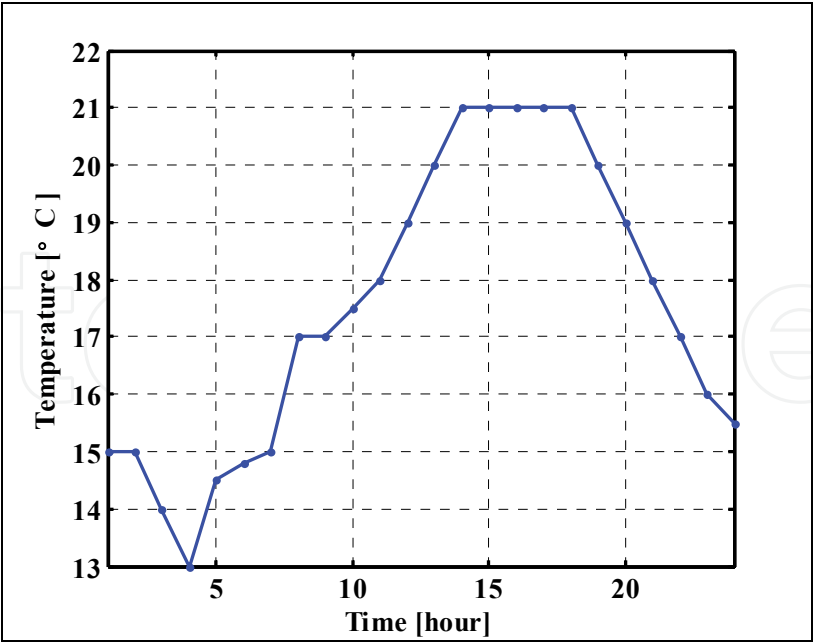Fig. 3. The input wind speed as used in the model.
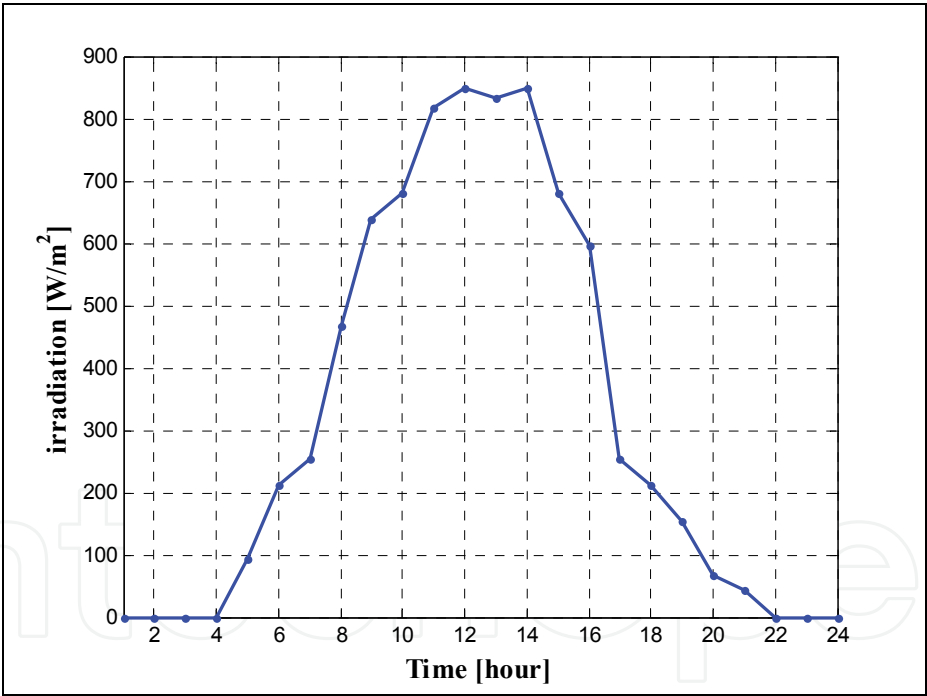
Fig. 4. The input temperature data as used in the model.

Fig. 5. The input irradiation data as used in the model.

4. Optimization model

4.1 Wind turbine

To model the wind turbine, several important factors should be known. They are the availability of the wind and the wind turbine power curve. The following is the model used to calculate the output power generated by the wind turbine generator as a function of the wind velocity (Chedid et al., 1998):

$$\begin{cases} P_{WT} = 0, & V_{ac} < V_{ci} \\ P_{WT} = aV_{ac}^2 + bV_{ac} + c, & V_{ci} \le V_{ac} < V_r \\ P_{WT,r} = 130, & V_r \le V_{ac} > V_{co} \end{cases} \tag{1}$$

where $P_{WT,r}$, V_{ci}, and V_{co} are the rated power, cut-in and cut-out wind speed respectively. Furthermore V_r, and V are the rated, and actual wind speed. Constants **a**, **b**, and **c** depend on the type of the WT.

