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

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Abstract

In this study, the short-term operation planning of a typical microgrid (MG) with diverse units is optimized for achieving the maximum profit, considering technical and economical constraints for 24 hours and the effect of ramp rate in the planning is investigated. The MG consists of a diverse variety of power system components such as wind turbine, microturbine, photovoltaic, fuel cell, electrolyzer, Hydrogen storage tank, reformer, a boiler, and electrical and thermal loads. Moreover, MG is connected to an electrical grid for exchange of power. The MG is managed and controlled through a central controller. The system costs include the operational cost, thermal recovery, power trade with the local grid, and hydrogen production costs. Total obtained profit from the MG is found to be higher based on gravitational search algorithm (GSA), \$2.272596×10^3, as compared to improved genetic algorithm (GA), \$2.268914×10^3. However, the ramp rate constraint confines optimum performance of binary section of the algorithms, which decides whether the units should be on or off and, it causes a decrease in the final profit. Considering ramp rate, the total profit is \$2.260919×10^3 based on GSA and it is \$2.259976×10^3 using GA.

Nomenclature

t	time (hour)	C_L	costs of curtailment strategy
j	the number of independent DG units	β_L and γ_L	cost factors of curtailment strategy
k	microturbine numbers	P_{sh}	curtailed power at controllable load (kW)
p	the related prices (¢)	T_{i-1}^{on}	on-time of the *ith* unit
u	the on/off state of each unit	T_{i-1}^{off}	off-time of the *ith* unit
OM	operation and maintenance cost of each unit	MUT	minimum up-time
P_G	the exchanged power with the grid (kW)	MDT	minimum down-time
P_d	the electrical load demand (kW)	T_{shed}	the maximum shedding duration
P_{el}	produced power from electrolyzer (kW)	DR and UR	min and max ramp rate
P_j	produced power from independent DGs (kW)	X_i^d	the position of *ith* agent in the *dth* dimension
P_{therm}	thermal load demand (kW)	F_{ij}^d	the force acting on mass *i* from mass *j* in direction *dth*
P_{boiler}	produced power from boiler (kW)	v_i^d	the velocity of *ith* agent in direction *dth*

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$P_{mt\text{-}k}$	produced power from microturbine k (kW)	a_j^d	acceleration of the agent *j* in direction *dth*
P_{wt}	produced power from WT (kW)	F_i^d	the total force that acts on agent *i* in dimension *d*
P_{pv}	produced power from photovoltaics (kW)	M_{aj}	active gravitational mass related to agent j
C_{therm}	thermal load cost (¢)	M_{pi}	the passive gravitational mass related to agent i
$C_{mt\text{-}k}$	costs of generation in microturbine k (¢)	g	gravitational constant
$\alpha_{stmt\text{-}k}$ and $\beta_{stmt\text{-}k}$	startup factors of microturbine	Rij	the Euclidian distance between two agents *i* and *j*
t_{off}	the off-time	M_{ii}	the inertial mass of ith agent
τ	time constant for the cooling	fit_i	the fitness value of the agent *i*
C_{fc}	generation costs of fuel cell (¢)	α_{fc} and β_{fc}	hot and cold startup factors of fuel cell
C_{NG}	natural gas price	C_{el}	generation costs in electrolyzer (¢)
G	natural gas consumption rate (m^3/h)	α_{el} and β_{el}	hot and cold startup factors of electrolyzer

Introduction

In microgrids (MGs), energy management systems (EMSs) provide for decision making for generating electric power and heat, storage system planning, load management and appropriate selling or purchasing from 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 MG is improving the system reliability and demand supply. The significance of the MG is that the power generation is distributed so as to be closer to the end users. MG can be either connected to the network or be operated independently in island mode. When it is connected to the network, MG may act either as a load or a small power source. MG has 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, the low capital cost potentially enables low-cost entry into competitive markets. [1-4]

