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RESEARCH ARTICLE

Optimal Energy Management System for Grid-Tied Microgrid: An Improved Adaptive Genetic Algorithm

MUHAMMAD ASGHAR MAJEED[1], SOTDHIPONG PHICHAISAWAT[1], (Member, IEEE), FURQAN ASGHAR[2], AND UMAIR HUSSAN[3]

[1]Department of Electrical Engineering, Faculty of Engineering, Chulalongkorn University, Pathumwan, Bangkok 10330, Thailand
[2]Department of Energy Systems Engineering, Faculty of Agricultural Engineering and Technology, University of Agriculture, Faisalabad (UAF), Faisalabad 38000, Pakistan
[3]College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518000, China

Corresponding author: Sotdhipong Phichaisawat (Sotdhipong.P@chula.ac.th)

ABSTRACT Grid-tied microgrids play a crucial role by connecting renewable energy sources to the main power grid, contributing to sustainability and resilience in a balanced and effective manner. However, the dynamic interplay between the intermittent nature of renewable energy sources and the volatility of load fluctuations presents a multifaceted array of intricate energy management complexities. This study aims to formulate optimization techniques for energy management systems based on renewable energy resources and standalone diesel systems. The proposed system consists of a wind turbine, a photovoltaic system, a standalone diesel generator, and a battery energy storage system, along with flexible and non-flexible loads tied to the local grid. Battery energy storage acts as a primary backup system, while diesel generators act as a standalone secondary backup system. The performance of the proposed optimization technique is validated using Matlab/Simulink, substantiating its performance and robustness, thus affirming its pragmatic suitability for real-world implementation. A comparison has been made with other optimization techniques and found that the proposed technique gives enhanced efficiency, improved resource allocation, load scheduling, and greater adaptability to varying demand and supply dynamics. Moreover, the proposed system exhibits a superior ability to achieve optimal energy utilization and realize noteworthy cost savings in comparison to the alternatives that underwent evaluation.

INDEX TERMS Adaptive genetic algorithm, grid-tied microgrid, bidirectional converter, cost optimization, renewable energy resources, peak average ratio, load scheduling, resource allocation.

I. INTRODUCTION

Over the course of the last few decades, countries have intensified efforts towards sustainability, prioritizing environmental, social, and economic well-being. A portion of the energy supply in various countries is derived from renewable resources such as solar, wind, or hydroelectric sources. However, among these countries, only a small number have taken substantial steps to invest in the development of advanced smart grid infrastructure [1]. Smart grids incorporate digital technologies to enhance efficiency, reliability, and flexibility. Governments' focus on sustainable policies, integration of renewables, promotion of hybrid electric vehicles and plug-in electric vehicles, and fostering energy efficiency have collectively contributed to significant progress. By embracing these strategies, they aim to pave the way towards a greener and more environmentally conscious energy landscape [2]. This paper examines residential energy management systems, delving into smart home energy technology. It outlines components, compares approaches, and addresses challenges like cost, implementation, and privacy [3].

Researchers are currently exploring energy management systems using soft computing techniques and stochastic models. Fuzzy Inference Systems are particularly notable

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for their ease of implementation, efficiency, and accessibility in comparison to conventional models. This work proposes a rule-based energy management system that completely relies on the genetic algorithm. Their findings lead to minimized costs, maximized profits, and reduced system complexity as outcomes [4], [9]. In another scholarly exploration [5], the central theme centers on the integration of intelligent energy management within a microgrid. This strategy involves the utilization of a forecasting-driven, multi-objective optimization methodology embedded within a genetic algorithm framework. It provides an optimal energy management system, which results in enhanced global performance, efficiency, and cost of the proposed system. The authors suggest optimizing generation costs in a renewable energy-integrated power system using a blend of two techniques: an artificial neural network and a hybrid whale optimization algorithm. The main objective is to reduce generation expensed by accounting for the irregularities and fluctuations of renewable energy sources. After implementation, it provides the entire required objective in an optimal way [6]. This research presents a multi-objective method for assessing battery thermal management while also accounting for its state of health. The approach combines the effects of dynamic programming and the genetic algorithm to minimize the cost, reliability, and efficiency of the system [7]. This study employed a genetic algorithm for battery health management, optimizing battery utilization to extend its lifespan. The genetic algorithm facilitates battery load scheduling and ensures stability through thermal management [8].

A multi-island-based genetic algorithm is deployed for electric vehicles for energy management systems. It is cost effective due to its long drive range and low fuel consumption. It also provides a reduction in carbon emissions that could be caused by the use of conventional vehicles, i.e., ICE-based engines [9]. The work discussed in this research includes an energy management system for fuel cell-based hybrid electric vehicles for start-stop conditions. It deploys a hybrid effect of genetic and neural network algorithms. It regulates the power between resources during the start-stop duration. Application of the hybrid algorithm results in parameter optimization of the neural network, which increases fuel efficiency while reducing carbon emissions [10]. The research proposes an optimization approach for intelligent energy management in microgrids using a genetic algorithm [20], [21], [22]. It creates an adaptive energy management system for microgrids, capable of varying energy demands over time. It results in a microgrid that is more adaptive to energy demands and sustainability goals [11]. This study aims to enhance the scheduling of hybrid microgrids (MGs). The deployment of these techniques results in an optimal management system that addresses the uncertainty and reduces the energy costs arising from hybrid microgrids [12], [14], [24]. This study models renewable energy resources as probability density functions (PDFs) and market prices as random functions. When these are obtained, their error results in a standard deviation. It results in normal distribution and an optimal energy management system [13], [15], [16], [17], [18].

