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RESEARCH ARTICLE

Optimization of Operating Cost and Energy Consumption in a Smart Grid

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ABSTRACT This paper introduces an optimal bi-objective optimization methodology customized for micro-grid systems, encompassing economic, technological, and environmental considerations. The framework portrays the objectives of an intelligent microgrid, aiming to minimize operational costs, CO2 emissions, peak-to-average ratio (PAR), and energy consumption while concurrently enhancing user comfort (UC). A scheduled power allocation strategy is formulated to efficiently cater to the energy needs of residential loads. The stochastic nature of wind and solar resources is characterized by modeling wind speed and solar radiation intensity using a beta probability density function (PDF). The non-dominated sorting genetic algorithm II (NSGA-II) is employed to address optimization challenges. A decision-making process is implemented to select the optimal solution from the non-dominated alternatives. The study presents three scenarios illustrating the optimal operational values for various parameters and energy consumption, providing a comprehensive analysis of the proposed algorithm's efficacy. Leveraging the NSGA-II algorithm, coupled with renewable energy resources and optimal energy storage system scheduling, yielded significant reductions in overall expenses, PAR, CO2 emissions, user discomfort, and energy consumption. MATLAB simulations were conducted to substantiate the efficacy of our proposed approach. The obtained results underscore the effectiveness and productivity of our devised NSGA-II-based approach. Notably, the proposed algorithm demonstrated a substantial reduction in electricity costs by 19.0%, peak-to-average ratio (PAR) by 30.7%, and carbon emissions by 21.7% in scenario-3, as evidenced by a comparative analysis with the unscheduled case.

INDEX TERMS Smart grid energy, storage system, operating cost, carbon emission, heuristic, optimization.

I. INTRODUCTION

In today's world, Energy is one of the primary and significant problems the world needs to overcome. Energy problems include generation, transmission, and receiving problems, but the most important is excess and maintaining electricity production and distribution demand. Research shows that 15% of the people around the globe have no electricity usage due to no access or are away from the grid stations and live in off-grid areas. The only solution for the off-grid community to provide electricity is installing renewable systems in those areas [1]. Environmental activists encourage people and authorities to install renewable systems like PV, Wind, and Biomass. According to estimated research, in 2035, renewable energy will be counted as one-third of the total energy in the world. To achieve long-term expectations from the system, it is necessary to carefully isolate and predict the solar system of the region where it is installed and keep the door open to expand the system further when the demand increases [2]. The engineer also plays a vital role in making these systems more efficient by improving the power demand and quality and maintaining the system grid stability for unpredictable solar irradiation and sudden climate weather conditions [3]. Renewables become more stable when a