Up to now, several studies have focused on optimizing the energy and operation management of MGs. In [5], a smart energy management system is presented to optimize the operation of the MG. The characteristic of the photovoltaic (PV) output in different weather conditions has been studied and then a day-ahead power forecasting module has been presented. In [6], a performance metric is applied to MGs operated as stand-alone, grid-tied, and networked modes. In [7], a general formulation is presented to determine the optimal operating strategy and cost optimization scheme as well as to reduce the emissions from a MG. In [8], an effective algorithm for optimizing the distribution system operation in a smart grid, from cost and system stability point of view, is proposed. Mathematical techniques are applied to build accurate forecasting models for different sources and loads. In [9], a general methodology is studied to determine the optimal configuration of MGs and maximize the benefits. A hybrid smart grid management system based on multiagents is examined in [10], in order to measure and control the loads inside a building while power generation is forecasted using neural networks. In [11], the main functions of the MG central controller required for the optimization of the operation is described for the efficient participation in future real-time markets following different policies. An algorithm for the MG planning as an alternative to the co-optimization of the generation and transmission expansion planning in electric power systems is proposed in [12]. Researchers in [13] show a load forecast method and an optimized operation planning for DGs in MG considering the heat sources which run according to heat load prediction. The aim of [14] is to promote green energy usage, discuss concerns regarding energy supply during disasters, and improve the efficiency of waste heat usage. Moreover, the optimal capacities of the solar cell, fuel cell (FC), electrolyzer (EL), and heat pumps are computed, while operating independently. In [15], a methodology for the operation of a hybrid plant with wind power and hydrogen storage is studied. Forecasts of wind power is used for maximizing the expected profit from power exchange in a day-ahead market, while a penalty cost for unprovided hydrogen demand is taken into account. In [16], the study focuses on how an electrical tracking demand is economically shared between micro-turbines and diesel generators on the basis of the multi-objective optimization of the fuel cost as well as emission. In [17], a new multi-objective modified honey bee mating optimization algorithm is presented to investigate the distribution feeder reconfiguration problem considering RESs connected to the distribution network. The study in [18] is focused on the development of a novel EMS based on the application of Neural Networks. In [19], an optimal design and planning of a MG considering various distributed energy technology options such as solar PV, wind generator, biomass gasified system, diesel generator and battery storage for different applications and with realistic inputs on their physical, operating and economic characteristics is developed. In that study, the break-even distance for connecting the MG with the main grid is determined, as compared with that of the cost of the isolated MG. In [20], the study focuses on development of a mathematical model to optimally manage the smart polygeneration MG which contains combined heat and power (CHP) and considers thermal demand in order to minimize daily operational costs. In [21], the aggregation and implementation of a determinist energy management method for business customers in a MG power system is presented. In [22], the study presents a MG energy management optimization method with the presence of PV-based active generators. To accommodate the high demand of renewable energy and the environment policy, the planning and operation of micro-source generators is studied in [23]. In [24], the scheduling of the power generation in a MG that has a group of dispatchable and non-dispatchable generators is studied. In [25], hedging strategies for renewable resource integration and uncertainty management in the smart grid is evaluated. In [26], an optimization model is formulated to solve the problem of the day-ahead optimal scheduling of a DC MG. In [27], a three-step method for the optimal generation scheduling of a MG in island operation mode is studied by solving the thermal unit commitment problem. In [28], the short-term regulation service optimization linked to the long-term economical dispatch of a grid-connected MG is addressed. In [29], a distributed multi-agent system is developed for generation scheduling and monitoring of energy resources for optimized MG operation. In [30], a tool for the day-ahead operation plan of a grid-connected MG, including distributed generators, electrical and thermal loads and storage devices, is proposed. The purpose of [31] is to perform economic analysis, formulate an optimization model, and determine optimal operating strategies for smart MG systems. In [32], a multi-period optimization model is developed for an interconnected MG with hierarchical control that participates in wholesale energy market to maximize its benefit.

In this study, the short-term operation planning of typical MG with diverse units is optimized for achieving the maximum profit, considering technical and economical constraints for 24 hours and the effect of ramp rate in the planning is investigated.

System Description

The studied MG is connected to the network for exchange of power, where it is managed and controlled through a central controller. In the MG model, energy suppliers include: two DG units, which are managed or owned independently; DG units that are owned by MG manager including wind turbine (WT), PV, three conventional microturbines (MTs), controllable loads and thermal loads provided by boiler that recover heat from MTs and FC. Storage system consists of EL, hydrogen storage tank, FC, reformer and related accessories. Further, there are four types of loads namely: critical load, controllable load, sensitive to price load and thermal load. The MG model is depicted in Figure 1. In this study, parameters such as prices, capacities and characteristics of DGs and demands are extracted from [1].

