Ramp Rate Effect on Maximizing Profit of a Microgrid using a Gravitational Search Algorithm

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Abstract

In this study, the short-term operation planning of a typical microgrid (MG) consisting of different units was optimized for achieving maximum profit, considering technical and economic constraints over a 24-hour period. Also investigated was the effect of ramp rate. The MG consisted of a diverse variety of power system components such as a wind turbine, microturbine, photovoltaic cell, fuel cell, electrolyzer, hydrogen storage tank, reformer, boiler, and electrical and thermal loads. Moreover, the MG was connected to an electrical grid for the exchange of power. The MG was managed and controlled through a central controller. The system costs included operation and maintenance costs, the cost of purchasing the natural gas for the required thermal energy, purchasing energy from the local grid, and the penalty costs in the curtailment strategy. The problem was a mixed-integer, nonlinear program that contained both real and binary parts. As such, metaheuristic methods were suitable and a gravitational search algorithm (GSA) was proposed.

The total profit obtained from the MG, based on the GSA but without considering ramp rate was $2272.60; the total profit considering ramp rate was about $2260.92. That is why the ramp rate constraint confined optimum performance of the binary section of the algorithms, which determined whether the units should be on or off and if that would cause a decrease in the final profit. Moreover, the results from the proposed algorithm were compared to a kind of improved genetic algorithm (GA) that is commonly used for these problems. Although the number of required iterations for the convergence of the problem using the GSA was lower, it took more computational time compared to the GA. Using the GA, the total profit not considering the ramp rate was $2268.91, compared to $2259.98 for the calculation taking into account the ramp rate limitations.

Introduction

In microgrids (MGs), energy management systems (EMSs) provide decision making for the generation of electric power and heat, storage systems, loading, and the power exchanges with the local grid. MGs are low voltage distribution networks comprising electrical and thermal loads, energy storage systems (ESSs), and distributed generation sources (DGs), which are operated with a common controller. The main benefit of MGs is improving system reliability and demand supply. The significance of an MG is that the power generation is distributed so as to be closer to the end users. MGs can be either connected to the network or be operated independently in the island mode. When connected to the network, a MG may act either as a load or a small power source. MGs have many benefits that include: a) providing reliable, secure, efficient, and sustainable energy from renewable energy sources (RESs), while reducing transmission losses; and, b) reducing capital risk and supply growth in the demand based on a small investment. Moreover, low capital costs potentially enable low-cost entry into competitive markets [1-4].

Several studies have focused on optimizing the energy and operation management of MGs. Chen et al. [5] presented a smart energy management system in order to optimize the operation of a MG. They studied the characteristics of the photovoltaic (PV) output under different weather conditions and then presented a day-ahead power forecasting module. Zhang et al. [6] applied a performance metric to a MG's operation as stand-alone, grid-tied, and networked modes. Mohamed and Koivo [7] presented a general formulation to determine the optimal operating strategy and cost optimization scheme and to reduce the emissions from a MG. Mohamed and Mohammed [8] proposed an effective algorithm for optimizing the operation of the distribution system in a smart grid, from a cost and system stability point of view. They applied mathematical techniques to build accurate forecasting models for different sources and loads. Quashie and Joos [9] studied a general methodology for determining the optimal configuration of a MG and maximizing associated benefits. A hybrid smart-grid management system based on multiagents was examined by Ricalde et al. [10] in order to measure and control the loads inside a building, while power generation was forecasted using neural networks. Hatziargyriou et al. [11] described the main functions of the MG's central controller, required for optimization of the operation for the efficient participation in future real-time markets following different policies.

Khodaei and Shahidehpour [12] proposed a MG plan for the simultaneous optimization of the generation and transmission expansion in the power systems.

Shimoda et al. [13] showed a load forecast method and an optimized operation plan for DGs in a MG considering the heat sources, which run according to the thermal load prediction. The aim of Watanabe et al. [14] was to promote green energy usage, discuss concerns regarding energy supply during disasters, and improve the efficiency of the waste heat usage. Moreover, the optimal capacities of the solar cell, fuel cell (FC), electrolyzer (EL), and heat pumps were computed, while operating independently. Korpås and Holen [15] studied the operation of a hybrid plant consisting of wind turbines and hydrogen storage, while forecasts of the wind power were used for maximizing the expected profit from the power exchange in a day-ahead market; a penalty cost for un-provided hydrogen demand was also taken into account. Basu et al. [16] focused on how tracking electrical demand was economically shared between microturbines and diesel generators, on the basis of the multi-objective optimization of fuel costs and emissions. Niknama et al. [17] presented a new multi-objective, modified honey bee mating optimization algorithm for investigating the distribution feeder reconfiguration problem, assuming that RESs were connected to the distribution network.