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backup system is installed, which works when sudden climate change occurs and at nighttime when no solar power is available [4]. The use of ESSs also increased pollution emissions. The idea of a smart grid was introduced due to renewable energy and storage issues. An intelligent system in the shape of a smart grid was developed, which provided energy to loads by performing a bi-way communication between them through an advanced measuring infrastructure (AMI) [5]. Different renewable sources, i.e., PV, WT, Fuel cells, and Non-renewable sources, i.e., Diesel generators, MT, etc., are used by smart grids to provide electrical energy to different types of load [6]. The energy requirement of the consumers is made possible by the energy exchange between the utility and smart grid due to uncertainties in renewable sources [7]. Obtaining the energy with minimum operating cost cannot only be solved by modeling the source side. Different DSM strategies can be used to deal with it. A vast amount of contribution has been made to energy management in smart grids by optimizing its source side as well as consumption side research. For the reduction of operating costs and pollution emissions, the MOPSO algorithm is used, whose optimal solution uses fuzzy-based logic [8]; however, they have not considered peak average ratio (PAR) to reduce peaks in the system. Modeling uncertainty in renewable energy sources and reducing cost and emission in [9] by MOPSO algorithm. Reference [10] introduced an efficient energy management system that successfully reduced the cost of storage systems under DSM strategy by using Branch and Reduce Optimization Navigator (BARON); however, carbon emission due to EES was ignored. Demand was managed by real-time pricing aided by an inclined block rate. Also, power scheduling is performed by normalizing its function using the Genetic algorithm [4]. Dual composition is used to model constraints in a real-time proposed system that performs a two-way communication [11] for optimal scheduling. In [12], the cost associated with energy consumption is reduced by using an artificial bee colony (ABC) algorithm and a quasi-static technique that also improves the load factor. Non-dominated genetic sorting algorithm II (NSGA-II) is used to reduce the microgrid's operating cost [13], increasing the system's efficiency by using PVs, batteries, and utility grid as the energy inputs. SQP algorithm is used in [14] to increase customer comfort by reducing customer bills and PAR with the B technique. This algorithm solves the above equation as a mixed integer linear programming (MILP) problem [15]. It introduces the concept of DC microgrids, which has reduced the system's cost and increased its availability [16]. Two scenarios describe results obtained from the Multi-Objective Genetic Algorithm (MOGA). Operating cost and pollution emissions are minimized using the MOPSO algorithm, whose results are distributed to 3 scenarios [17]. Cost, emission, and customer satisfaction were modeled as the three objectives in [18] using a non-dominated genetic sorting algorithm III (NSGA-III) algorithm. At the same time, the load factor has not been improved. In [19], DSM Load curtailment and shifting strategies are used to reduce operating costs and pollution. ϵ-constraint approach is used to solve Mixed Integer Non-linear Programming (MILNP) and obtain Pareto fronts. The comparison is drawn for different techniques to reduce consumption and operating costs in an intelligent grid. Reference [20] also described different algorithms, i.e., MOPSO and GA. PSO, MILP, etc., for obtaining objectives. In [21], the total cost of the smart grid is reduced by using the MAPPO algorithm. Real-time pricing (RTP) and load schedules were used as the DSM method's optimal functioning. Reference [22] described different DSM strategies for an intelligent microgrid to work for demand response. Case studies showed that peak clipping, valley filling, and load shifting were experimented with to operate microgrids [23]. Minimizing operational costs and energy consumption are the important issues considered in smart grids. Reference [24] uses artificial intelligence (AI) techniques for different management applications, i.e., integrating renewable sources, Demand side management, ESS summation, and energy management smart grid. The peak-to-average ratio is minimized by reducing the peak load for residential consumers using load shifting as DSM strategy, and results were formulated for both cases with and without DSM strategy [25]. Reference [26] proposed an energy management system (EMS) for an intelligent building that increases customer comfort by managing the system's cost and energy consumption, which also increases the overall security. A fair pricing scheme is introduced to help reduce low-energy consumers' bills by introducing a fair pricing scheme as in [27] that helps him calculate the energy cost of both high-energy consumers and low-energy consumers and charge them accordingly [28] and reduces computational costs for managing energy consumption is smart building (SB) using genetic algorithm (GA) with DSM strategies. The smart grid architecture model (SGAM) is presented in [29] and uses powerful tactics for modeling the condition of a microgrid on the generation and management sides. In [30], different algorithms are compared for demand-side management strategies to reduce operating costs and energy consumption in a smart grid. Cost and PAR are minimized for load in a residential area, and an optimal scheduling model is proposed for EVs in smart grids by MILP, whose results are optimized under the proposed model [31]. Reference [32] uses Grey wolf optimization for optimal energy management in PHEVs, and Monte Carlo simulations model intermittent behavior of renewable sources. Table 1 summarizes the findings from the survey above.

It is clearly understood from the above research that many numbers of models have been proposed that were efficient in reducing cost and energy consumption in intelligent grids. However, substantial research gaps in proposed models remain regarding several technical and physical factors: Different models have reduced operating and emissions but ignored energy consumption and consumer comfort, which produced inconvenience on the customer side. Load curtailment and Load shifting are used as demand response programs that have also caused discomfort to customers.

TABLE 1. Summarizes of literature review.