A novel technique uses forecasted load and PV profiles to establish dynamic demand and feed-in limits. It uses rule-based scheduling and PSO optimization to charge and discharge batteries, which lowers the average peak grid power across a range of loads and PV patterns, as shown in MATLAB [29]. Introducing the enhanced velocity differential evolutionary particle swarm optimization algorithm, which updates velocity using enhanced velocity and position using the deceleration factor, for effective energy problem solving [30].

A model integrates blockchain and microgrids to address energy underutilization in a gaming competition. The proposed optimized particle swarm algorithm exhibits strong search capability and high convergence accuracy [31]. With the growing complexity of microgrid energy sources, a study presents an operator-oriented dispatch scheduling solution aiming to minimize microgrid costs and carbon emissions [32]. A method is presented for optimal placement and sizing of battery energy storage systems (BESS) in distribution systems, addressing the duck curve phenomenon. The Whale optimization algorithm (WOA) demonstrates effective exploration and exploitation, validated against particle swarm optimization and the firefly algorithm [33].

This work adopts an adaptive differential evolution (ADE) algorithm to optimize virtual resistances in droop control of grid-connected converters. The goal is to regulate power flow effectively [34]. A model focuses on achieving the lowest daily electricity cost while considering the return of unused energy to the distribution company. It is validated using various usage patterns and climate forecasting methods [35]. Proposing a machine learning-based feature selection approach, this study enhances short-term electricity demand forecasting accuracy in distributed energy systems [37].

The main objective of the proposed work is to provide an energy management system that is completely based on an adaptive genetic algorithm for microgrids. The contribution of this research works are

- Utilize the adaptive genetic algorithm to optimize the scheduling and allocation of energy from different sources, including renewables and storage systems
- Optimization of microgrid energy usage, prioritizing renewables, exporting surplus, and importing from the grid when needed, leading to cost reduction
- Efficiently manage renewable energy resources by exporting surplus energy to the grid after meeting load requirements and seamlessly importing energy from the grid to compensate for any deficit in renewable energy
- Minimize overall energy costs for the microgrid through efficient energy allocation and utilization

The block diagram for the proposed system can be seen in Fig 1.

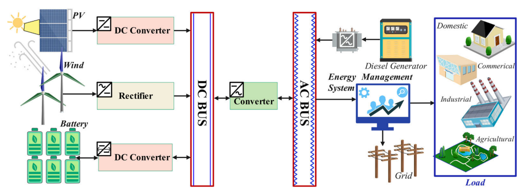

FIGURE 1. The energy management system of a microgrid.

A microgrid is designed based on real-time data for commercial buildings on all the above-mentioned resources. Renewable resources on site are a hybrid PV system, a wind turbine, and a diesel generator as a backup supply system. The ratings of the resources can be seen in Table 1.

TABLE 1. The parameters of various components in a microgrid.

Symbol	Quantity	Values
P_{PV}	Photovoltaic Power	1,000 kW
P_{WF}	Wind Farm Power	500 kW
P_{BESS}	Battery Storage System	500 kWh
P_{DG}	Diesel Generator Power	1,000 kW
V_{DC}	DC Bus Bar Voltage	1,000 V
V_{AC}	AC Bus Bar Voltage	400 V
I_{DL}	Domestic Load	100 V
I_{CL}	Commercial Load	400 V

The structure of the paper is organized as follows: modeling of renewable energy resources and backup supply system has been performed in Section II. Mathematical modeling of proposed system with constraints parameter are describe in Section III. Working principle of adaptive genetic algorithm is expressed in Section IV. The simulation results and findings are presented in Section V. Concluding remarks has been established in Section VI.

II. MODELING OF RENEWABLE ENERGY RESOURCES

A. WIND FARM

The mathematical equation that represents the power output of a wind turbine is based on the principles of the aerodynamics of the rotor and the energy in the wind [25], [26]. The power output can be calculated using the following equation:

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot C_P(R, \theta, N) \cdot V^3 \tag{1}$$

where P is the power output of the wind turbine (kW), ρ is the air density (kg/m^3) at the site, A is the swept area of the rotor (m^2), C_P is the power coefficient, V is the wind speed (m/s) at the site, R is rotor radius (m), θ is the tip speed ratio and N is rotor speed (rad/s). These parameters vary depending on the geographic location of the wind turbine. Parameter values are shown in Table 2.

The main objectives of the wind turbine modeling are as follows:

TABLE 2. The wind farm parameters.

Symbol	Quantity	Values
P_{WF}	Wind Farm Power	500 kW
ρ	Air Density	1.25 kg/m^3
C_P	Power Coefficient	0.3
V	Wind Speed	2.5 m/s

- Maximize power output by finding optimal design parameters (rotor radius, blade twist angle, and number of blades);
- Efficiently explore large solution spaces for global optima;
- Handle non-linear and multi-modal fitness landscapes effectively;
- Robust and adaptable to handle noisy fitness evaluations and avoid local optima;
- Explore a wide range of design parameter combinations to identify high-power configurations;
- Incorporate additional constraints (e.g., materials, cost, and safety;
- Flexible for various problem types and constraints;
- Enable parallelization for faster computation;
- Find the best wind turbine design considering constraints and operating conditions.