Celli et al. [18] focused on the development of a novel EMS based on the application of neural networks. Mohanty et al. [19] developed an optimal design and plan for a MG containing different distributed-energy technology options such as PV, WT, a biomass gasified system, and diesel generator and battery storage for different applications and characteristics. In their study, the break-even distance for connecting the MG with the main grid was determined, as compared with the cost of the isolated MG. Bracco et al. [20] focused on the development of a mathematical model to optimally manage a smart, poly-generation MG, which contained combined heat and power (CHP) and considered thermal demand in order to minimize daily operational costs. Colas et al. [21] presented the aggregation and implementation of a determinist energy management method for business customers in a MG power system. Kanchev et al. [22] presented a MG energy management optimization method with the presence of PV-based active generators. To accommodate the high demand of renewable energy and the environmental policy, the planning and operation of micro-source generators was studied by Su et al. [23]. Alabedin et al. [24] studied the scheduling of power generation in a MG that had a group of dispatchable and non-dispatchable generators. Narayanaswamy et al. [25] evaluated hedging strategies for renewable resource integration and uncertainty management in the smart grid.

Carpinelli et al. [26] formulated an optimization model to solve the problem of the day-ahead optimal scheduling of a DC MG. Logenthiran and Srinivasan [27] studied a three-step method for the optimal generation scheduling of a MG in island-operation mode by solving the thermal unit commitment problem. Garcia and Bordons [28] addressed the short-term regulation service optimization linked to the long -term economical dispatch of a grid-connected MG. Logenthiran et al. [29] developed a distributed multi-agent system for the generation scheduling and monitoring of energy resources for optimized MG operation. Laera et al. [30] proposed a tool for the day-ahead operation plan of a grid-connected MG including distributed generators, electrical and thermal loads, and storage devices. The focus of the work by Chen et al. [31] was to perform an economic analysis, formulate an optimization model, and determine optimal operating strategies for smart MG systems. Mashhour and Tafreshi [32] developed a multi-period optimization model for an interconnected MG that participated in the wholesale energy market in order to maximize total profit.

In this current study, the authors investigated the short-term operation planning of a typical MG with diverse units and optimized it for achieving maximum profit, considering technical and economic constraints over a 24-hour period along with the effect of ramp rate.

System Description

The MG in this study was connected to the network for the exchange of power, where it was managed and controlled through a central controller. In this MG model, energy suppliers included: two DG units, which were managed or owned independently; DG units that were owned by the MG manager including WT, PV, three conventional microturbines (MTs), controllable loads, and thermal loads provided by a boiler that recovered heat from MTs and FC. The storage system included the EL, hydrogen storage tank, FC, and reformer. Furthermore, there were four types of loads: thermal, critical, controllable, and price-sensitive. The MG model is depicted in Figure 1. In this study, parameters such as price, capacity, and characteristics and demands of DGs were extracted from the work by Bagherian and Tafreshi [1].

Problem Formulation

The objective function for the operation of an EMS is to maximize the profit of a MG owner over the next 24-hour period, which is defined as income minus cost and is expressed by Equation (1). The total income of the MG includes the income from the sale of electrical energy to the local grid as well as consumers inside the MG control area and the income from the sale of thermal energy. The operational costs consist of the cost of the purchased electrical energy from independent DG units, the cost of purchased energy from the local grid, the cost of purchased gas for thermal loads, while the production of thermal energy is not sufficient, and the cost of energy production through MG generation units such as MTs and FC. Moreover, a penalty is considered when load shedding is applied to controllable loads. The bids from independent DGs depend on many parameters such as startup, operation and maintenance costs of the units, consumer demand, energy price in the power market, and weather forecast data.

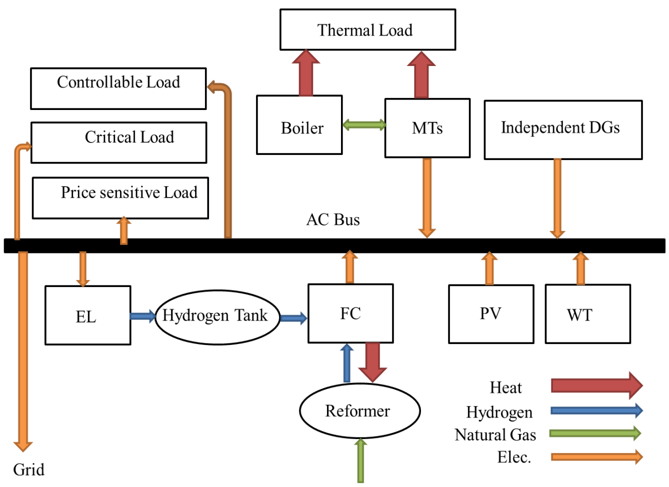


Figure 1. MG Schematic Diagram

$$
\begin{aligned}
OF = \sum_{t=1}^{24} \{ & P_G(t)\times p_G(t) + P_d(t)\times p_d(t) + \\
& P_{therm}(t)\times p_{therm}(t) - \sum_{j=1}^{2} u_j(t)\times P_j(t)\times p_j(t) \\
& -\sum_{k=1}^{3} C_{mt-k}(P_{mt-k}(t)) - C_{fc}(t) - C_{el}(t) \\
& -C_{therm}(P_{therm}(t)) - C_L(P_{sh}(t))\}
\end{aligned} \tag{1}
$$