Ref	Method used	Comments
[8]	Fuzzy-based.	The researcher has not considered the peak average ratio (PAR) to reduce peaks in the system.
[9]	MOPSO algorithm.	Considering the pollution function as the main objective, the operational costs increased.
[10]	Branch and Reduce Optimization Navigator (BARON).	Carbon emission due to EES was ignored.
[11]	Dual composition.	Considering the cost of technical issues as the main objective, Carbon emission was ignored.
[12]	Artificial bee colony (ABC).	Considering the cost of technical issues as the main objective, Carbon emission was ignored.
[13]	Non-dominated genetic sorting algorithm II (NSGA-II).	Focusing on the consumer's bill, the consumers can also sell power to the primary grid, but Carbon emission was ignored.
[14]	SQP algorithm.	Focusing on the consumer's bill, the consumers can also sell power to the primary grid, but Carbon emission was ignored.
[15]	Mixed integer linear programming (MILP).	They focused on increasing availability and reducing network costs, but carbon emissions were ignored.
[16]	Multi-Objective Genetic Algorithm (MOGA).	It focused on the home appliances scheduling problem, incorporating realistic aspects and ignoring User Comfort, Electricity cost.
[17]	MOPSO algorithm.	It focused on two objectives, operation cost, and emission propagation, and was ignored User Comfort.
[18]	Non-dominated genetic sorting algorithm III (NSGA-III) algorithm.	The load factor has not been improved.
19	Mixed Integer Non-linear Programming (MILNP).	User Comfort was not taken into consideration.
21	MAPPO algorithm.	Reducing the total cost of the smart grid, but not considering the other parameters.
25	DSM strategy.	Focusing on the daily consumption patterns, but was not considered the other parameters.
26	Energy management system (EMS)	Focusing on home management and privacy issues ignored the cost.
27	A fair pricing scheme.	They are focusing on reducing the cost and ignoring emissions and user Comfort.
28	Genetic algorithm (GA).	They focus on reducing the cost to the consumer regardless of the impact on consumer comfort.
29	The innovative grid architecture model (SGAM).	They focused on challenges and cybersecurity aspects related to the impact on consumer comfort. The cost and propagation of emissions were ignored.
30	Different algorithms are compared for demand-side management strategies.	Several algorithms have been used as optimization problems, leading to application difficulty, regular maintenance, and complexity during work.
31	Mixed integer linear programming.	Focusing on reducing the energy cost of the residential household while reducing costs without making a comparison with consumer convenience.
32	Grey wolf optimization.	Focusing on User Comfort and ignoring the cost and Peak to Average Ratio

This study represents a scheduled way to minimize operating costs and energy consumption in an intelligent microgrid consisting of WTs, PVs, MTs, and ESSs. The proposed model supplies energy to residential types of consumers (RC). Non-dominated genetic sorting algorithm II (NSGA-II) is adopted to find the Pareto fronts of the optimization problem, and the real solution is selected by the decision-making method. The rest of the paper's organization is: Section II introduces the concept of a smart grid. The system model is explained in Section III. Section IV deals with the proposed methodology and its related approaches for the optimization problem. In Section V, simulations and results are discussed. Finally, a conclusion is drawn in Section VI.

II. OVERVIEW OF SMART MICROGRID

A smart microgrid is a technical device that provides electrical energy to loads using intelligent energy meters, which perform a bi-way communication between the system and the utility grid. Daily load demand from the customer is received by the smart meter in the installed advanced metering infrastructure (AMI) in a typical micro smart grid. The smart meter also receives electricity prices a day ahead of the utility. After receiving both price and demand, it devises a plan to supply optimal energy to load connected, observing all technical, economic, and environmental situations. Figure 1 shows an overview of a smart grid in which photovoltaic cells (PVs) and wind turbines (WTs) are used as renewable energy resources, Micro Gas Turbines (MGTs) are used as distributed energy sources (DESs), Electrical energy storage systems (ESSs) in the form of batteries are used as storage elements, and utility grid (UG) is used to exchange power with the system when required. Three classes of consumers, including Residential Consumers (RCs), Commercial Consumers (CCs), and Industrial Consumers (ICs), are used as loads.

