Optimization of Microgrid Energy Management using a Genetic Algorithm

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Received: 17 January 2025 | Revised: 29 March 2025 | Accepted: 9 April 2025

 DOI: https://doi.org/10.48084/etasr.10278

ABSTRACT

Microgrids (MGs) are used in systems of clean and renewable energy. This research presents an efficient Energy Management System (EMS) for the economic operation of grid-connected integrated solar renewable MGs. The proposed MG consists of a Photovoltaic (PV) generator and a battery storage system and uses a Genetic Algorithm (GA) based on a one-day scheduling timeframe. The main objectives of this study are, achieving the load power requirements at a minimum operating cost, improving the overall efficiency, and protecting the battery from depletion and overcharging. The obtained results were compared with the state-space heuristic optimization technique using two different load profiles to demonstrate the effectiveness of the proposed method. The results show that the total operating cost is reduced by 17.66% and 17.04%, respectively, compared to the state-space heuristic optimization approach.

Keywords-microgrid; optimization; genetic algorithm; state-space heuristic; energy management; energy storage system; photovoltaic

I. INTRODUCTION

The development of industry and increasing population density in recent years have led to an increase in energy demand, which has a negative impact on the environment. Therefore, reducing the use of fossil fuels and shifting to the development of clean energy sources has become inevitable [1]. MGs have become an important research focus as a critical interface for connecting the power generated by renewable energy-based distributed generators to the power system [2]. MG is a small-scale power system [3], described by the Consortium of Electric Reliability Technology Solutions (CERTS) as a semi-autonomous system of distributed generators and dispatchable loads working together to provide reliable and secure power and heat to a local community [4], such as a college campus, hospital complex, business center, or neighborhood [5]. MGs operate in two modes: grid-connected mode and islanded mode, when they are disconnected from the grid [6, 7]. All modern MGs are equipped with an EMS, which is responsible for the optimal allocation of energy resources to meet the load demands. This system ensures that the MG does not violate any technical or operational standards during its operation, while trying to achieve a certain objective [8]. MGs may encounter more complex situations, such as increased difficulty in management and control due to the diversity of components. Unregulated mode switching between grid-connected and islanded states can also lead to energy congestion or instability [9]. Many researchers have focused on optimizing the EMS of MGs using numerous methods. Authors in [10] presented two optimization problems: a single-objective problem that aims to minimize the total operating cost or emissions, and a multi-objective problem that combines both simultaneously using the Sparrow Search Algorithm (SSA). Authors in [11] proposed the optimal design of a grid-independent solar fuel cell-biomass energy system using an extended Salp Swarm algorithm (SS) with a rule-based energy management strategy. Authors in [12] studied an optimal multi-MG energy management employing the information gap decision theory and tunicate swarm algorithm, while authors in [13] proposed the economic optimization scheduling of an MG group via a chaotic mapping Butterfly Optimization (BOA). Authors in [14] presented the management of EMS in an MG deploying the Linear Programming (LP) method. An improved Soft Actor-Critical (SAC) algorithm was proposed in [15] in order to solve high dimensional energy management mathematical models in MG energy optimization. Authors in [16] utilized Harris Hawk Optimization (HHO) for MG energy planning. Authors in [17] presented an efficient design of energy MG management using the Promoted Remora Optimization (PRO) algorithm. Authors in [18] proposed Artificial Neural Networks (ANNs) to manage renewable grid energy. Multi-objective energy management in a renewable and EV integrated MG using an iterative map based self-adaptive crystal structure algorithm was proposed in [19], while authors in [20] incorporated Demand Side Management (DSM) techniques and the heuristic optimization approach to reduce operational costs. The improved Moth-Flame algorithm [21] was employed to optimize the scheduling of an MG cluster. Authors in [22] presented a pioneering optimization model for efficient and resilient energy management in smart MGs. Authors in [23] proposed an EMS for a public building under demand response. Authors in [24] developed the Sandpiper Optimization (SO) algorithm for techno-economic optimization in MG. Multi-objective Grey Wolf Optimization (GWO) was proposed to reduce the cost of Electric Vehicles (EVs) in MG [25]. Authors in [26] applied the Lévy arithmetic algorithm in order to minimize the energy cost and emission level of MG. Authors in [27] proposed an artificial rabbit optimized neural network-based MG EMS. This study develops a simulation-based model for MG EMS incorporating a solar PV array and ESS. The proposed approach assumes that the MG can operate in grid-connected or islanded modes, although it often operates independently of the utility grid. It is also assumed that the cost of renewable energy is negligible. This model outlines the development of an optimization strategy that utilizes predicted price and load conditions to determine the optimal strategy for storing or selling energy from a grid-scale battery system. A battery controller manages the excess power from the energy storage process when the MG produces more than required, and provides additional power during a shortfall. Two control techniques are evaluated: a heuristic method using a state-space heuristic and a GA optimization method deploying a GA command in MATLAB. The model dynamically regulates power distribution, highlighting the importance of battery controllers in grid-scale storage.