Cost components are described by Equations (2)-(5). Equation (2) contains the operational and startup costs of MT units. The first term of Equation (3) is the cost of hydrogen production in the reformer unit that depends on the natural gas price, C_{NG}, and the natural gas consumption rate, G. The second term refers to the startup cost, while the third term indicates the operational costs of the FC. Hydrogen costs are not considered in Equation (3) because the FC consumes the hydrogen that is produced in the EL. Since operation and maintenance costs are assumed constant, they do not depend on the performance of the EL and the FC. Equation (4) contains the operational costs of the EL. It must be noted that C_{fc} and C_{el} do not depend on the power because the useful life of EL and FC are considered as not dependent on the power. The ppenalty factor that is considered when a MG cannot supply the load demand and has to shed a P_{sh} amount of controllable loads, is modeled as a convex quadratic cost function, as given in Equation (5).

$$
\begin{aligned}
C_{mt-k} = {} & \alpha_{mt-k} + \beta_{mt-k}P_{mt-k} + \gamma_{mt-k}P_{mt-k}^2 \\
& +(\alpha_{stmt-k} + \beta_{stmt-k}(1-e^{-\frac{toff}{\tau}})) \\
& \times u_{mt-k}(t)(u_{mt-k}(t) - u_{mt-k}(t-1))
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
C_{fc} = {} & C_{NG}\times G + (\alpha_{fc} + \beta_{fc}(1-e^{-\frac{toff}{\tau}})) \\
& \times u_{fc}(t)(u_{fc}(t) - u_{fc}(t-1)) + OM_{fc}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
C_{el} = {} & (\alpha_{el} + \beta_{el}(1-e^{-\frac{toff}{\tau}})) \\
& \times u_{el}(t)(u_{el}(t) - u_{el}(t-1)) + OM_{el}
\end{aligned} \tag{4}
$$

$$
C_L = \beta_L P_{sh} + \gamma_L P_{sh}^2 \tag{5}
$$

Case Studies

The active and thermal power balances require two equality constraints each hour; this is given by Equation (6):

$$
\begin{aligned}
P_d + P_{el} = {} & P_G + \sum_{j=1}^{2} P_j + \sum_{k=1}^{3} P_{mt-k} \\
& + P_{wt} + P_{pv} + P_{fc}
\end{aligned} \tag{6}
$$

P_{therm} is supplied from the boiler (P_{boiler}) and the heat from the MT is given by Equation (7):

$$
P_{boiler} + \sum_{k=1}^{3} P_{mt-k} = P_{therm} \tag{7}
$$

Power produced by the system is limited according to the particular capacity and demand of the system and is always more than a certain amount. There are also some limitations regarding the unit's minimum on and off times. The load shedding time should not exceed a certain period in the day. Ramp rate effect was investigated in this study and results with and without this limitation were compared. Unequal constraints are expressed by Equations (8)-(15).

$$P^{\min} \le P_{mt\text{ - }k} \le P^{\max} \quad (8)$$

$$P^{\min} \le P_{fc} \le P^{\max} \quad (9)$$

$$P^{\min} \le P_{el} \le P^{\max} \quad (10)$$

$$(T_{i-1}^{on} - MUT)(u_{i-1} - u_i) \ge 0 \quad (11)$$

$$(T_{i-1}^{off} - MDT)(u_i - u_{i-1}) \ge 0 \quad (12)$$

$$P^{\min} \le P_d \quad (13)$$

$$T_{shed} \le T^{\max} \quad (14)$$

$$-DR \le P(t) - P(t-1) \le +UR \quad (15)$$

Since the WT and PV produce power from free inputs, it was assumed that the optimized production would yield the highest possible amount that is predicted. Hence, the power of these units was not considered in the optimization function. However, they were considered in the power balance equality constraint. The power that is generated by the WT was predicted, while considering the wind speed, the output power, PV output, and the temperature and solar radiation. The power predicted from the PV and WT is depicted in Figure 2 and the connected grid load in Figure 3 [1].