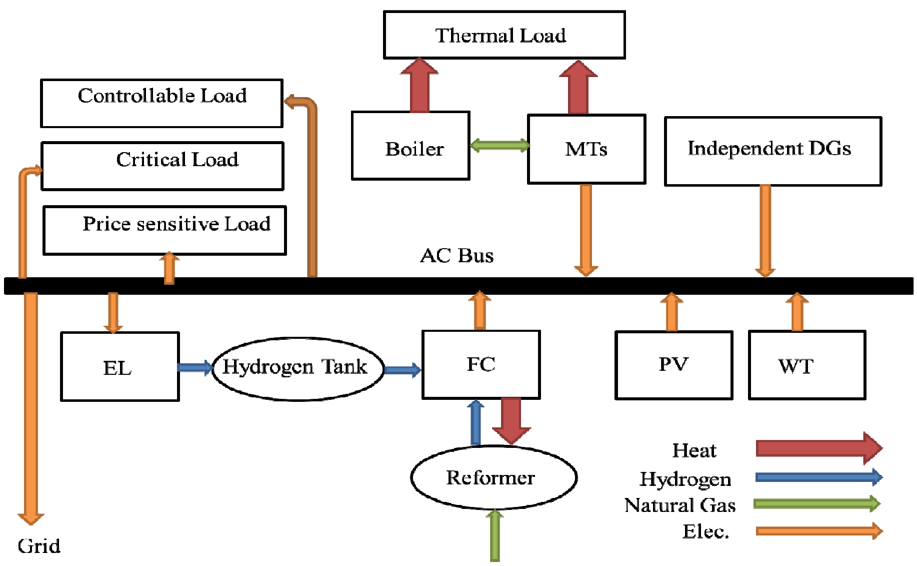

Figure 1: MG Schematic Diagram.

Problem Formulation

The objective function for operation of EMS is to maximize the profit of MG owner in the next 24 hours which is incomes minus costs expressed by Eq. (1). The total system income includes the income from the sale of electrical energy to local grid and consumers in MG control area and income from the sale of thermal energy. The operational cost consists of the cost of purchased electrical energy from independent DG units, the cost of purchased energy from 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 and operation cost of the units, consumers demand, energy price in power market and the weather forecast data.

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

Cost components are described as

$$C_{mt-k} = \alpha_{mt-k} + \beta_{mt-k}P_{mt-k} + \gamma_{mt-k}P_{mt-k}^2 + (\alpha_{stmt-k} + \beta_{stmt-k}(1 - e^{-\frac{t\,off}{\tau}}))\times u_{mt-k}(t)(u_{mt-k}(t) - u_{mt-k}(t-1)) \tag{2}$$

Equation (2) contains the operation cost and startup cost of MT units.

$$C_{fc} = C_{NG}\times G + (\alpha_{fc} + \beta_{fc}(1 - e^{-\frac{t\,off}{\tau}}))\times u_{fc}(t)(u_{fc}(t) - u_{fc}(t-1)) + OM_{fc} \tag{3}$$

The first term of Eq. (3) is the cost of the hydrogen production in reformer unit that depends on natural gas price C_{NG} and natural gas consumption rate of the reformer G. The second term represents the startup cost and the third term refers to operation and maintenance cost of the FC. Hydrogen fuel cost is not considered in Eq. (3), because the FC consumes produced hydrogen by the EL. Since operation and maintenance costs are assumed constant, they do not depend on the performance of the EL and the FC.

$$C_{el} = (\alpha_{el} + \beta_{el}(1 - e^{-\frac{t\,off}{\tau}}))\times u_{el}(t)(u_{el}(t) - u_{el}(t-1)) + OM_{el} \tag{4}$$

It is 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.

Penalty factor that is considered when MG cannot supply the load demand and has to shed P_{sh} amount of controllable loads, is modeled as a convex quadratic cost function:

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

System Constraints

The active and thermal power balances require two equality constraints in each hour:

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

P_{therm} is supplied from the boiler (P_{boiler}) and the heat from MTs.