II. MICROGRID MATHEMATICAL MODEL

A. Photovoltaic Array

This study used daily solar radiation data on an optimally inclined surface, as the measurement sites are accurately aligned. The computation of the output power of the PV array is achieved through:

$$P_{PV} = \eta_{PV} \times G_t \times A_{PV} \quad (1)$$

where P_{PV} represents the PV power, η_{PV} is the PV efficiency of the panel, G_t is the irradiance, A_{PV} is the PV area.

B. Energy Storage System

The Energy Storage System (ESS) is basically a lithium-ion battery with a capacity of 2500 Wh:

$$V_{bat}(T) = V_0(T) - \frac{m \times Q_{bat}(T)}{Q_{bat}(T) - \int I_{bat}(T)dt} + A\exp(-B\int I_{bat}(T)dt) \quad (2)$$

where $Q_{bat}(T)$ represents the capacity of the battery, $I_{bat}(T)$ is the current of the battery, B is the exponential battery capacity, m is the polarization voltage, A is the exponential voltage and $V_0(T)$ is the constant voltage of the battery. The State of Charge (SOC) is varying:

$$SOC_{bat}(T) = SOC_0(T) \pm \frac{I_{bat}(T) \times \Delta t)}{Q_{bat} \times 3600} \quad (3)$$

where $SOC_0(T)$ is the initial SOC, Δt is the varying time. The output energy of ESS can be determined by:

$$E_{bat}{}^{out}(T) = Q_{bat}(T) \times V_{bat}(T) \times SOC_{bat}(T) \quad (4)$$

and the necessary energy for storage into the battery:

$$E_{bat}{}^{stored}(T) = E_{bat}{}^{rated}(T) - E_{bat}{}^{out}(T) \quad (5)$$

where $E_{bat}{}^{stored}(T)$ is the energy stored in the battery and $E_{bat}{}^{rated}(T)$ is the rated capacity of the battery.

III. FITNESS FUNCTION

A. Definition

To maximize the usage of the PV array and minimize the cost related to utility grid, the following cost function was applied:

$$F_{cost} = min \sum_{i=0}^{N} \left(C_{grid}(i) \times E_{grid}(i) \right) \quad (6)$$

where $C_{grid}(i)$ is the cost related to the utility grid and $E_{grid}(i)$ is the power supplied by the utility grid. The decision variables in the optimization problem are:

$$X = [P_{grid}(1:N) \;\; P_{bat}(1:N) \quad E_{bat}(1:N)]^T \quad (7)$$

where $P_{grid}(1:N)$, $P_{bat}(1:N)$ and $E_{bat}(1:N)$ are: grid power, battery power, and battery energy, respectively.

B. Constraints

Several system constraints and limitations should be considered:

$$P_l(i) = P_{PV}(i) + P_{grid}(i) + P_{bat}(i) \quad (8)$$

$$E_{bat}(i) = E_{bat}(i-1) + P_{bat}(i) \quad (9)$$

$$SOC_{bat,min} \le SOC_{bat} \le SOC_{bat,max} \quad (10)$$

$$P_{bat,min} \le P_{bat} \le P_{bat,max} \quad (11)$$

IV. GENETIC ALGORITHM

GA is a distinguished intelligent algorithm grounded in the tenets of natural evolution, consisting of multiple phases [28, 29]. Initially, a random population of potential solutions, commonly expressed as chromosomes, is generated to promote diversity. Subsequently, the fitness function is used to evaluate each individual in the population. Then, the selection of parents is frequently executed through a process known as tournament selection, which aims to identify potential candidates for reproduction. These parents undergo crossover, often at a single junction, to generate progeny. Following this, a predetermined rate of mutation is executed to ensure the preservation of genetic variability within the population. The new offspring replace the previous generation, and the process from the parental selection to the replacement is repeated until a defined termination condition, such as when the maximum number of generations is met, as shown in Figure 1.