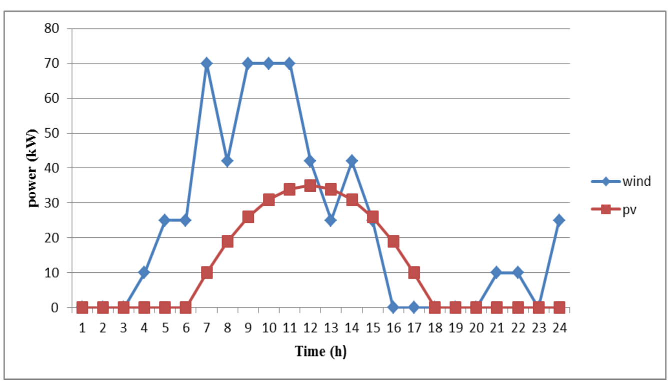


Figure 2. PV and WT Predicted Power (kW)

Solution Methodologies

The case studied was a Mixed-Integer Nonlinear Programming (MINLP) case that contained both real and binary parts. There are few methods that can solve this kind of problem and classic methods usually have shortages. Exact optimization algorithms are not able to provide an appropriate solution for solving optimization problems with a high-dimensional search space. In these problems, the search space grows exponentially with the problem size; therefore, an exhaustive search was not practical. Also, classical approximate optimization methods make several assumptions to solve the problems. Sometimes, the validation of these assumptions is difficult in each problem. However, metaheuristic algorithms are robust and can adapt solutions with changing conditions and environments; they can be applied in solving complex multimodal problems and may incorporate mechanisms for avoiding getting trapped in local optima. Furthermore, these algorithms are able to find promising regions in a reasonable time, due to exploration and exploitation abilities. Hence, metaheuristic algorithms, which make few or no assumptions about a problem and can search very large spaces of candidate solutions, have been extensively developed to solve optimization problems. Among these algorithms, population-based metaheuristic algorithms are proper for global searches, due to global exploration and local exploitation abilities [33].

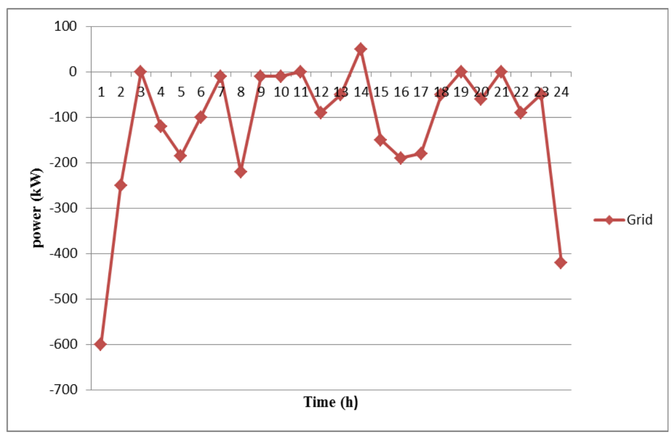


Figure 3. Predicted Grid Load (kW)

Scheduling problems represent a large class of combinatorial optimization problems. In most of these cases, finding the optimal solution is very difficult. In fact, with few exceptions, the only known method for solving the problem of optimality would be to enumerate an exponential number of possible solutions. Under these conditions, a metaheuristic method is necessary in order to find a good quality solution in a reasonable amount of time. [34] Thus, metaheuristic methods were proposed for this problem.

The Gravitational Search Algorithm (GSA) is a rather novel metaheuristic algorithm that has proved to have an appropriate performance in many optimization problems [35 -41] and the Genetic Algorithm (GA) is a commonly used metaheuristic algorithm [2], [42-50]. Hence, the GSA was used to optimize MG planning for the next 24-hour period and the results were compared with the GA. The objective function contains both real and binary parameters; real parts determine the optimum power and binary parts decide whether the units should be on or off. Binary and real parts must be optimized simultaneously and hybrid algorithms are used for this problem.

Gravitational Search Algorithm

The GSA is based on the laws of gravity and mass interactions. Each mass (agent) has four specifications including: position, inertial mass, active gravitational mass, and passive gravitational mass. Every position of the mass corresponds to one solution of the problem, and gravitational and inertial masses are determined via a fitness function. In fact, the GSA is navigated by properly adjusting the masses. For this reason, the masses obey the Newtonian laws of gravitation and motion. According to the law of gravity, each mass attracts other masses. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the distance between them, R. Here R is used instead of R^2 because the experiment proves that R provides better results than R^2. Masses must be attracted by the heaviest one, which presents an optimum solution in the search space.

Considering a system with N agents, the position of the *ith* agent is defined by Equation (16):

$$X_i = (X_i^1, \dots, X_i^d, \dots, X_i^n) \text{ for } i = 1, 2, \dots, N \tag{16}$$

The force acting on mass i from mass j is defined by Equation (17):

$$F_{ij}^d(t) = g(t)\frac{M_{pi} \times M_{aj}}{R_{ij}(t) + \varepsilon}(X_j^d(t) - X_i^d(t)) \tag{17}$$

Rij(t) is the Euclidian distance between agents i and j, as given by Equation (18):