These equations represent the essential components of a adaptive genetic algorithm optimization for wind turbine design parameters. The GA uses selection, crossover, and mutation to evolve a population of individuals and find the best combination of R,, and N that maximizes the power output of the wind turbine. Wind turbine is used with controller to harness energy from variable wind as shown in Fig 2 below:

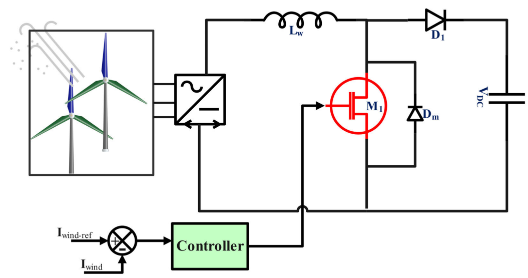

FIGURE 2. The wind farm along with its control mechanism.

B. PHOTOVOLTAIC SYSTEM

The mathematical modeling of a photovoltaic (PV) system involves the equations that describe the behavior of the PV panels and the conversion of solar irradiance into electrical power. In the context of using an adaptive genetic algorithm for optimization, we focus on the equations that calculate the PV system's output power and the fitness function to be used in the genetic algorithm [27]. The PV system is designed based on a Canadian solar panel of mono-perc half-cut 330 W, while the inverter is the ABB UNO Trio Series of 50 kTL. The equivalent circuit of a photovoltaic system has been illustrated in in Fig 3. PV panels can be calculated as follows:

$$P_{\mathrm{PV}} = V_{\mathrm{PV}} \cdot I_{\mathrm{PV}} \tag{2}$$

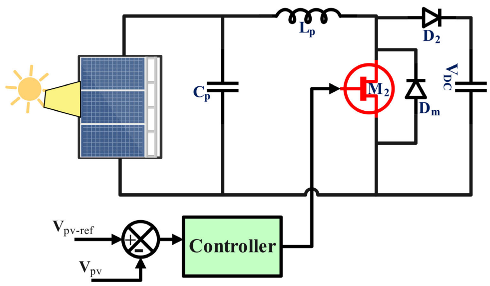

FIGURE 3. The photovoltaic system and control mechanism.

I-V curve can be found by using the below equation.

$$I_{\mathrm{PV}} = I_{\mathrm{L}} - I_0 \cdot (e^{\frac{qV_{\mathrm{PV}}}{kT}} - 1) \tag{3}$$

where I_L is the light-generated current (A), I_0 is the diode saturation current (A), q is the elementary charge (C), k is Boltzmann's constant, and T denotes the temperature of the PV panel (K). A Canadian mono-perc half-cut perc PV panel has been used in the proposed model, whose parameters are shown in Table 3.

TABLE 3. The photovoltaic system parameters.

Symbol	Quantity	Values
P_{max}	Maximum Power	1,000 kW
V_{max}	Maximum Voltage	1,000 V
I_{max}	Maximum Current	20 A
I_{sc}	Short Circuit Current	9.45 A
T_O	Operating Temperature	25°C–45°C

The main objectives of the said system are as follows:

- Maximize Energy Output and Efficiency;
- Optimize Performance under Real-World Conditions;
- Balance PV System Parameters;
- Consider Constraints.

C. BATTERY ENERGY STORAGE SYSTEM

The battery energy storage system serves as the primary energy source for the microgrid. When the stored energy is able to handle the load adequately, it becomes active. In cases where the load exceeds the capacity of the storage system, a secondary backup supply system is activated to meet the additional demand [17]. The system is shown in Fig. 4 below:

The equation for the battery energy storage system in a microgrid can be represented as follows:

$$E_{\min}(t) \leq E_{\mathrm{bat}}(t) \leq E_{\max}(t) \tag{4}$$

$$E_s(t + \Delta t) = E_s(t) + \Delta t \times (E_i - E_o) \tag{5}$$

$$\mathrm{SoC}_{\min}(t) \leq \mathrm{SoC}_{\mathrm{bat}}(t) \leq \mathrm{SoC}_{\max}(t) \tag{6}$$

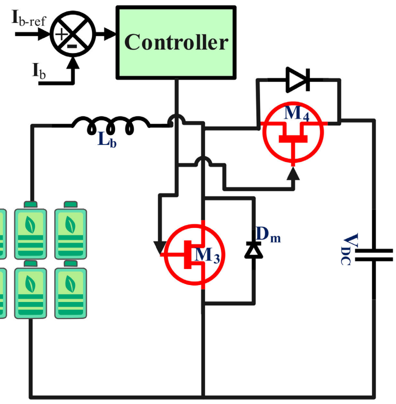

FIGURE 4. The battery energy storage system.

where E_s represents the energy stored in the battery, Δt is the time interval, E_i is the energy input to the battery, and E_o is the energy output from the battery. The system utilized the battery banks with the microgrid, and its parameters for SoC are shown below in Table 4.

TABLE 4. The battery energy storage system parameters.

Symbol	Quantity	Values
η_{Charge}	Charging Efficiency	85
$\eta_{Discharge}$	Discharging Efficiency	15
K_{Charge}	Maximum Charge Ratio	0.15
$K_{Discharge}$	Maximum Discharge Ratio	0.15
τ	Self-Discharge Decay	0.001

This equation represents the energy balance of the battery storage system, taking into account the energy stored at the current time, the energy inputs, and the energy outputs to calculate the energy stored at the next time step ($t + \Delta t$). It enables the modeling of the battery's behavior and the optimization of its operation within the microgrid [14], [28].

D. DIESEL GENERATOR

Diesel generators have been employed as a secondary source. It's a standalone system for meeting the load requirements of the system when renewable energy generation is low and the grid is not available, as shown in Fig. 5.