III. SYSTEM MODEL

A. SUPPLIED POWER RESOURCES

Supplied Power resources are the energy sources that transmit the generated energy to the total number of loads connected with the proposed model. The number of power-provided sources in our proposed model is of two types which are:

- known resources.
- unknown resources.

Our proposed model, described in 2 Micro Turbines (MTs), constitutes known resources, whereas PV and wind turbines (WTs) explain the unknown resources. Batteries are

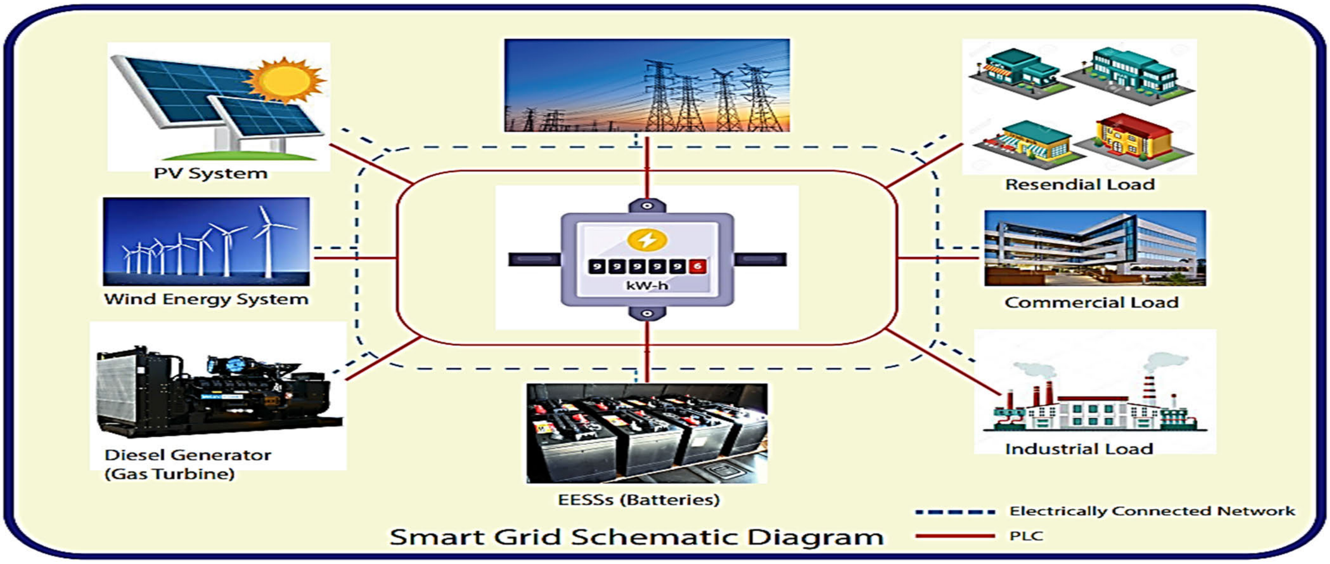

FIGURE 1. Smart microgrid.

used as Electrical energy storage systems (ESSs) in the model, along with the power resources. The exchange of electricity is made possible by using a utility grid (UG) between the customer and the energy distributor in the proposed model.

B. LOAD TYPES

The type of load fed by our model consists of different home appliances, i.e., electric bulbs, fans, water motors, washing machines, etc., with a maximum load range of 4-35KW, falling into the residential consumer category.

Uncertainties are associated with renewable energy resources due to their erratic behavior, i.e. solar source (PV) and wind depend on availability. Both renewable energy resources.