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

Produced powers are limited according to their particular capacities and demand is always more than a certain amount. There are also some limitations regarding the units minimum on and off time. The load shedding time should not exceed a certain period in the day. Ramp rate effect is investigated in this study and results are compared with and without this limitation. Unequal constraints are expressed as follows:

$$P^{\min} \le P_{mt\text{-}k} \le P^{\max} \tag{8}$$

$$P^{\min} \le P_{fc} \le P^{\max} \tag{9}$$

$$P^{\min} \le P_{el} \le P^{\max} \tag{10}$$

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

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

$$P^{\min} \le P_d \tag{13}$$

$$T_{shed} \le T^{\max} \tag{14}$$

$$-DR \le P(t) - P(t-1) \le +UR \tag{15}$$

Since the WT and PV produce power from free inputs, it is assumed that the optimized production is the most possible amount that is predicted. Hence, the power of these units is not considered in optimization function. However, they are considered in power balance equality constraint. Power output of WT is predicted according to the relation between the wind speed and the output power and PV output is calculated considering the effect of the temperature and the solar radiation. PV and WT predicted power is depicted in figure 2 and the connected grid load in figure 3. [1]

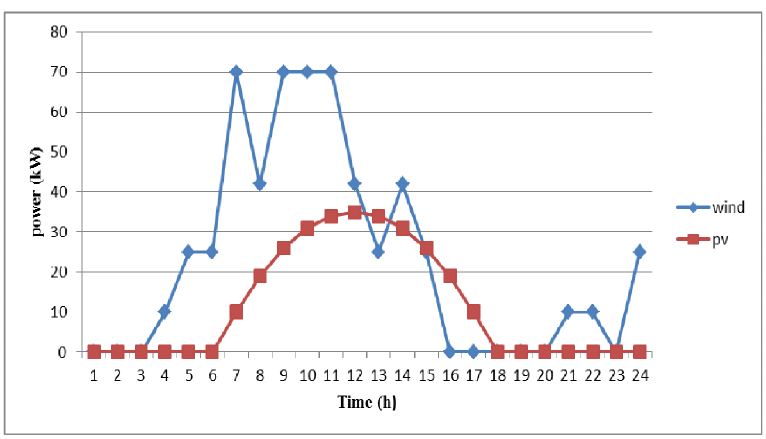

Figure 2: PV and WT Predicted Power (kW).

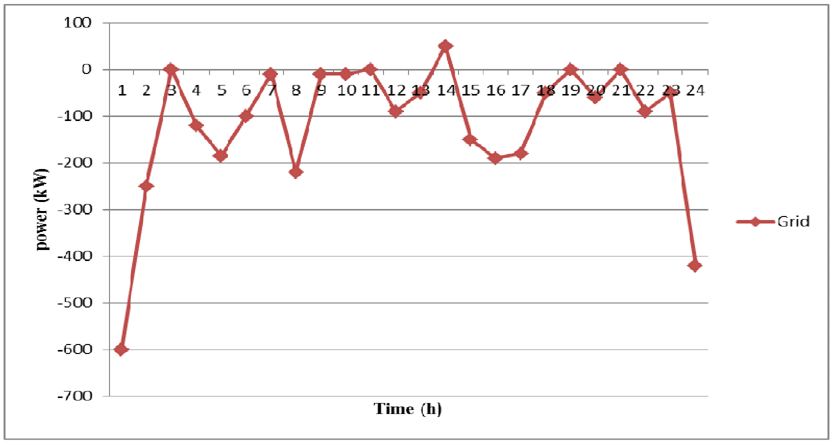

Figure 3: Predicted Grid Load (kW).

Solution Methodologies

In this study, Gravitational Search Algorithm (GSA) and Genetic Algorithm (GA) are used to optimize MG planning for the next day. The objective function contains both real and binary parameters, real parts determine the optimum powers 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.

1. Gravitational Search Algorithm

GSA is based on the law 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 to use a fitness function. In fact, the GSA is navigated by properly adjusting 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*. We use *R* 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:

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

The force acting on mass *i* from mass *j* is defined as:

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

Rij(t) is the Euclidian distance between two agents *i* and *j*:

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

To give a stochastic characteristic to the algorithm, the total force that acts on agent *i* in dimension *d*, F_d^i is randomly weighted sum of *dth* components of the exerted forces from other agents. To improve the performance of GSA by controlling exploration and exploitation, it is assumed that only the *Kbest* agents will attract the others. *Kbest* is a function of time, with the initial value *K0* at the beginning and decreases 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.