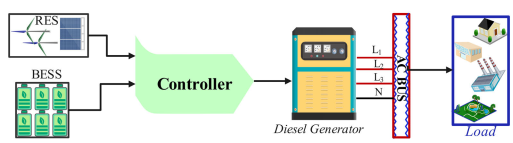

FIGURE 5. The diesel generator with a load scheduling controller.

The main objectives of this system are as shown below:

- Ensure a reliable backup power source during grid outages or insufficient renewable energy generation;
- Provide stable energy supply to critical loads for uninterrupted operation;

- Support load balancing during peak demand or fluctuating renewable generation;
- Minimize fuel consumption and operating costs while meeting microgrid energy needs;
- Minimize emissions and the environmental impact of diesel generator operation.

The mathematical equations of the system are shown below with generator power, fuel consumption, and its cost being evaluated respectively by:

$$P_{\text{gen}}(t) = \sum_{t=1}^{k} \eta_{\text{gen}}(t) \times F_{\text{gen}} \tag{7}$$

$$F_{\text{gen}}(t) = \text{SFC}_{\text{gen}}(t) \times P_{\text{gen}} \tag{8}$$

$$\text{Cost}_{\text{gen}} = C_{\text{Fuel}} \times F_{\text{gen}}(t) \tag{9}$$

where P_{gen} represents the generator output power (kW), η_{gen} is the generator efficiency (%), F_{gen} is the fuel consumption rate (l/h), SFC_{gen} is the specific fuel consumption rate (l/kWh), C_{Fuel} is the cost of fuel ($/liter), and Cost_{gen} denotes the cost of operation ($).

These equations and objectives help optimize the diesel generator's operation as a backup supply for the microgrid, considering energy reliability, cost efficiency, and environmental considerations [36].

III. MATHEMATICAL MODELING OF ADAPTIVE GENETIC ALGORITHM

The main objective in the development of an electrical system harnessing microgrid (MG) sources revolves around the precise determination of output power. This determination must effectively meet the load demand in an economically efficient manner, while minimizing emissions. Consequently, the selection and configuration of system components become subject to careful scrutiny and consideration:

- To minimize the operating cost;
- To maximize the renewable utilization;
- To minimize the battery degradation;
- To provide peak shaving and load following of the grid.

The specific choice of the objective function depends on the microgrid's characteristics, the energy sources available, the cost structure, environmental considerations, and the overall goals of the microgrid operator. The EMS aims to find the optimal control strategy that aligns with these objectives.

A. OBJECTIVE FUNCTION

1) MINIMIZING THE OPERATING COST

The operating cost of a microgrid, a key economic indicator, comprises fuel, operation and maintenance, dispatch, and other expenses. It could be shown by the equation below:

$$Z(t) = \min \sum_{t=1}^{k} (\alpha \times C_O(t) + \beta \times E_g(t)) \cdot \Delta t \tag{10}$$

where Z represents the objective function, α and β are weighted coefficients, C_O is the total cost, E_g is gas emission, and Δt is the time interval of operation.

2) MINIMIZING THE CARBON EMISSION

With the implementation of this strategy, the sustainable development goal could be achieved. PV, wind, and battery energy storage systems do not exhibit carbon emissions or other toxic emissions that pollute the environment. The degree of pollution will only be due to diesel generators and grid voltage absorption. It could be modeled using the following formula:

$$\begin{aligned} \min PD = \sum_{t=1}^{k} \Big(& \omega_{CO2} E_{CO2}(t) + \omega_{SO2} E_{SO2}(t) \\ & + \omega_{NOx} E_{NOx}(t) + \omega_{grid} P_{absorbing}(t) \Big) \end{aligned} \tag{11}$$

The equation represents the degree of pollution (PD) calculation. Here, ω denotes the weighted average of respective gases ($CO2$, $SO2$, NOx, and $grid$), and E signifies the equivalent discharge of relevant gases emitted from a diesel generator and the grid.

B. PARAMETRIC CONSTRAINTS

1) POWER BALANCE

The power balance constraints can be calculated by the following equation:

$$P_{\text{RER}} = \sum_{t=1}^{k} (P_{\text{wind}}(t) + P_{\text{pv}}(t)), \tag{12}$$

where $k = 100$.

$$\begin{aligned} P_{\text{load}}(t) = \sum_{t=1}^{k} \Big(& P_{\text{RER}}(t) + P_{\text{DG}}(t) + P_{\text{BESS}}(t) \\ & + P_{\text{Import}}(t) - P_{\text{Export}}(t) \Big) \end{aligned} \tag{13}$$

2) OUTPUT POWER

The output power constraints of microgrid can be evaluated by:

$$\sum_{t=1}^{k} P_{\min}(t) \leq \sum_{t=1}^{k} P_{\text{O}}(t) \leq \sum_{t=1}^{k} P_{\max}(t) \tag{14}$$