We assume AIR403 wind turbine model in this paper. According to the data from the manufacturer, the turbine output $P_{WT,r}$ is roughly 130 W if the wind speed is greater than approximately 18 m/s.

In Fig 6. we model the wind turbine power curve according to equation 1, with the actual power curve obtained from the owner's manual. The parameters used to model the power curve are as follows:

a = 3.4; b = -12; c = 9.2; $P_{WT,r}$ = 130 watt; V_{ci} = 3.5 m/s; V_{co}= 18 m/s; V_r =17.5 m/s.
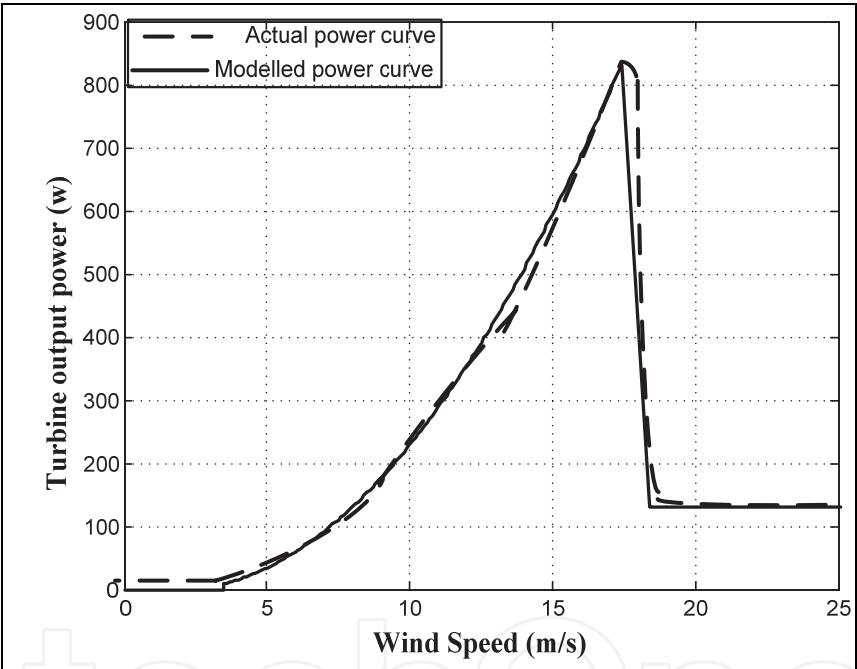

Fig. 6. The actual and modeled power curve of AIR403.

4.2 Photovoltaic

Photovoltaic generations are systems which convert the sunlight directly to electricity. The characteristics of the PV in operating conditions that differ from the standard condition (1000 W/m², 25C° cell temperature), the effect of solar irradiation and ambient temperature on PV characteristics are modeled. The influence of solar intensity is modeled by considering the power output of the module to be proportional to the irradiance (Gavanidou & Bakirtzis 1992), (Lasnier & Ang 1990). The PV Modules are treated at Standard Test Condition (STC). The output power of the module can be calculated using:

$$P_{PV} = P_{STC} \frac{G_{ING}}{G_{STC}} [1 + k(T_c - T_r)] \tag{2}$$

where:

P_{PV} The output power of the module at Irradiance G_{ING},

P_{STC} The Module maximum power at Standard Test Condition (STC),

G_{ING} Incident Irradiance,

G_{STC} Irradiance at STC 1000 (W/m2,

k   Temperature coefficient of power,

T_c The cell temperature,

T_r The reference temperature.

We assume that SOLAREX MSX-83 modules are used in this paper. Their output characteristics are: peak power = 83W, voltage at peak power = 17.1V, current at peak power = 4.84A, short circuit current = 5.27A, and open circuit voltage =21.2V at STC.

4.3 Diesel generator costs

Diesel engines are the most common type of MG technology in use today. The traditional roles of diesel generation have been the provision of stand-by power and peak shaving. The fuel cost of a power system can be expressed mainly as a function of its real power output and can be modeled by a quadratic polynomial (Wood & Wollenberg 1996. The total $/h DG fuel cost $\mathbf{F_{DG,i}}$ can be expressed as:

$$F_{DG,i} = \sum_{i=1}^{N}(d_i + e_i P_{DG,i} + f_i P_{DG,i}^2) \tag{3}$$

where $\mathbf{N}$ is the number of generators, $\mathbf{d_i}$, $\mathbf{e_i}$, and $\mathbf{f_i}$ are the coefficients of the generator, $\mathbf{P_{DG,i}}$, $\mathbf{i}$ = 1,2,...,$\mathbf{N}$ is the diesel generator $\mathbf{i}$ output power (kW), assumed to be numerically known. Typically, the constants $\mathbf{d_i}$, $\mathbf{e_i}$, and $\mathbf{f_i}$ are given by the manufacturer. For example, diesel fuel consumption data of a 6-kW diesel generator set (Cummins Power) model DNAC 50 Hz is available in L/h at 1/4, 1/2, 3/4 and full loads. From the data sheet the parameters in eq (3) are: $\mathbf{d_i}$=0.4333, $\mathbf{e_i}$ =0.2333, and $\mathbf{f_i}$ =0.0074. Figure 7 shows the fuel consumption as function of power of the DNAC 50 Hz diesel engine.
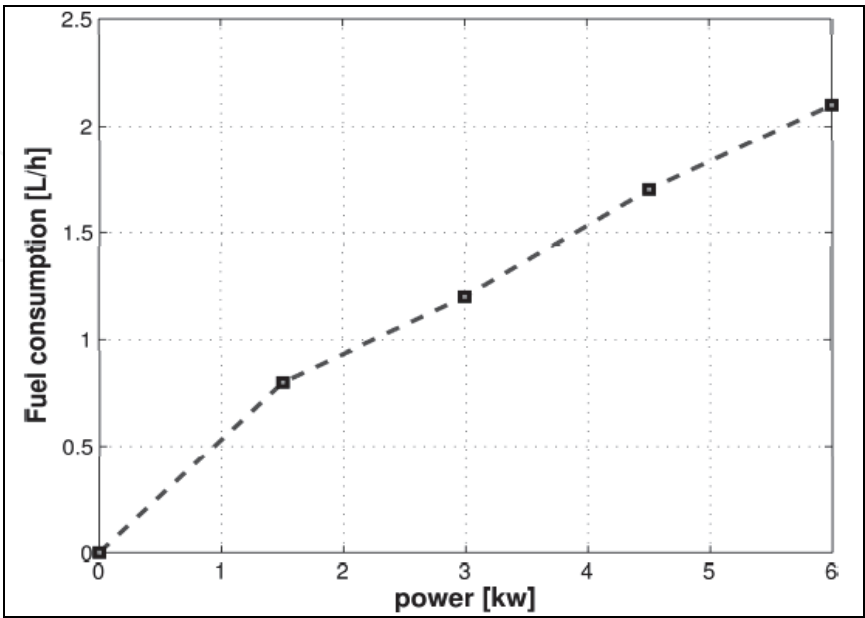

Fig. 7. Fuel consumption of DNAC 50 Hz diesel engine.

4.4 Fuel cell cost

Fuel cells work by combining hydrogen with oxygen to produce electricity, heat, and water. DC current and heat are produced by a chemical reaction rather than by a mechanical process driven by combustion. Fuel cells can operate as long as fuel is being supplied, as opposed to the fixed supply of chemical energy in a battery.

The efficiency of the FC depends on the operating point, and it refers to the ratio of the stack output power to the input energy content in the natural gas. It is normally calculated as the ratio of the actual operating voltage of a single cell to the reversible potential (1.482V) (Barbir & Gomez, 1996). The overall unit efficiency is the efficiency of the entire system including auxiliary devices.

We assume the typical efficiency curves of the Protone Exchange Membrane (PEM) fuel cell including the cell and the overall efficiencies (Barbir & Gomez, 1996). The efficiency of any fuel cell is the ratio between the electrical power output and the fuel input, both of which must be in the same units (W), (Azmy & Erlic, 2005):

The fuel cost for the fuel cell is calculated as follows:

$$F_{FC,i} = C_{nl} \sum_J \frac{P_J}{\eta_J} \tag{4}$$

where

C_{nl} the natural gas price to supply the fuel cell ($/kWh),

P_J the net electrical power produced at interval J,

η_J the cell efficiency at interval J.

To model the technical performance of a PEM fuel cell (Barbir & Gomez, 1996), a typical efficiency curve is used to develop the cell efficiency as a function of the electrical power and used in equation (4).

4.5 Microturbine cost

Microturbines use a simple design with few moving parts to improve reliability and reduce maintenance costs. Microturbine models are similar to those of fuel cells (Campanari & Macchi,2004). However, the parameters and curves are modified to properly describe the performance of the MT unit. From a typical electrical and thermal efficiency curves of a 25 kW Capstone- C30 microturbine (Yinger, 2001) we obtain the efficiency as function of the generated power. The total efficiency of a microturbine can be written as:

$$\eta_J = \frac{P_{el} + P_{th,rec}}{m_f LHV_f} \tag{5}$$

where

P_{el} the net electrical output power (kW),

$P_{th,rec}$ the thermal power recovered (kW),

LHV_f the fuel lower heating rate (kJ/kgf),

m_f the mass flow rate of the fuel (kg/s).