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \tag{18}$$

To give a stochastic characteristic to the algorithm, the total force that acts on agent i, in dimension d, F_d^i, which is shown in Equation (19), is the randomly weighted sum of the *dth* components of the exerted forces from other agents. To improve the performance of the GSA by controlling exploration and exploitation, it was assumed that only the *Kbest* agents would attract the others. *Kbest* is a function of time, with the initial value, *K0*, at the beginning and decreasing with time. At the beginning, all agents apply the force but, as time passes, *Kbest* is decreased linearly and, at the end, only 2% of the agents apply force to the others. Thus, *Kbest* is the set of first K agents with the best fitness value and the biggest mass, as shown in Equation (19):

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i} rand_j F_{ij}^d(t) \tag{19}$$

where, $rand_j$ is a random number in the interval [0,1]. According to the law of motion, the acceleration of the agent i at time t, and in the *dth* direction (a_j^d), is calculated by Equation (20):

$$a_j^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{20}$$

The next position and velocity can be calculated using Equations (21)-(22):

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{21}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{22}$$

where, $rand_i$ is used to give a randomized characteristic to the search.

The gravitational factor, g, is initialized at the beginning and reduced with the time in order to control search accuracy. In other words, g is a function of the initial value and time, and is shown in Equation (23):

$$g(t) = g(g_0, t) \tag{23}$$

Gravitational and inertia masses are calculated by the fitness evaluation. A heavier mass is a more efficient agent. Assuming the equality of masses, they are calculated using the map of fitness. The gravitational and inertial masses are updated in each iteration by Equations (24)-(26):

$$M_{ai} = M_{pi} = M_{ii} = M_i,\ i = 1, 2, \dots, N \tag{24}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{25}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{26}$$

For maximization problems, Equations (27)-(28) are used [51-52]:

$$best(t) = max\{fit_j(t)\}\ j \in \{1,...,N\} \tag{27}$$

$$worst(t) = min\{fit_j(t)\}\ j \in \{1,...,N\} \tag{28}$$

In this study, the GSA population and the number of GSA iterations were considered 500 and 200, respectively.

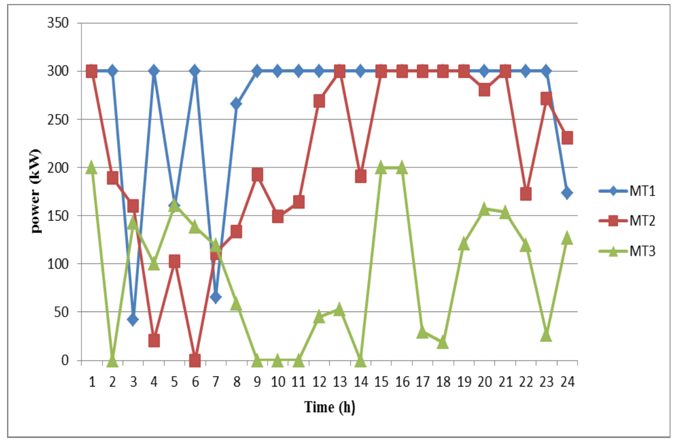
Genetic Algorithm

The GA is a conventional optimization method that is inspired from the evolution and heredity of living organisms. It has six steps including generating the initial population, ranking and probability calculations, selection, crossover, mutation, replacement, and checking the final conditions. There are different ways to choose each step, depending on the optimization problem. In this study, the exponential function was used for ranking. After calculating the probability of the intervention of each chromosome in developing the next generation, the Roulette Wheel method was used for the selection. In the crossover step, the Affin method, which is a combination of the arithmetic and linear crossover, was employed. Also, the dynamic mutation and generational replacement were utilized. In order to optimize the GA method, the most competent members were sorted and kept in any repetition, and which replaced the previous members. In this study, the probability of mutation was assumed to be 0.03; the probability of crossover to be 0.8; the GA population to be 500; and, the number of GA iterations to be 1000 [53].

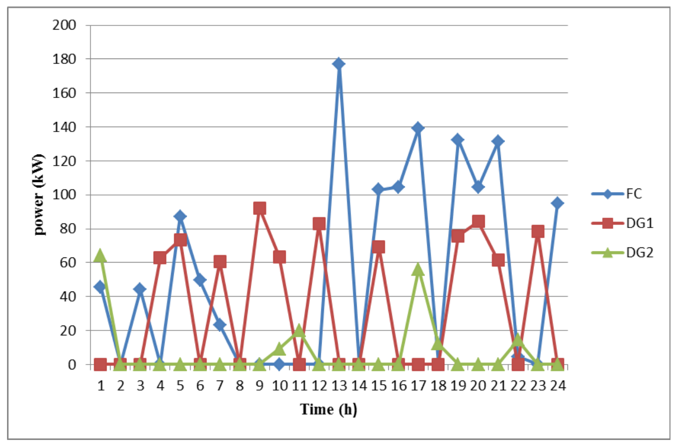
Results

The results from optimum MG planning for units without ramp rate were compared with the results of optimum planning of the units with ramp rate; the proposed plan is illustrated in Figures 4 and 5, respectively. The total obtained profit from the objective function of the given MG using the GSA was $2272.60 without considering ramp rate, and estimated to be about $2260.92 with considering ramp rate limitations in generation plants.