3) BATTERY SOC

The charging and discharging constraints of battery energy storage system can be evaluated by:

$$P_{\text{BESS}}(t) = \begin{cases} P_{\text{RER}}(t) \geq P_{\text{load}}(t), P_{\text{DG}}(t) = 0, \\ \quad P_{\text{Import}}(t) \geq 0, P_{\text{Export}}(t) \geq 0, P_{\text{BESS}}(t) \geq 0 \\ P_{\text{RER}}(t) \leq P_{\text{load}}(t), P_{\text{DG}}(t) = 0, \\ \quad P_{\text{Import}}(t) \geq 0, P_{\text{Export}}(t) = 0, P_{\text{BESS}}(t) \leq 0 \\ P_{\text{RER}}(t) = 0, P_{\text{DG}}(t) \geq 0, \\ \quad P_{\text{Import}}(t) = 0, P_{\text{Export}}(t) = 0, P_{\text{BESS}}(t) \geq 0 \\ P_{\text{RER}}(t) = 0, P_{\text{DG}}(t) = 0, \\ \quad P_{\text{Import}}(t) = 0, P_{\text{Export}}(t) = 0, P_{\text{BESS}}(t) \leq 0 \end{cases} \tag{15}$$

while

$$E(t) = \min\left(E(t_0) + \int_{t_0}^{t} \eta_{\text{charge}} \cdot P_{\text{charge}}\, d\tau,\ E_{\max}\right) \quad (16)$$

$$E(t) = \max\left((t_0) - \sum_{t=1}^{N} \frac{P_{\text{discharge}} \cdot \Delta t}{\eta_{\text{discharge}}},\ E_{\min}\right) \quad (17)$$

where $E(t)$ represents the state of charge at time t, $E(t_0)$ represents the state of charge at time t_0, P_{charge} denotes the charging power, $P_{\text{discharge}}$ denotes the discharge power, η_{charge} represents the charging efficiency, and $\eta_{\text{discharge}}$ denotes the discharging efficiency of the battery.

4) OPERATING COST

The operating cost of the microgrid can be represented as:

$$C_{\text{OC}}(t) = \sum_{i=1}^{k} \left(C_f(t) + C_m(t) + C_g(t) + C_o(t)\right) \quad (18)$$

where generator fuel cost is

$$\sum_{t=1}^{k} C_f(t) = \sum_{t=1}^{k} \left(F_c + P_{\text{DG}} + \frac{1}{\eta_{\text{DG}}(D)}\right) \quad (19)$$

where C_f is the cost of fuel per unit, P_{DG} is the power output of the generator, η_{DG} is the efficiency of the generator, and D are the total duty hours of the generator.

This research employs an adaptive genetic algorithm (GA) to illustrate how load scheduling can influence a microgrid. An adaptive genetic algorithm (GA) presents a powerful approach for optimizing the intricate task of managing diverse energy sources within a system. In this method, solutions take the form of chromosomes, encapsulating control parameters governing wind generation, photovoltaic systems, diesel generators, and battery energy storage systems. The initial population comprises a range of potential strategies, each embodying a unique combination of these energy sources and their respective control settings. The fitness function then steps-in to evaluate each solution's effectiveness. This assessment considers factors such as the utilization of wind generation and photovoltaic systems to harness renewable energy, the judicious activation of diesel generators to cover demand peaks, and the optimal deployment of battery energy storage systems to enhance grid stability, as shown in Fig. 6.

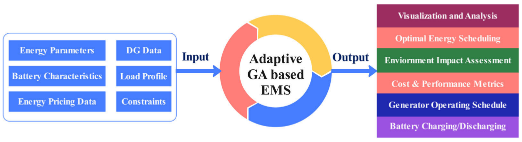

FIGURE 6. The adaptive genetic algorithm-based energy management system.

Through a process reminiscent of natural selection, solutions demonstrating superior energy efficiency, load balancing, and effective utilization of all resources are chosen for replication. Crossover enters the scene, mixing genetic material from two parent solutions to produce innovative combinations. This infusion of diversity mirrors the integration of wind, photovoltaic, diesel, and battery elements in novel ways. All parameters are based on a Canadian poly solar panel of 330 W, while the inverter is the ABB UNO Trio Series of 50 kTL. Mutation complements the process by occasionally introducing subtle modifications to these offspring, thereby encouraging exploration of previously unconsidered strategies. As generations progress, the GA steadily advances toward refined solutions. This evolutionary trajectory aligns with the dynamic process of adapting to changing energy demands and resource availability. However, the GA's efficacy pivots on meticulous design. The method of representing solutions, the formulation of the fitness function, and the fine-tuning of crossover and mutation operators all necessitate thoughtful configuration tailored to the intricate interactions between wind generation, photovoltaic systems, diesel generators, and battery energy storage systems. Ultimately, the iterative refinement orchestrated by the GA converges towards energy management strategies that holistically optimize the use of these resources. By synergizing wind and photovoltaic generation, judiciously integrating diesel generators, and strategically utilizing battery energy storage systems, the algorithm strives to achieve an equilibrium that maximizes energy efficiency while mitigating the complexities of demand fluctuations and renewable resource intermittency. The flow chart of the proposed adaptive genetic algorithm is shown below in Fig. 7.

Table 5 presents the pseudocode outlining the AGA implementation, wherein real-time data is gathered from the microgrid. Parameters are configured to align with specifications and limitations. The AGA commences its operations as depicted below.

To control convergence speed, adjust algorithm parameters like population size, mutation rate, crossover rate, and selection methods. Use adaptive strategies for dynamic parameter changes to balance exploration and exploitation. Simplify implementation for efficiency by addressing resource needs and optimizing data structures. Evaluate algorithm performance against alternatives, considering real-time constraints in microgrid energy management decisions.