Unlike the fuel cell, the efficiency of the MT increases with the increase of the supplied power. The MT fuel cost is as follows:

$$C_{MT} = C_{nl} \sum_J \frac{P_J}{\eta_J} \tag{6}$$

where

C_{nl} is the natural gas price to supply the MT,

P_J is the net electrical power produced at interval J,

η_J is the cell efficiency at interval J.

Since power required by our assumed MG is much lower than the level in (Yinger, 2001), the curves of this MT are rescaled to be suitable for a unit with a 4kW rating. These curves are used to derive the electrical efficiency and power as functions of the electrical power to be used in the economic model of the MT.

4.6 Battery storage

Battery banks are electrochemical devices that store energy from other AC or DC sources for later use. The power from the battery is needed whenever the microsources are insufficient to supply the load, or when both the microsources and the main grid fail to meet the total load demand. On the other hand, the energy is stored whenever the supply from the microsources exceeds the load demand.

The following assumptions are used to model the battery bank: the charge and discharge current is limited to 10% of battery AH capacity (the storage capacity of a battery is measured in terms of its ampere-hour (AH) capacity) (Chedid & Rahman, 1997) and (Manisaet, 2004); the round- trip efficiency is 95 %.

When determining the state of charge for an energy storage device, two constraint equations must be satisfied at all times: First, because it is impossible for an energy storage device to contain negative energy, the maximum state of charge (SOC_{max}) and the minimum state of charge (SOC_{min}) of the battery are 100 % and 20 % of its AH capacity, respectively.

The constraints that represent the maximum allowable charge and discharge current to be less than 10% of battery AH capacity are shown in the following equations, respectively.

$$P_+ \leq (0.1 \times V_{sys} \times U_{batt}) / \Delta_t \tag{7}$$

$$P_- \leq (0.1 \times V_{sys} \times U_{batt}) / \Delta_t \tag{8}$$

where the parameter V_{sys} is the system voltage at the DC bus, Δ_t is the time in hours, and the parameter U_{batt} is the battery capacity in AH. The state of charge (SOC) of the battery can be obtained by monitoring the charge/discharge power of the battery, as shown in eq.(9).

$$SOC = SOC_{max} - P_- + P_+ \tag{9}$$

It is important that the SOC of the battery prevents the battery from overcharging or undercharging. The associated constraints can be formulated by comparing the battery SOC in any hour i with the battery SOC_{min} and the battery SOC_{max}, as shown in eq(10).

This research assumes that SOC_{min} and SOC_{max} equal 20% and 100% of the battery AH capacity, respectively. It is also assumed that the initial SOC of the battery is 100% at the beginning of the simulation.

The constraints on battery SOC are:

$$SOC_{\min} \leq SOC \leq SOC_{\max} \tag{10}$$

Finally, in order for the system with battery to be sustained over a long period of time, the battery SOC at the end must be greater than a given percentage of its **SOC$_{max}$**. This study assumes 90%.

5. Proposed objective function

The major concern in the design of an electrical system that utilizes MG sources is the accurate selection of output power that can economically satisfy the load demand, while minimizing the emission. Hence the system components are found subject to:
1.   Minimize the operation cost (\$/h).
2.   Minimize the emissions (kg/h).
3.   Ensure that the load is served according to the constraints.

5.1 Operating cost
As shown in Fig.1, the main utility balances the difference between the load demand and the generated output power from microsources. Therefore there is a cost to be paid for the purchased power whenever the generated power is insufficient to cover the load demand. On the other hand, there is income because of sold power when the power generated is higher than the load demand but the price of the sold power is lower than the purchased power tariff. It is possible that there will be no sold power at all. To model the purchased and sold power, the cost function takes the form

$$CF(\boldsymbol{P}) = \sum_{i=1}^{N}(C_iF_i(P_i) + OM_i(P_i) + STC_i + DCPE_i - IPSE_i) \tag{11}$$

$CF(\boldsymbol{P})$ represents the operating costs in \$/h, C_i fuel costs of the generating unit i in \$/l for the DG, natural gas price for supplying the FC and MT (\$/kWh), $F_i(P_i)$ fuel consumption rate of a generator unit i, $OM_i(P_i)$ Operation and maintenance cost of the generating unit i in \$/h, P_i decision variables, representing the real power output from generating unit i in kW and defined as: $P_i = P_{FC}$ or P_{MT} or P_{DG}, $\boldsymbol{P}$ is the vector of the generators active power and is defined as: $\boldsymbol{P} = [P_1, P_2, ..., P_N]$, N is the total number of generating units. where STC_i is the start-up costs of the unit generator i \$/h. The start-up cost in any given time interval can be represented by an exponential cost curve:

$$STC_i = \sigma_i + \delta_i\left[1 - \exp\left(\frac{-T_{off,i}}{\tau_i}\right)\right] \tag{12}$$