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

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 direction *dth* (a_j^d), is as equation (20):

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

The next position and velocity could be calculated as:

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

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

$rand_i$ is used to give a randomized characteristic to the search.
The gravitational factor *G* is initialized at the beginning and will be reduced with time to control the search accuracy. In other words, *G* is a function of the initial value and time:

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

Gravitational and inertia masses are simply 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 the following equations:

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

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

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

For maximization problems, the following equations are used: [37-38]

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

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

In this study, the GSA population and the number of GSA repetition are considered 500 and 200, respectively.

2. Genetic Algorithm

The Genetic Algorithm (GA) is a conventional optimization method that is inspired from the evolution and heredity of the living organisms. It has 6 steps including generating the initial population, ranking and probability calculation, 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 is used for ranking. After calculating the probability of intervention of each chromosome in developing the next generation, the Roulette Wheel method is used for selection. In the crossover step, Affin method, which is a combination of arithmetic and linear crossover, has been employed. Also, the dynamic mutation and generational replacement are utilized. In order to optimize the GA method, the most competent members are sorted and kept in any repetition, and then they replace the previous members. In this study, we assumed the probability of mutation 0.03, probability of crossover 0.8, the GA population 500 and the number of GA repetition 1000 [39].

Results

Results from optimum MG planning for units without or with a thrivial ramp rate via GSA and GA are illustrated in Figures 4 and 5, respectively. The total obtained profit from this MG through GSA was $\$2.272596\times10^3$ and it was estimated about $\$2.268914\times10^3$ using GA.

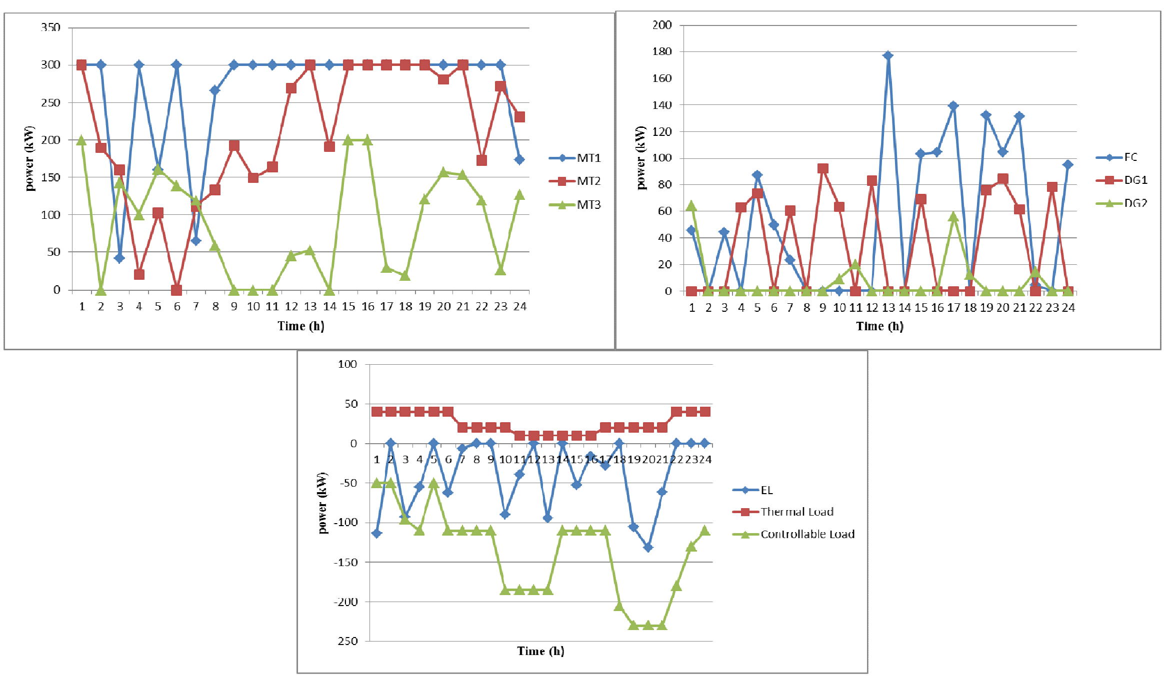

Figure 4: MG's Optimum Planning via GSA for Units without Ramp Rate.