Crucially depend on atmospheric conditions and climate which makes them vulnerable to obtaining their 24-hour day-ahead forecast. Different types of stochastic and probabilistic techniques containing fuzzy-based logic, beta PDF and CDFs, Maximum likelihood and Bayesian methods, and Monte Carlo (MC) simulations are used to model the intermittent behavior of PV and wind [33]. Our proposed model uses the probabilistic method to overcome the uncertain behavior of renewable sources. Solar and wind uncertainty is tackled using solar radiance, wind speed, and ambient temperature, as discussed in subsections.

C. PV MODELING

The photoelectric effect is used as a base for solar power generation by converting the light from the sun to electrical energy. The light rays in the form of solar radiation from the sun are utilized and absorbed by the material and converted to electrical particles that constitute the DC form of electricity. Beta PDF and linear power are used to model the uncertainty using ambient temperature and solar radiance (si) in 1 and 2. [18], [34].

$$L\left(si\right)=\left\{\begin{array}{ll}\dfrac{\lambda(\sigma+\phi)si^{(\sigma-1)}.(1-si)^{(\phi-1)}}{\lambda\left(\sigma\right)\lambda\left(\phi\right)} & \begin{array}{l}0\leq si\leq 1,\\ \sigma\geq 0,\phi\geq 0\end{array}\\ 0 & \end{array}\right\} \tag{1}$$

$$N(x)=TH_a+\frac{si}{si^{def}}\times(T_N-20),\quad t\in(1,\ldots,24) \tag{2}$$

where T_e is the ambient temperature, si is the solar irradiance, and T_N is the nominating cell temperature. σ and ϕ are the parametric values of beta PDF given in 3 and 4:

$$\sigma=\alpha(\frac{\alpha(1+\alpha)}{\varphi^2}-1) \tag{3}$$

$$\phi=(1-\alpha)(\frac{\alpha(1+\alpha)}{\varphi^2}-1) \tag{4}$$

Solar power can be determined by equation 5 using the values obtained from the above functions.

$$SP_s=S_s^{def}\times\frac{si}{si^{def}}\times(1+\xi\times(N(x)-N(x)^{def})\times M_{sc}\times\theta_{sc}) \tag{5}$$

D. MODELING OF WIND

A wind turbine generator (WTG) is used to produce wind power. The mechanical energy of wind is converted to electrical energy by WTG. The use of wind power is increasing exponentially; however, wind power generated is also associated with different uncertain and unknown elements that make it vulnerable to predicting its factual day forecast. The wind's direction, speed, and wind speed characteristic curve are the elements that affect the generated wind power. Weibull PDF utilizes wind speed as the modeling element to control the uncertain wind behavior, as given in equation 6 [18].

$$X_v(S_v) = 1 - \exp(-(\frac{S_v}{\beta_s})^2) \quad (6)$$

β_s is the value assumed of the scalar parameter of wind speed. It is given by equation 7.

$$\beta_s = \frac{2}{\sqrt{\gamma}} S_r \quad (7)$$

While S_r is the measured speed of wind for modeling the Wei-bull PDF given in equation 8.

$$S_r = \beta_s \zeta (1 + \frac{1}{2}) \quad (8)$$

Wind power output is calculated by equation 9 [31].

$$E_{WTurbine} = \left\{ \begin{array}{cc} 0 & S_s w < S_{st} \\ E_w(\frac{S_s w - S_{st}}{S_w - S_{st}}) & S_{st} \leq S_s w < S_w \\ E_w & S_w \leq S_s w < S_{sf} \\ 0 & S_s w \geq S_{sf} \end{array} \right\} \quad (9)$$

where E_w, $S_s w$, S_{st}, S_w and S_{sf} are the rated WT power, speed of the wind, cut-in speed of the wind, rated speed of the wind, and cut-out speed of the wind, respectively.