The start-up cost depends on the time the unit has been off prior to a start up. where, σ_i is the hot start-up cost, δ_i the cold start-up cost, τ_i the unit cooling time constant and $T_{off,i}$ is the time a unit has been off.
$DCPE_i$ is the daily purchased electricity of unit i if the load demand exceeds the generated power in \$/h. $IPSE_i$ is the daily income for sold electricity of unit i if the output generated

power exceeds the load demand in \$/h. the expression for $DCPE_i$ and $IPSE_i$ can be written as

$$DCPE_i = C_p \times \max(P_L - P_i, 0)$$
$$IPSE_i = C_s \times \max(P_i - P_L, 0)$$

(13)

where, C_p and C_s are the tariffs of the purchased and sold power respectively in (\$/kWh).
System Constraints:
Power balance constraints: To meet the active power balance, an equality constraint is imposed

$$\sum_{i=1}^{N} P_i = P_L - P_{PV} - P_{WT} - P_{batt}$$

(14)

where P_L is 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 in kW.
Generation capacity constraints: For stable operation, real power output of each generator is restricted by lower and upper limits as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad \forall_i = 1, ..., N$$

(15)

where, $P_i^{\min}$ is the minimum operating power of unit i and $P_i^{\max}$ the maximum operating power of unit i.
Each generating unit has a minimum up/down time limit (MUT/MDT). Once the generating unit is switched on, it has to operate continuously for a certain minimum time before switching it off again. On the other hand, a certain stop time has to be terminated before starting the unit. The violation of such constraints can cause shortness in the life time of the unit. These constraints are formulated as continuous run/stop time constraints as follows (Abido, 2003).

$$(T_{t-1,i}^{on} - MUT_i)(u_{t-1,i} - u_{t,i}) \geq 0$$
$$(T_{t-1,i}^{off} - MDT_i)(u_{t,i} - u_{t-1,i}) \geq 0$$

(16)

$T_{t-1,i}^{off} / T_{t-1,i}^{on}$ represent the unit i off/on time, at time $t-1$, while $u_{t-1,i}$ denotes the unit off/on [0,1] status.
Finally the number of starts and stops ($\varepsilon_{start-stop}$) should not exceed a certain number ($N_{\max}$).

$$\varepsilon_{start-stop} \leq N_{\max}$$

(17)

The operating and maintenance costs OM are assumed to be proportional with the produced energy, where the proportionally constant is K_{OM_i} for unit i.

$$OM = \sum_{i=1}^{N} K_{OM_i} P_i$$

(18)

The values of K_{OM_i} for different generation units are as follows :
where,

$$K_{OM_1} = K_{OM}(DG) = 0.01258 \ \$/kWh.$$

$$K_{OM_2} = K_{OM}(FC) = 0.00419 \ \$/kWh.$$

$$K_{OM_2} = K_{OM}(MT) = 0.00587 \ \$/kWh.$$

5.2 Emission level

The atmospheric pollutants such as sulphur oxides SO_2, carbon oxides CO_2, and nitrogen oxides NOx caused by fossil-fueled thermal units can be modeled separately. The total kg/h emission of these pollutants can be expressed as (Morgantown, 2001):

$$E(\boldsymbol{P}) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i) + \zeta_i \exp(\lambda_i P_i) \qquad (19)$$

where α_i, β_i, γ_i, ζ_i, and λ_i are nonnegative coefficients of the ith generator emission characteristics.
For the emission model introduced in (Talaq et al., 1994) and (Morgantown, 2001), we propose to evaluate the parameters α_i, β_i, γ_i, ζ_i, and λ_i using the data available in (Orero & Irving, 1997) Thus, the emission per day for the DG, FC, and MT is estimated, and the characteristics of each generator will be detached accordingly.

6. Implementation of the algorithm

The following items summarize the key characteristics of the proposed algorithm:
- Power output of WT is calculated according to power the relation between the wind speed and the output power.
- Power output of PV is calculated according to the effect of the temperature and the solar radiation that are different from the standard test condition.
- We assume that the WT and PV deliver free cost power in terms of running as well being emission free. Furthermore, their output power is treated as a negative load, determine the different between the actual load and WT and PV output power. If the output from PV and WT is greater than the load, the excess power is directed to charge the battery.
- The power from the battery is needed whenever the PV and WT are insufficient to serve the load. Meanwhile the charge and discharge of the battery is monitored.
- The net load is calculated if the output from PV and WT is smaller than the total load demand.
- Choose serving the load by other sources (FC or MT or DG) according to the objective functions.
- If the output power is not sufficient then purchase power from the main gird, and if the output power is more than the load demand, sell the exceed power to the main grid.