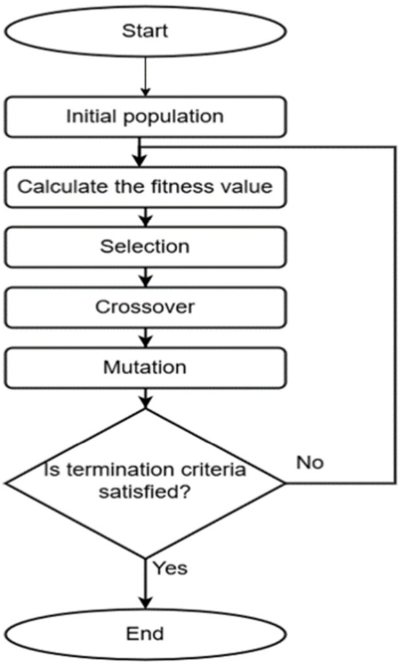

Fig. 1. Flowchart of GA.

V. RESULTS AND DISCUSSION

As illustrated in Figure 2, the test system consists of a solar array with a capacity of 535 kW and an ESS with a rating of 400 kW and a capacity of 2500 kWh. The system is equipped with a utility grid that boasts a capacity of 13.8 kV, which is linked to a three-phase transformer that is rated at 13.8 kV/5 kV. Subsequently, a three-phase circuit breaker is linked to a variable load of 320 kW and a constant load of 350 kW. Two load profiles are used to assess the total cost of electricity in this system. The RMS voltage of the MG, the SOC of the ESS, the power of the PV, grid, ESS and load, are presented for both the GA and heuristic methodologies. Figure 3 presents the simulation waveforms using the application of the first load profile and GA. From 00:00 to 06:30, the load demand is less than 535 kW. Consequently, the battery supplies power and supports the utility grid during the initial thirty minutes. After 00:30 hours, the solar array ceases to supply power; the grid then takes over, while the battery's charge is fully restored. Subsequent to 3:00 a.m., the decline in grid supply coincides with the commencement of solar array and battery operation, precipitating battery discharge. Consequently, the operating cost is at its lowest. From 6:30 a.m. to 12:30 p.m., the load increases to a level exceeding 535 kW. The PV power is increasing while the battery power is decreasing.

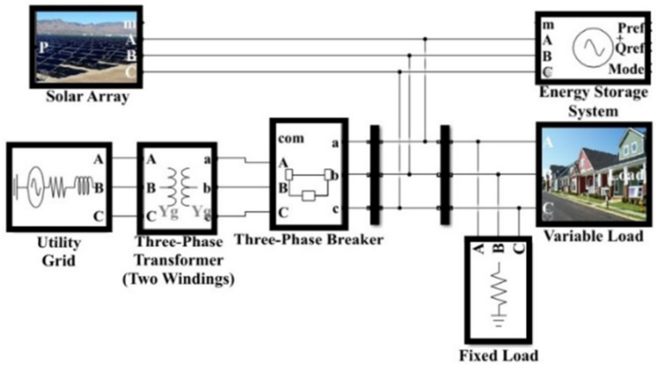

Fig. 2. Architecture of the proposed system.

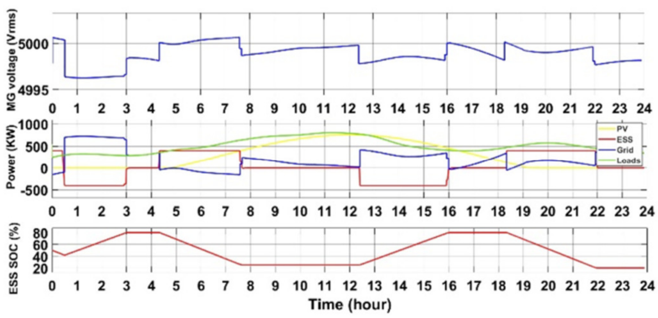

Fig. 3. Simulation results using the first load profile and GA.