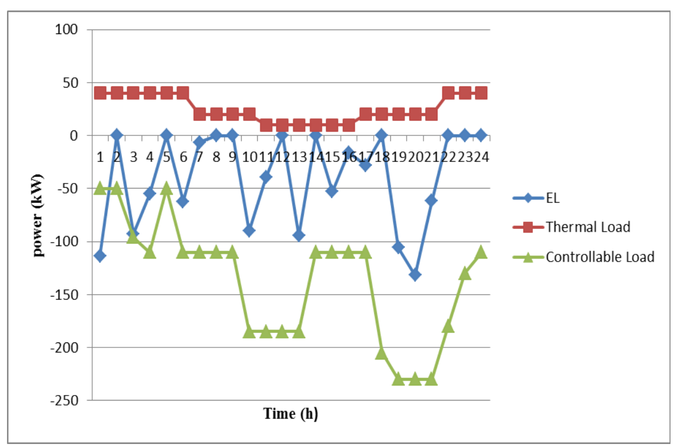
In order to compare the efficiency of the proposed algorithm with a commonly used method, the GA was applied to the problem. The results showed that, using the GA, the total gained profits from the objective function of the given MG was $2268.91 disregarding ramp rate and $2259.98 considering ramp rate limitations. The proposed plan is depicted in Figures 6-7.



(a) Microturbines

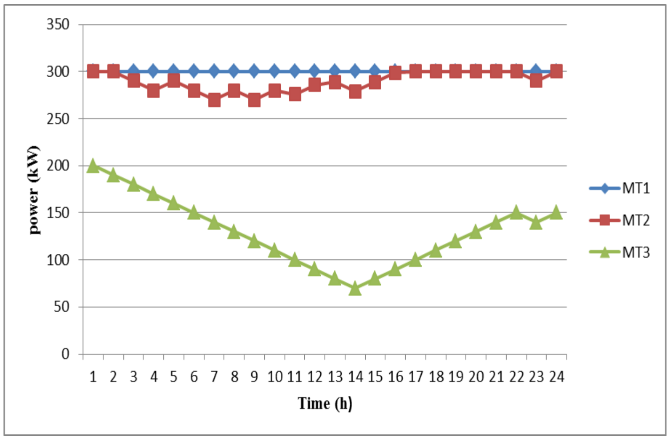


(b) Fuel Cell and Independent DGs

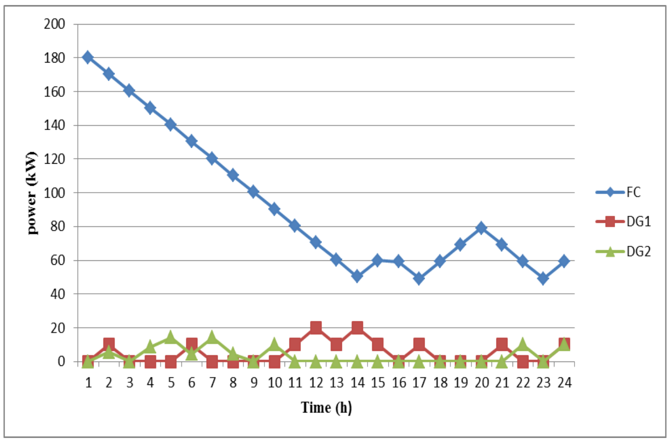


(c) Electrolyzer, Thermal Load, and Controllable Load

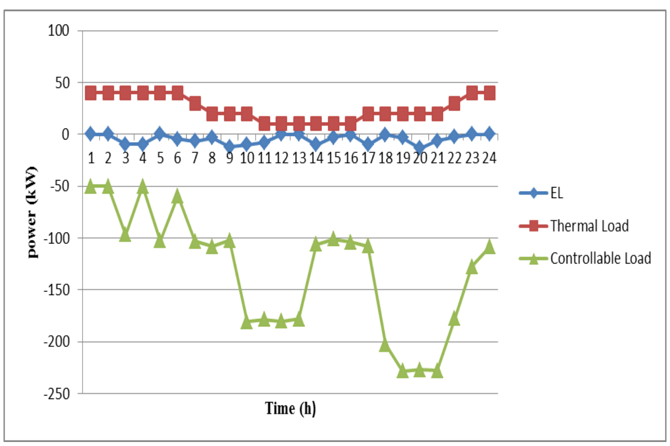
Figure 4. MG's Optimum Planning via the GSA for Units without Ramp Rate