7. Multiobjective genetic algorithm

There are two common goals in all multiobjective GA implementations. First, to move the population toward the Pareto optimal front; and second, to maintain diversity (either in parameter space or objective space) in the population so that multiple solutions can be developed. GA approaches to multiobjective optimization can be grouped into three categories: approaches that use aggregating functions, non-Pareto based approaches, and Pareto based approaches. The simplest and most obvious approach to multiobjective optimization is to combine the objectives into one aggregating function, and to treat the problem like a single objective optimization problem. Therefore, it is commonly used because of its simplicity and computational efficiency. The weighted sum approach combines objectives using weights.

The weighted sum approach combines k objectives f_i using weights, $w_i, i = 1,...,k$

$$fitness = w_1 f_2(\boldsymbol{P}) + w_2 f_2(\boldsymbol{P}) + ... + w_k f_k(\boldsymbol{P}) \tag{20}$$

The weights are real numbers $w_i \geq 0$ and $\boldsymbol{P}$ as in (11)

8. Results and discussion

At first, the optimization model is applied to the load. The load demand varies from 4 kW to 14 kW. The available power from the PV and the WT are used first. The best results of the cost and emission functions, when optimized individually, are given in Table 1. Convergence of operation cost and emission objectives for both approaches, when the purchased tariff is 0.12 \$/kWh and the sold tariff 0.07 \$/kWh, is as shown in Figure 8, where faster convergence is achieved.

Figure 9 illustrates the hourly operating costs and emissions. However, the costs and emissions are high when the generators are on and the load is high. Operational cost and emission objectives are optimized individually in order to explore the extreme points of the trade-off surface. The first case is when the cost objective function is optimized and the second when the emission objective function is optimized.

The set of power curve found by the optimization algorithms is shown in Figure 10. The figure confirms that when the load demand is low, the best choice in terms of cost is to use the output power from MT. The second best choice is the use of the fuel cell.

When the load is high at the peak time, all the generators are used to serve the load.
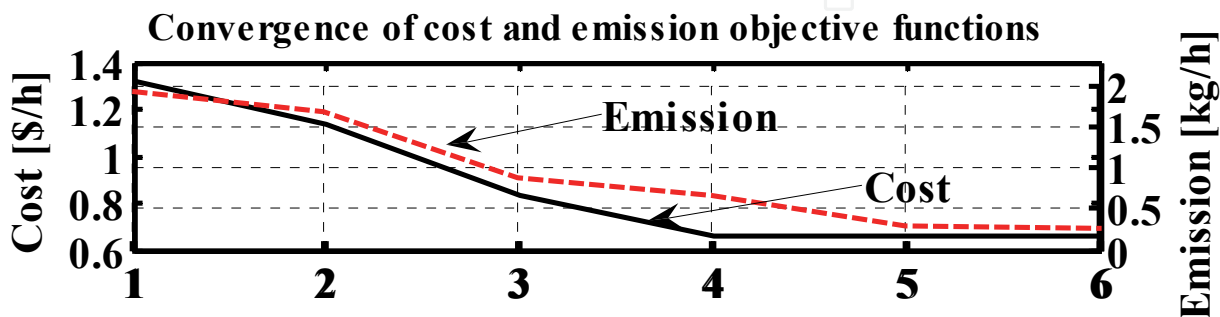