As a result, the cost of renewable generation is negligible, contributing to the overall reduction in costs. From 12:30 p.m. to 4:00 p.m., the load demand exceeds 535 kW, prompting the PV array and the grid to supply additional power. During this period, the battery transitions from power supply to charging mode. Renewable generation's cost is minimal, ensuring that the overall cost remains low. During the interval from 16:00 to 19:00, the load experiences a decline, remaining below 535 kW. The grid provides power, and the battery initiates its discharge at 18:30. However, the cost remains low due to the usage of stored battery power from renewable sources. From 7:00 p.m. to 10:00 p.m., the load increases to 535 kW, yet the power is still derived from both the battery and the grid. During this period, solar power is minimal, and the high price increases the cost to its maximum. After 10:00 p.m., the load experiences a decline to below 535 kW. At this juncture, the provision of power is contingent upon the grid, thereby engendering an elevated operating cost due to the complete reliance on external grid infrastructure. The total cost of the initial load profile using GA is $756.58. In Figure 4, the simulation waveforms are portrayed using the first load profile and the heuristic approach. Within the time frame of 00:00 h to 06:30 h, the load demand is less than 535 kW; the grid supplies power within the first five hours, resulting in high costs. During the hours between 5:00 a.m. and 7:30 a.m., the PV array and the battery supply power, and the grid ceases to supply power. Consequently, the financial implications of renewable energy generation and battery usage are negligible. From 7:30 a.m. to 12:30 p.m., the load increases by more than 535 kW. Consequently, the grid commenced power provision in conjunction with the PV array, coinciding with the battery's lowest SOC. As was previously discussed, the cost remains low because renewable generation costs are negligible. From 12:30 p.m. to 14:30 p.m. the load demand exceeds 535 kW. Therefore, the PV array supplies additional power to the grid and the battery's SOC remains at its minimum value.

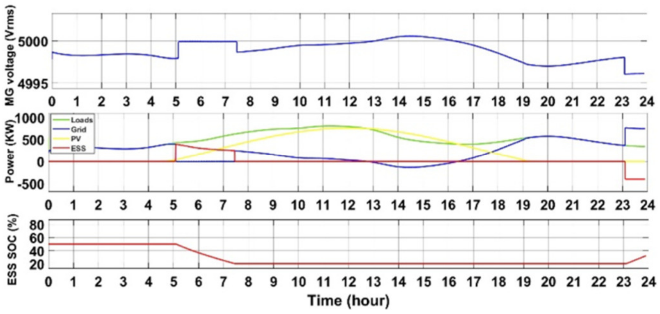

Fig. 4. Simulation results using the first load profile and heuristic approach.

The cost of renewable generation is minimal, which contributes to the overall cost of the project remaining low. From 2:30 p.m. to 4:30 p.m. the load drops below 535 kW. During this period, the PV array supplies power and the battery's SOC remains at its minimum value. The battery only functions in this way: it does not supply power to the grid. Furthermore, the financial cost of renewable energy is minimal, ensuring cost-effectiveness. From 4:30 p.m. to 7:00 p.m. the load remains below 535 kW, while the PV power experiences a decline and the grid power exhibits an increase, with the battery's SOC maintaining a constant level of 20%. Consequently, the cost is increasing. From 7:00 p.m. to 10:00 p.m. the load experiences a surge, reaching 535 kW. During this period, the grid supplies the majority of the energy, while the battery's SOC remains at its minimum level. The solar power generation remains negligible, leading to a substantial increase in costs. From 10:00 p.m. to 12:00 a.m. the load drops below 535 kW. During the initial hour of operation, the grid is the sole source of power, the battery's SOC remains at a constant minimum value, and the solar power is negligible. Subsequent to 11:00 p.m. the grid assumes responsibility for power provision, thereby initiating the charging process of the battery. Consequently, the operating cost is minimal due to the low price during this period. The total cost of the initial load profile, as determined by the heuristic approach, amounts to \$918.89. As presented in Figure 5, the simulation waveforms are plotted for the second load profile and the GA. Conversely, during the initial thirty minutes, the demand for electricity is minimal, resulting in the concurrent supply of power from the battery and the grid. Following this, the grid supplies power, resulting in the battery reaching a state of complete charge. As a result, the cost is minimal due to the low price during this period. From 04:30 h to 07:30 h, the load demand remains low; the grid supply decreases due to an increase in PV generation, and the battery supplies power and undergoes discharge. Consequently, the operating cost is minimized. The load exhibited a gradual increase from 07:30 h to 12:30 h, reaching a maximum of 535 kW. The PV array is the sole source of power, supplying electricity to the grid and generating excess power. In contrast, the battery does not contribute to power supply and its SOC value remains at 25%. The financial burden of renewable energy generation is minimal, ensuring that costs remain low over time. From 12:30 p.m. to 6:30 p.m. the load exceeds 535 kW. Concurrently, the battery is undergoing charging, while the PV power experiences a decline and the grid power undergoes an increase. However, the cost remains low due to the low price during this period and the use of renewable sources. From 6:30 p.m. to 10:00 p.m., the load remains at 535 kW, with both the grid and the battery supplying power, and the PV power being negligible. The elevated cost is attributable to the elevated prices during this period. After 10:00 p.m., the cost is maximized due to the exclusive provision of power by the grid. The total cost of the second load profile using GA amounts to \$616.08.