(a) Microturbines

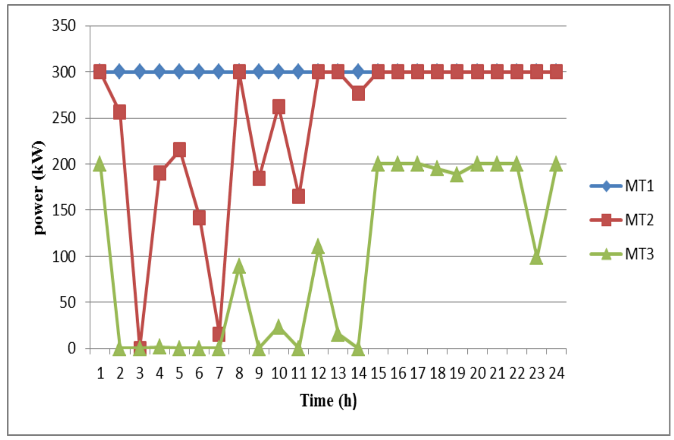


(b) Fuel Cell and independent DGs

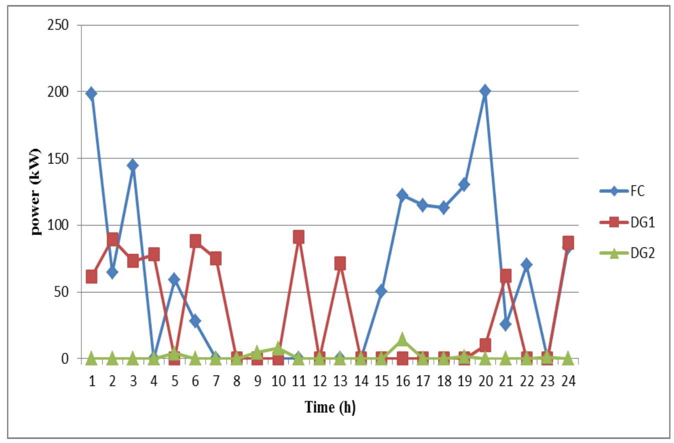


(c) Electrolyzer, Thermal Load and Controllable Load

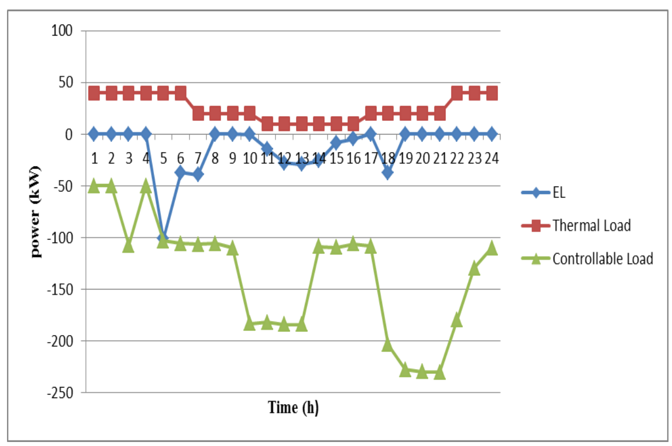
Figure 5. MG's Optimum Planning via GSA for Units with Ramp Rate