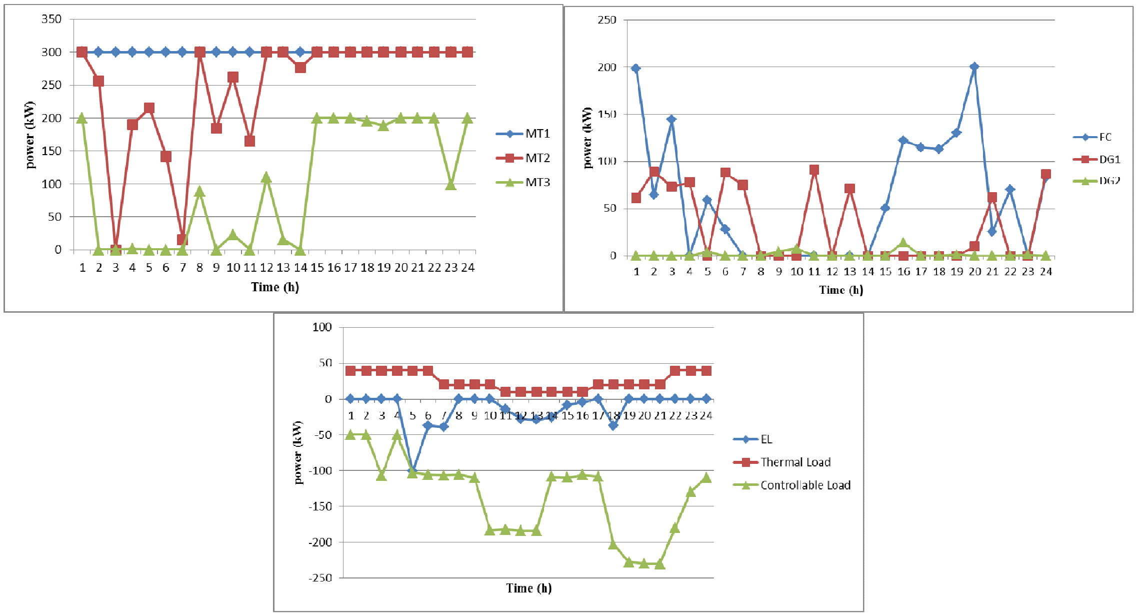

Figure 5: MG's Optimum Planning via GA for Units without Ramp Rate.

Considering ramp rate limitations in generation plants, total gained profits from the objective function of the given MG was $\$2.260919\times10^3$ through GSA and $\$2.259976\times10^3$ using GA. Optimized planning is depicted in Figures 6-7.