IV. SIMULATION AND RESULTS

When adaptive genetic algorithm is applied to the proposed system with prescribed the parameters, optimized results have been obtained after a number of iterations over a 24-hour time slot. The proposed algorithm gives the most appropriate results with efficient energy use according to the load profile. Primary resources of generation, i.e., renewable energy resources, are utilized on a production basis, while the deficient energy demand is met by secondary resources, i.e., diesel generators. The results are shown below with their optimal values. The real-time data has been collected for

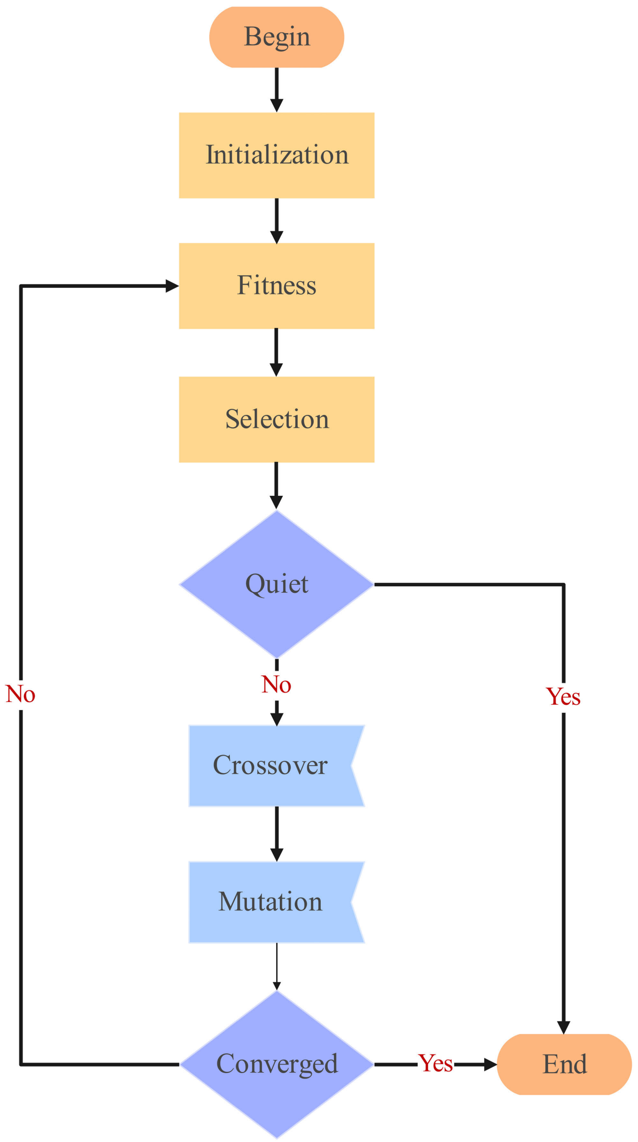

FIGURE 7. The flow chart of the adaptive genetic algorithm.

TABLE 5. The adaptive genetic algorithm pseudocode.

Data
Wind Generation, PV Generation, Load Profile, Electricity Pricing
Parameters
N_{pop}, $I_{\max}$, N_{c}, μ_{m}
Initialization
Create an initial population of size N_{pop} with random individuals.
Evaluate the fitness of each individual in the population.
Repeat for generation $= 1$ to $I_{\max}$
  Perform the following:
    Selection
    Crossover
    Mutation
    Replacement
    Evaluation
    If update $Z(t)$ criteria are met **then**
      Update the objective function
    Else
      Break out of the loop
    End If
End

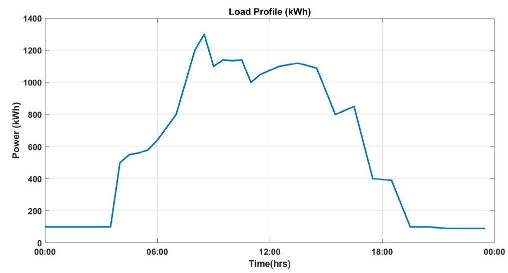

FIGURE 8. The real-time load profile of a commercial building.

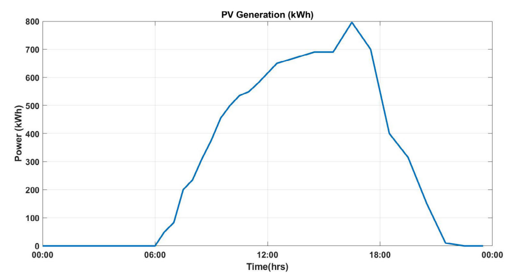

FIGURE 9. The real-time PV generation of a commercial building.

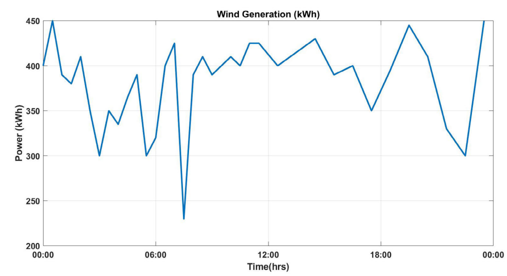

FIGURE 10. The real-time wind generation of a commercial building.

commercial buildings in a 24-hour time slot starting from dawn to dusk, as shown below in Fig. 8.

The commercial building is composed of a roof-mounted photovoltaic system of 1 MW. The tilt angle for the PV panel is 15Â°. Peak hours of generation start at 6:00 a.m. to 6:00 p.m. In this grid-tied configuration, surplus energy is exported to the grid, and when production is below the specific value, energy is imported from the grid to meet the abrupt load demand. The PV generation profile can be seen in Fig. 9.

The building is connected to the 500 kW wind farm located at a distant location. Due to variable wind, the generation is different for a 24-hour time slot. Real-time data has been plotted, and the optimization technique has been implemented to find the best use of the generation. A real-time plot is shown below in Fig. 10.

An adaptive genetic algorithm is utilized for optimal resource allocation so that the best-suited energy demand can be harnessed while the rest of the energy can be stored in a battery storage system. If energy is greater than the capacity of BESS, then the system will allow electric vehicles to plug in to restrain their batteries. Microgrid resource capacities and their contribution to the load meeting are shown in Fig. 11 and their optimal usage is shown in Fig. 12.