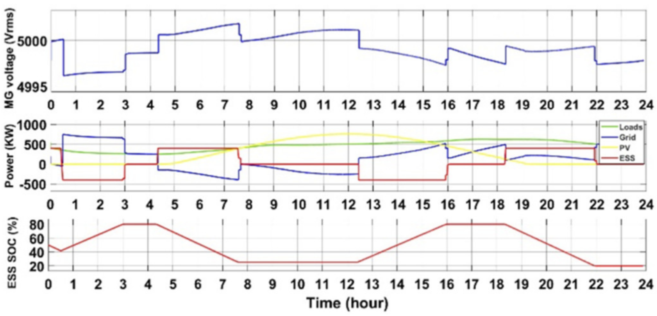

Fig. 5. Simulation results using the second load profile and GA.

In Figure 6, the simulation waveforms demonstrate the usage of the second load profile and the heuristic approach. The period between 00:00 and 05:00 hours exhibit a demand for electricity that remains below 535 kW. During this time, the primary source of energy is the grid, the battery's SOC maintains its initial value, the PV power generation is negligible, and the cost is minimal due to the low cost during this time period. From 5:00 a.m. to 7:40 a.m., the load demand remains below 535 kW, and the PV array and battery supply power are not synchronized with the grid. Thus, the financial implications of renewable energy generation and battery usage are negligible, contributing to the overall cost-effectiveness of the system. From 7:40 a.m. to 2:00 p.m., the load demand is approximately 535 kW, and the PV array functions as the sole power supply, with any surplus energy stored in the battery. Hence, the financial expense associated with the usage of the PV array is minimal. From 2:00 p.m. to 3:00 p.m., the load demand remains at 535kW, with the PV array serving as the exclusive power source. The surplus energy is then fed into the grid, while the cost remains low because of the low price of PV power. From 3:00 p.m. to 4:00 p.m., as the PV array's energy production declines, the grid provides support by meeting the array's energy demands. Concurrently, the battery's SOC remains at its maximum level. The cost is also low because of the low cost of using renewable energy generation and the low price during this period. From 4:00 p.m. to 5:30 p.m., the battery and the PV array supply power, and the excess is fed into the grid. Therefore, the cost is minimal. From 5:30 p.m. to 7:30 p.m., the load is approximately 600 kW. The power supply is derived from the battery, the grid, and the solar system. The cost is elevated due to the elevated price during this period. From 7:30 p.m. to 11:10 p.m., the load decreased to 500 kW. The usage of grid power, in conjunction with the elevated costs observed during this period, results in a substantial total cost. After 23:10 hours, the power required for the load is supplied by the grid power, thereby reaching its maximum cost. The total cost of a clear day when deploying the heuristic approach amounts to $742.70.