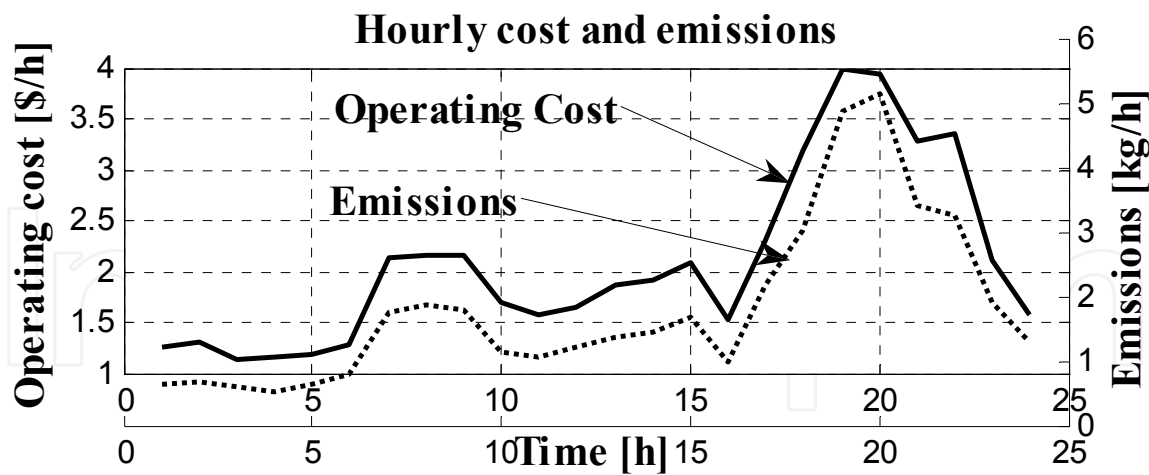Fig. 8. Convergence of cost and emission objective functions.
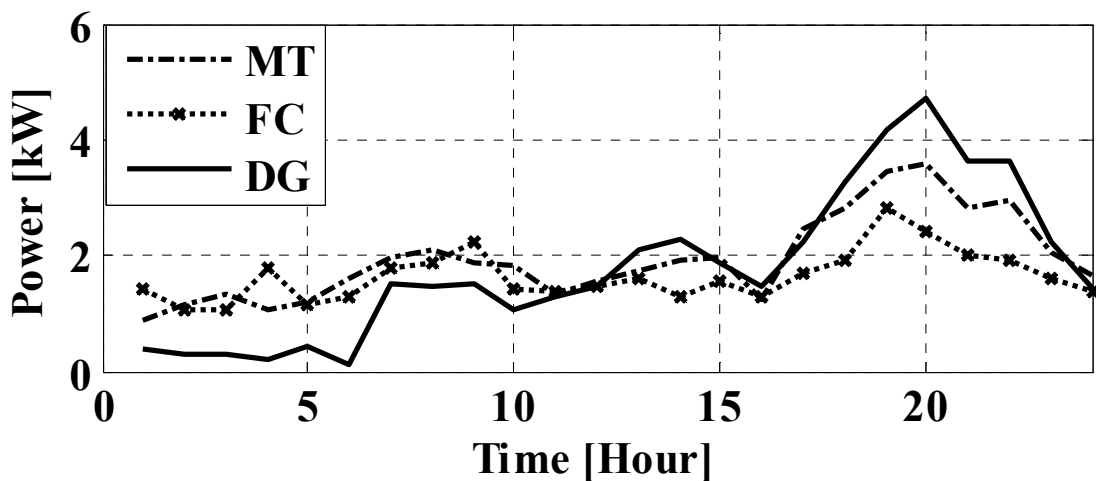
Fig. 9. Hourly operating cost and emission

Fig. 10. Power Generation distribution.

	TOTAL LOAD (KW/DAY)	TOTAL EMISSIONS (KG/DAY)	Total Costs ($/Day)	Optimal Generation (kW/Day)	Sold Power (kW7Day)	Purchased Power (kW/Day)
Case 1	171.4009	127.250	86.3466	352.8773	70.5188	14.8635
Case 2	171.4009	9.6045	224.4015	31.8217	00.0000	135.3149

Table 1. The Objective Function when Optimized Individually.

Figure 11 shows the relationship (trade-off curve) of the operating cost and emission objectives of the non-dominated solutions obtained for different purchased and sold tariffs. The operating costs of the non-dominated solutions thus appear to be inversely proportional to their emissions.

Table 2. shows the effect of changing the purchased and sold tariffs on the optimal setting of the MG. There are all together four cases.
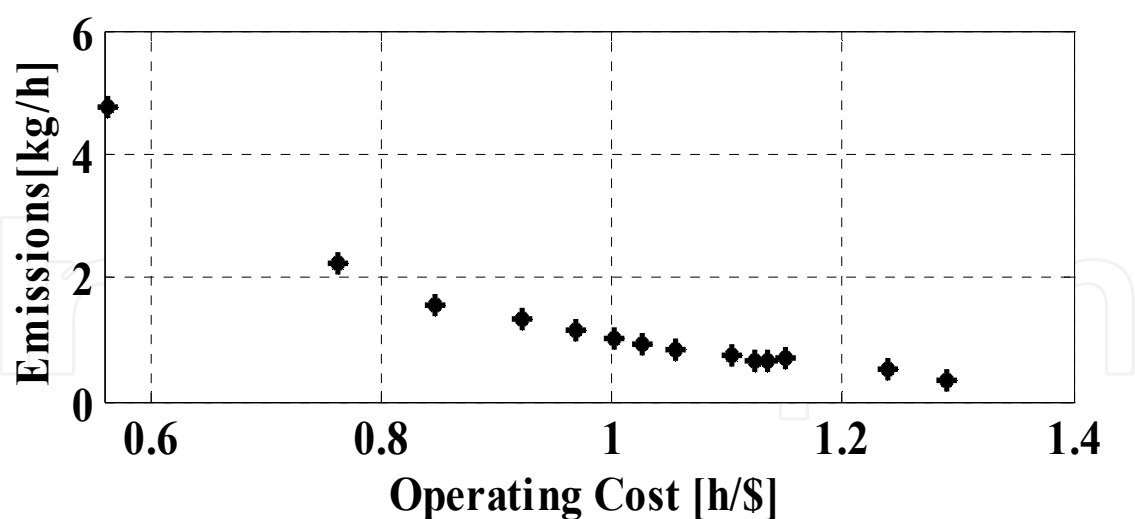
Fig. 11. Trade- off in cost and emission.