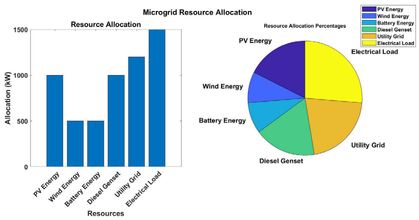

FIGURE 11. The microgrid resource capacities.

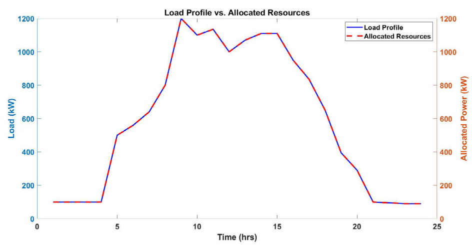

FIGURE 12. The optimal resource allocation using an adaptive genetic algorithm.

Voltage regulation for microgrids is of great concern. Due to the availability of different renewable resources in microgrids, a platform is chosen to harness energy from resources and gather it in a single form. A bus bar is utilized to serve the said purpose.The complete power stage shows the DC and AC bus bar voltages. The controller has to track 1000 Vdc for DC and 400 Vac for AC bus bars. The overshoots shown in voltage regulations are due to load demand spikes and return to reference tracking after a short duration, as shown in Fig. 13.

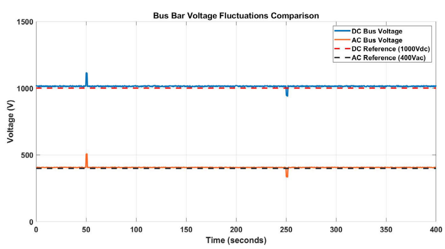

FIGURE 13. The voltage regulation of the bus bar.

The building has a standalone diesel generator of 1 MW and a battery energy storage system of 500 kWh to meet the load demand in case of grid or power failure. The backup system will power up the utility when energy generation from renewable resources is below the threshold and there is a blackout from the grid side.The backup system is shown below in Fig. 14.

The proposed system is a grid-tied microgrid. Power is imported from the grid when renewable production is below the load profile.This will cost depending on the energy slab price of distribution companies. The export mechanism becomes active when renewable generation is above the threshold for efficient utilization of energy. Billing depends on the net difference between the import and export of energy from the grid. The grid status is shown below in Fig. 15.

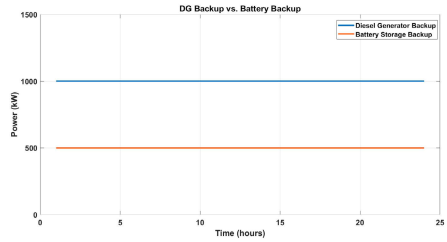

FIGURE 14. The DG and battery backup system.

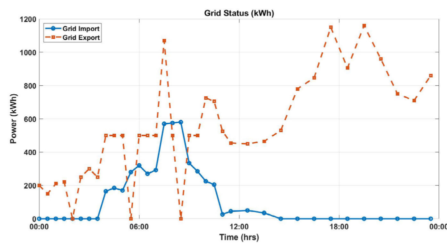

FIGURE 15. The energy is imported and exported from the grid.

An adaptive genetic algorithm finds the best fit of energy management to reduce the cost in cents per kWh, as shown in Fig. 16. This algorithm prioritizes the consumption of renewable energy generation to increase savings in cents per kWh, as shown in Fig. 17. Additionally, when excess energy is exported, it can be utilized to charge electric vehicles on the road, thereby reducing the carbon footprint, as depicted in Fig. 18.

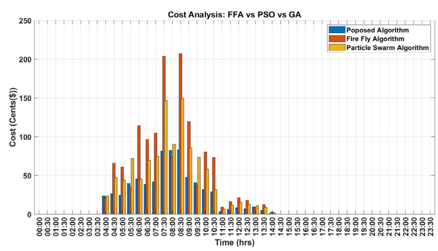

FIGURE 16. The energy cost per kWh.

V. COMPARATIVE STUDIES

Different optimization techniques have been applied to grid-tied microgrids. It has been observed that the choice of optimization technique depends on the specific application. Among the applied techniques, the firefly algorithm yielded the least favorable energy management result for the proposed application. Following optimization, the average cost was found to be 670.778 cents per kWh. On the

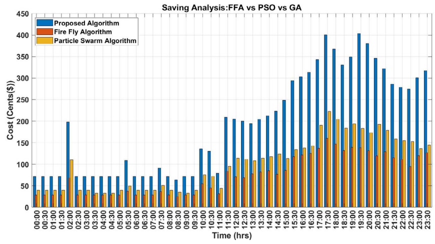

FIGURE 17. The energy savings per kWh.

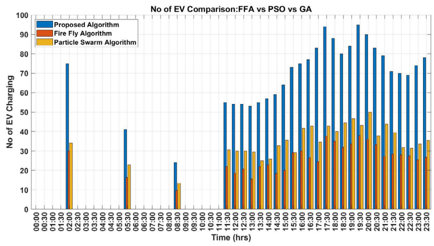

FIGURE 18. The number of EVs in charging mode during zero export.

other hand, the particle swarm optimization algorithm achieved significantly better results compared to the firefly algorithm, with a cost of 88.63513002 cents per kWh. The proposed algorithm demonstrated superior performance, making it the most suitable choice for the energy management system of the grid-tied microgrid. The cost achieved by the proposed algorithm was 52.5352239 cents per kWh. Various iterative results are presented in Fig. 19.