(a) Microturbines

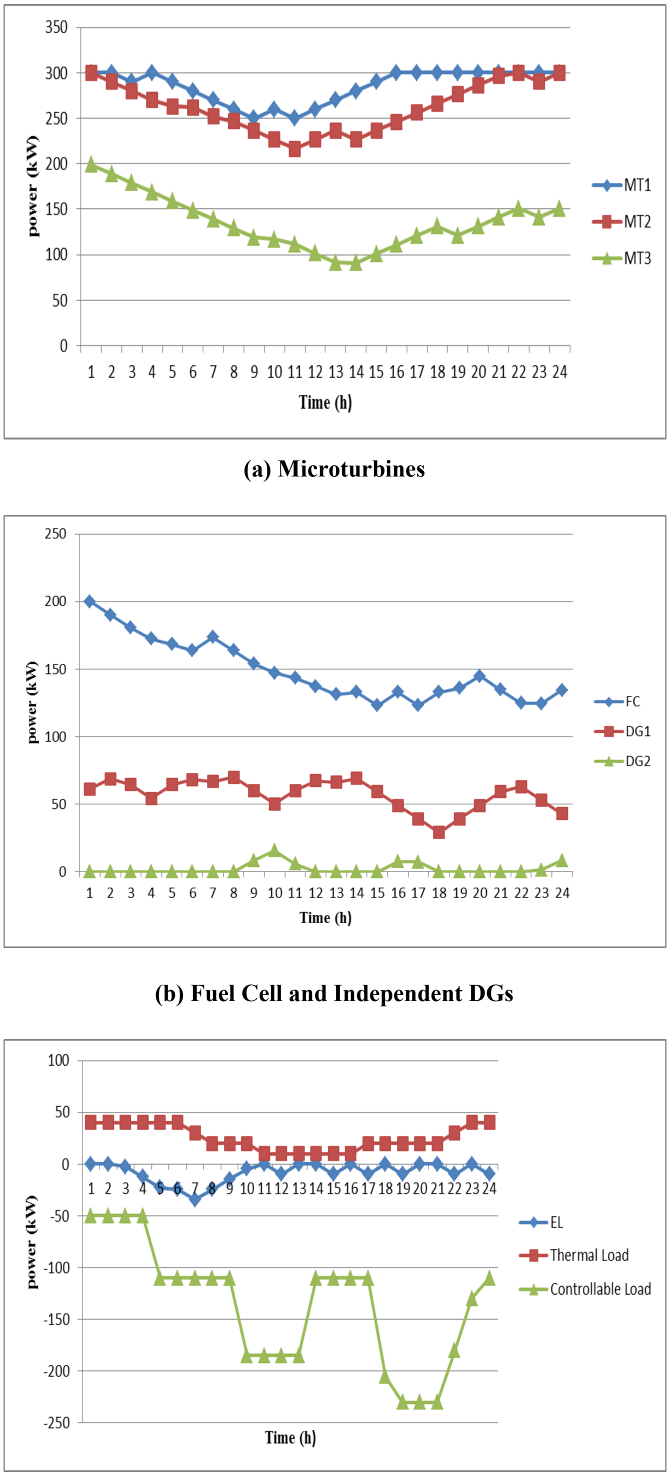


(b) Fuel Cell and Independent DGs



(c) Electrolyzer, Thermal Load, and Controllable Load

Figure 6. MG's Optimum Planning via the GA for Units without Ramp Rate



(a) Microturbines

(b) Fuel Cell and Independent DGs

(c) Electrolyzer, Thermal Load, and Controllable Load

Figure 7. MG's Optimum Planning via the GA for Units with Ramp Rate

The results showed that, despite the fact that the number of required iterations for convergence to the optimal solution via the GSA was less than the GA, it performed slower than the GA. Hence, the GSA is suggested for cases in which the accuracy is more important.

Conclusions

In this study, the optimum operation of a MG was presented over the next 24-hour period. The studied MG contained a diverse variety of possible MG components including: electrical and thermal loads, three MTs, FC, PV arrays, WT, EL, hydrogen storage tank, boiler, and reformer. Moreover, the MG was connected to the network that allowed the power exchange with the local grid. Some constraints were considered in the optimization problem in order to take into account the limitations that are usually found in the power generation of MGs. It was found that considering ramp rate caused an additional limitation, which hindered the optimal performance of the binary part to a certain extent and, thus, decreased the total profit. Furthermore, although the GSA performed slower than the GA in this problem and required more computational time, it gave a more optimized solution for maximizing the profit.

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Appendix A

Nomenclature

t	time (hour)
j	the number of independent DG units
k	microturbine numbers
p	the related prices (¢(
u	the on/off state of each unit
OM	the operation and maintenance costs of each unit
P_G	the exchanged power with the local grid (kW)
P_d	the electrical load demand (kW)
P_{el}	the power produced from the electrolyzer (kW)
P_j	the power produced from independent DGs (kW)
P_{therm}	the thermal load demand (kW)
P_{boiler}	the power produced from the boiler (kW)
P_{mt-k}	the power produced from the *kth* microturbine (kW)
P_{wt}	the power produced from WT (kW)
P_{pv}	the power produced from PV (kW)
P_{fc}	the power produced from fuel cell (kW)
C_{therm}	the thermal load cost (¢)
C_{mt-k}	the costs of generation in the *kth* microturbine (¢)
α_{stmt-k} and β_{stmt-k}	the startup factors of the microturbine
t_{off}	the off-time
τ	time constant for the cooling
C_{fc}	generation costs of the fuel cell (¢)
C_{el}	generation costs of the electrolyzer (¢)
C_{NG}	the cost of purchasing the natural gas
C_L	costs of the curtailment strategy
β_L and γ_L	cost factors of the curtailment strategy
P_{sh}	the curtailed power at controllable load (kW)
T_{i-1}^{on}	on-time of the *ith* unit
T_{i-1}^{off}	off-time of the *ith* unit
MUT	the minimum up-time
MDT	the minimum down-time
T_{shed}	the maximum shedding duration
DR and UR	the minimum and maximum ramp rate
x_i^d	the position of the *ith* agent in the *dth* dimension
F_{ij}^d	the force acting on mass *i* from mass *j* in the *dth* direction
v_i^d	the velocity of the *ith* agent in the direction *dth*
a_j^d	acceleration of agent *j* in the direction *dth*
F_i^d	the total force that acts on agent *i* in dimension *d*
M_{aj}	active gravitational mass related to agent *j*
M_{pi}	the passive gravitational mass related to agent *i*
g	the gravitational constant
Rij	the Euclidian distance between two agents *i* and *j*
M_{ii}	the inertial mass of the *ith* agent
fit_i	the fitness value of agent *i*
α_{fc} and β_{fc}	hot and cold startup factors of the fuel cell
α_{el} and β_{el}	hot and cold startup factors of the electrolyzer
G	natural gas consumption rate (m^3/h)