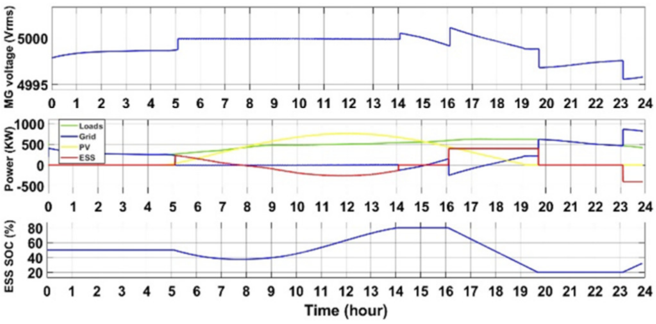

Fig. 6. Simulation results using the second load profile and heuristic approach.

TABLE I. COST COMPARAISON RESULTS

Load profile	Grid cost per day ($)		Cost savings with GA (%)
	G A	Heuristic	
1	756.58	918.89	17.66
2	616.08	742.70	17.04

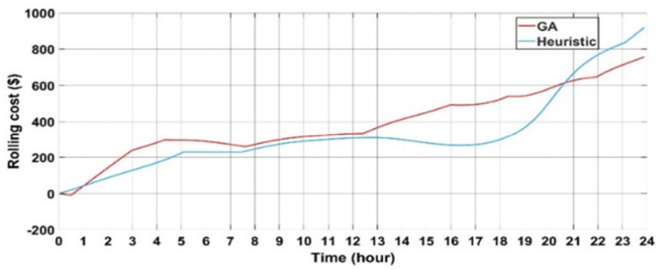

Fig. 7. Rolling cost using the first load profile.

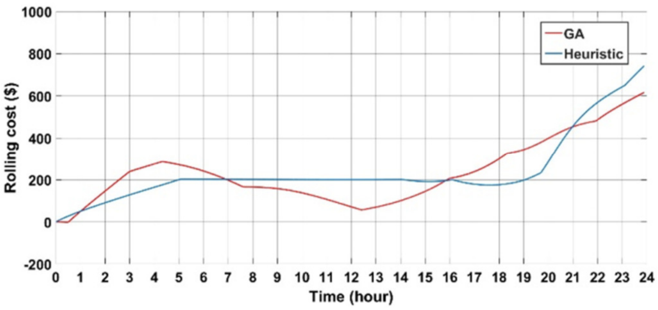

Fig. 8. Rolling cost using the second load profile.

In Table I, Figure 7, and Figure 8, a cost comparison was conducted using two distinct load profiles, while Figure 9 shows the grid energy price. GA usage led to a reduction in the daily cost of the grid by 17.66% and 17.04% for the two load profiles, compared to the heuristic approach.

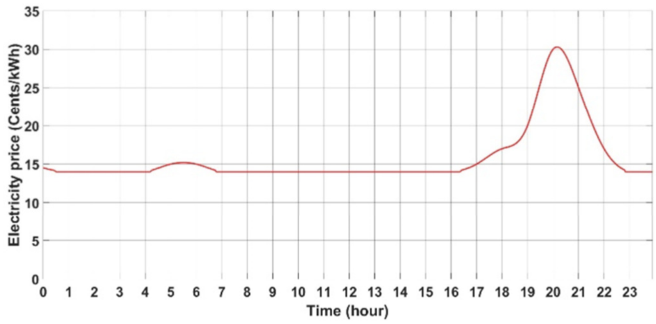

Fig. 9. Grid energy price.

VI. CONCLUSIONS

This study presents an Energy Management System (EMS) for a Microgrid (MG) that employs Genetic Algorithm (GA) to minimize operational expenditures. GA efficacy was demonstrated by a simulation model with two distinct load profiles, which was used to compare the results obtained with those from the heuristic technique. The total cost for the initial load profile for the GA and heuristic method is $756.58 and $918.89, respectively. In contrast, the total cost of the second load profile employing the same methods is $616.08 and $742.70. The numerical findings indicate that GA surpassed the heuristic method, achieving a substantial reduction in operating expenses by 17.66% and 17.04% across two distinct load profiles. GA demonstrated superior system efficiency and reduced operational expenditures in comparison with the heuristic approach. This study will establish the foundation for exploring economical energy management strategies for MGs. GAs have been shown to require substantial computational resources, especially in scenarios involving extensive generations and considerable population sizes. This disadvantage may result in prolonged processing durations, rendering it unsuitable for real-time applications. In the future, there is an objective to develop and evaluate innovative methods for enhancing MG energy management.

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