	TOTAL LOAD (KW/DAY)	Optimal Generation (KW/DAY)	Total Cost ($/Day)	TOTAL EMISSION (kg/Day)
Case 1	171.4009	88.3430	38.8254	25.9907
Case 2	171.4009	117.2192	45.1067	37.2475
Case 3	171.4009	110.5423	43.8823	34.3452
Case 4	171.4009	110.3820	43.9964	34.5317

Table 2. The effect of the purchased and sold tariffs on the optimal generation using MOGA.

In case 1, the effect of the changing the purchased ariffs is studied, when the sold power was 0.04 $/kWh and the purchased tariffs were 0.1 $/kWh, while in Case 2 the value of the purchased tariffs has increased to 0.16 $/kWh and the sold was the same as in Case 1. During changing the purchased tariffs values, it was noticed that when the tariffs were low, it was preferable to buy as much power from the main grid as possible. However, when the tariffs were higher, it was more economic to generate the required power from the MG.

In Cases 3 and 4, the purchase power tariff is kept constant at 0.12 $/kWh, while the sold tariffs was 0.0 $/kWh in case 3 and 0.04 $/kWh in case 4. It is noticeable that, the changing of the sold tariffs has no effect for such a small change. It only reacts if the change is much larger.

Table 3. illustrates the cost savings and emission reductions of the MG using different cases and compares them with the proposed technique.

The results obtained using the proposed technique to minimize the total cost and total emissions are compared with some conventional strategies of settings. The first case is when the DG, FC, and MT operate at their rated power for the whole day (Case A). The second is to optimize the cost individually (Case B). The third scenario is to optimize the emissions objective function individually (Case C).

Case A gives higher operating cost and higher emissions which indicates that it is not relevant. The larger generating power, the larger costs and emissions are attained. In the

Case B, the cost is relatively reduced, while the emissions were increased. In the third case, the cost increased while the emissions decreased and the optimal choice was to purchase more power from the main grid.

For achieving the completeness and checking the effectiveness of the proposed cost function and proposed solution, the problem was treated as single objective optimization problem by a linear combination of the cost and emission objectives as follows (Abido, 2003a) (case D):

$$\underset{P}{Minimize} \quad \omega CF(\boldsymbol{P}) + (1-\omega)\rho E(\boldsymbol{P}) \tag{21}$$

where ρ is the scaling factor and ω is the weighting factor.

With the proposed free power sale the total operating cost was reduced to 42.3054 \$/day and 33.9223 kg/day for the emissions after increasing the number of WT and PV, also switching off one of the load comparing to other settings.

Table 3. confirms that the MO optimization technique has made reasonable selections. The selections were not so straightforward; because of the existing the start-stop time limit constraints which have a big effect on the performance of the algorithm. It can be seen that the load was served perfectly.

	AVERAGE COST & EMISSION			AVERAGE DIFFERENCE WITH RESPECT TO THE OPTIMAL CASE		
	COST (\$/DAY)	EMISSIONS (KG/DAY)	COST (\$/DAY)	EMISSIONS (KG/DAY)	COST %	Emission %
Case A	99.9283	229.4892	57.6229	195.5672	136.2%	576.5151%
Case B	92.6276	224.6428	25.2862	27.3513	59.77%	80.6292%
Case C	119.3319	8.1371	70.3539	-25.7852	166.3%	-76.01%
Case D	54.1359	57.7628	11.8205	24.9295	27.94%	70.279%
Ref[10]	43.3754	34.0102	1.07	0.0879	2.5292%	0.2637%
Optimal Setting	**42.3054**	**33.9223**	**00.0000**	**00.0000**	**00.000%**	**00.0000%**

Table 3. Saving and emissions reductions of the MG using MOGA.

9. Conclusion

This chapter has presented modling and the GA approach to solve the multiobjective problem. From the results obtained, optimization of the above-formulated objective functions using MOGA yields not only a single optimal solution, but a set of Pareto optimal solutions, in which one objective cannot be improved without sacrificing other objectives. For practical applications, however, one solution is needed to be selected, which will satisfy the different goals to some extent. Such a solution is called the best compromise solution. One of the challenging factors of the trade-off decision is the imprecise nature of the decision maker's judgment.

Initially in all the three scenarios, minimum and maximum values of each original objective function are computed in order to obtain the last compromise solution. Minimum values of the objectives are obtained by giving full consideration to one of the objectives and

neglecting the others. In this study, two objective functions are considered. Operating costs and emission level are optimized individually to obtain minimum values of the objectives. Owing to the conflicting nature of the objectives, emission level has to have maximum values when operating cost is minimum. The GA transforms the original multiobjective optimization problem into a single-objective problem and, thus, the set of noninferior solutions can be easily obtained. Compared with the other strategies of settings, the proposed approach significantly reduces the operating cost and emission level, while satisfying the load demand required by the multiobjective MG problem.

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