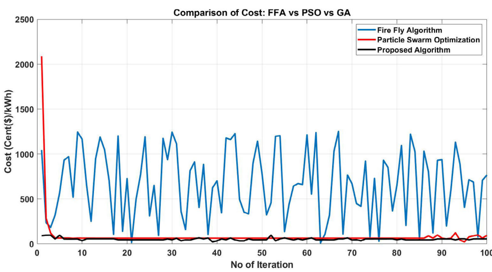

FIGURE 19. The comparison of costs using different techniques.

A comparative analysis of the proposed technique with PSO and FFA has been performed to determine the numerical difference in costs between the algorithms. The average values of the iterative results are shown below in Table 6.

TABLE 6. The average cost of energy for different techniques.

No. of Iteration	FFA (cents)	PSO(cents)	AGA (cents)
100	670.77863	88.63513002	52.5352239

It has been observed that the proposed algorithm provides the best resource allocation. Optimal resource utilization results in cost reductions for the system during on-peak and off-peak hours. A bar graph is generated to showcase the effectiveness of the proposed system, as shown below in Fig. 20.

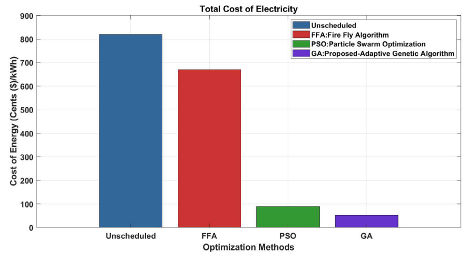

FIGURE 20. The comparison of the cost of electricity under load scheduling.

VI. CONCLUSION

A robust and reliable optimization-based energy management system has been presented in this research work. The design aims to effectively distribute energy resources, optimizing consumption, cost, and system stability across diverse applications via an adaptive genetic algorithm. Moreover, the adaptive genetic algorithm chooses individuals from a population according to their fitness, applies genetic operators to generate new individuals, and subsequently assesses their fitness. Through successive iterations, the algorithm progressively hones the population, gradually converging towards solutions that more effectively fulfill the optimization objectives. Furthermore, the proposed approach furnishes utility companies with an energy management instrument for the optimal exploitation of installed renewable energy sources and storage systems, effectively catering to the adaptable demands of residential, commercial, and industrial loads.A comparative analysis has been conducted among the proposed algorithm, particle swarm optimization, and the firefly algorithm. The findings indicate that the firefly algorithm yields a cost of 670.77863 cents per kWh, particle swarm optimization provides 88.63513002 cents per kWh, and the proposed technique delivers 52.5352239 cents per kWh. The overall results and their comparison with in-use techniques prove that the proposed system has fulfilled the desired objectives for the efficient operation of the hybrid microgrid system. Future research directions include multi-objective optimization, scalability, machine learning integration, cybersecurity, and regulatory compliance for real-time microgrid applications.

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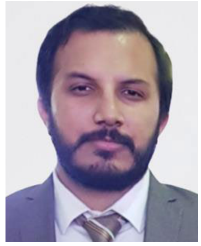
MUHAMMAD ASGHAR MAJEED received the B.S. degree in electrical engineering from The University of Faisalabad, Pakistan, in 2012, and the M.S. degree in electrical engineering from FAST-NUCES, in 2018. He is currently pursuing the Ph.D. degree in electrical engineering with Chulalongkorn University, Thailand. His research interests include notably microgrid optimization systems, inverter control, and hybrid energy storage systems (HESS) for hybrid electric vehicles. His dedication to advancing these domains underscores the commitment to innovation and sustainable energy solutions.

SOTDHIPONG PHICHAISAWAT (Member, IEEE) received the B.Eng. and M.Eng. degrees from Chulalongkorn University, Thailand, in 1995 and 1997, respectively, and the Ph.D. degree from Brunel University London, in 2002. He is currently a Lecturer with Chulalongkorn University, Thailand. His research interests include power system planning, smart grids, renewable energy, and energy storage.



FURQAN ASGHAR received the B.S. degree in electrical engineering from The University of Faisalabad, Pakistan, and the integrated M.S. and Ph.D. degree in electrical, electronics and control engineering from Kunsan National University, South Korea, in 2018. From 2014 to 2018, he was a Research Assistant with the Factory Automation and Intelligent Control Laboratory (FAIC), South Korea. Since July 2018, he has been an Assistant Professor with the Department of Energy Systems Engineering, University of Agriculture, Faisalabad (UAF). He has played a vital role in various renewable energy-based development projects as a co-convener, a focal person, and a technical member, including green energy solutions (125-kW solar system), integrated energy system (100-kW solar–100-kW biogas), retrofitting of energy inefficient appliances with UAF, funded by World Bank, installation of 1.5-MW solar photovoltaic system. His research interests include hybrid microgrids, fault detection and diagnosis, AI and ML-based control systems, renewable energy, power quality, and precision agriculture.

UMAIR HUSSAN received the bachelor's degree in electronics from Hajvery University, Pakistan, in 2015, and the master's degree in electrical engineering from The University of Faisalabad, Pakistan, in 2019. He is currently pursuing the Ph.D. degree in mechatronics and control engineering with Shenzhen University, China. He was a Senior Laboratory Technologist, from 2015 to 2020, and a Lecturer, from 2020 to 2023, with The University of Faisalabad. His research interests include converters, power system optimal operation and control, distributed optimization methods, integrated energy systems, and electricity markets.