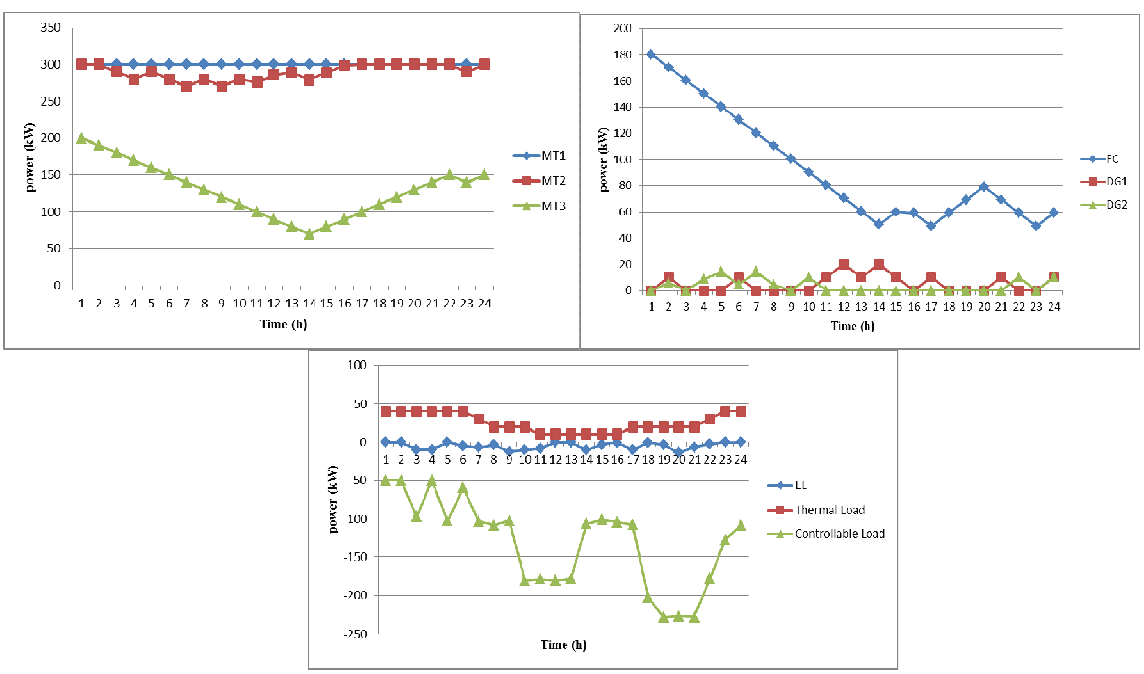

Figure 6: MG's Optimum Planning via GSA for Units with Ramp Rate.

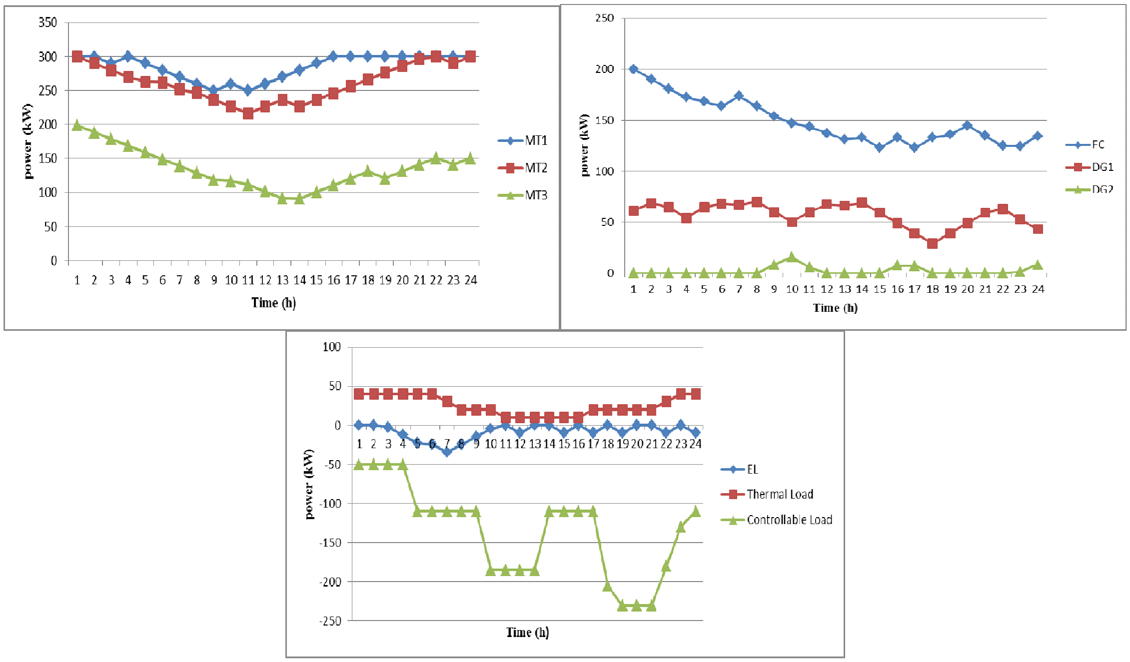

Figure 7: MG's Optimum Planning via GA for Units with Ramp Rate.

Conclusions

In this study, the optimum operation of a MG is presented over 24 hours of the next day. The studied MG contains a diverse variety of possible MG components including: a FC, three MTs, PV arrays, WT, EL, hydrogen tank, boiler, reformer and electrical and thermal loads. Moreover, the MG is connected to a network and considers possibility of power trade with the local grid. Related constraints are added to the optimization problem in order to consider the limitations that are usually found in the generation of MGs.

It is found that GSA performs betther than GA for maximising the profit. Furthermore, considering ramp rate causes an additional limitation, which hinders the optimal performance of the binary part to a certain extent so decreases the total profit.

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