IV. OBJECTIVE FUNCTIONS

The main objective of our model is to simulate an intelligent microgrid to reduce operational expenses and energy usage. Bi-objective functions are utilized to optimize the smart grid in the proposed model, which is described as follows;

1. Operating cost, the first objective function
   This function minimizes the cost associated with the operation of the smart grid, known as the operational cost of the smart grid, as given in equation 10:

$$\begin{aligned} \min OB_1 = & \sum_{c=1}^{C} \mu_c \sum_{t=1}^{T} (\sum_{g=1}^{G} PRICE_{MT}(c,t,g) \\ & + \sum\nolimits_{e=1}^{E} PRICE_{Battery}(c,t,e) \\ & + PRICE_{Utility}(c,t)) \end{aligned} \quad (10)$$

2. Energy Consumption, the second objective function
   The energy utilized by the smart grid under study is given by equation 11:

$$\min OB_2 = \sum\nolimits_{h=1}^{H} ES_{MG}(h) \times TimeS_{MG}(h)) \quad (11)$$

V. SMART GRID CONSTRAINTS PERFORMANCE AND METRICS

Some limits must be observed to operate the microgrid effectively, known as constraints. Constraints impose bounds on the smart grid that affect the overall efficiency. Technical conditions for renewable sources and power balance constraints constitute the general constraints for the smart grid. Smart Grid performance metrics [35], [36] and constraints are utilized in our model, which is described in the subsection:

A. POWER BALANCE

This constraint is used to model the generated power and load required in our model. According to this constraint, the power provided to the model must be equal to the power utilized by consumers, as in equation 12.

$$\begin{aligned} & \sum\nolimits_{c=1}^{C} \mu_c \sum\nolimits_{t=1}^{T} ((\sum\nolimits_{g=1}^{G} P_{MT}(c,t,g)) + \sum\nolimits_{sc=1}^{SC} P_{sc}(c,t,sc)) \\ & + (\sum\nolimits_{tv=1}^{T} VP_t v(c,t,TV)) + \sum\nolimits_{s=1}^{S} P_{battery}(c,t,s) \\ & \times P_{GRID}{}^{Bought}(c,t)) = \sum\nolimits_{c=1}^{C} \mu_c \sum\nolimits_{t=1}^{t} T(P_{RESLOAD}(c,t) \\ & \times P_{COMLOAD}(c,t) + P_{INDLOAD}(c,t) + P_{GRID}{}^{Sell}(c,t)) \end{aligned} \quad (12)$$

B. ELECTRICITY COST

The rate structure is one based on real-time pricing (RTP), with tariffs changing throughout the day, every day, to reflect the actual cost of energy. There would be no demand costs with RTP, just energy prices that may change on an hourly basis.

C. PEAK TO AVERAGE RATIO (PAR)

The Performance Assessment Ratio (PAR) represents the proportion of the highest energy consumption level to the average energy consumption level over a specific timeframe. To decrease PAR and prevent peak power plant operations, utility providers encourage customers to shift their energy consumption from on-peak to off-peak timeslots. This PAR reduction is beneficial for both utility companies and customers due to two main reasons: first, it smoothens out the load curve and reduces peaks in the demand load curve, and second, it lowers the energy costs for consumers. The PAR can be computed by dividing the highest energy consumption level by the average energy consumption level during the designated period.

$$PAR = \frac{\max(E_{tot}(t))}{\frac{1}{T}\sum_{t=1}^{T} E_{tot}(t)} \quad (13)$$

D. CARBON EMISSIONS

It represents the CO2 emissions in kg/kWh as in equation 14:

$$CO_2 = \frac{EP_{avg}}{\mu \times \gamma} \quad (14)$$

where EP_{avg} indicates the average monthly energy bill and reflects the price per kWh. μ refers to the average price per kWh, which is set to 0.2\$, while γ represents the electricity emissions factor, which is almost 1.37.

E. USER COMFORT

This research investigates user comfort by assessing the duration of time consumers must wait for an activity after their energy consumption shifts from on-peak to off-peak timeslots. As consumers transfer their loads to off-peak hours, they may experience some level of discomfort. The analysis highlights a trade-off between the costs of energy and waiting time, wherein reducing energy costs may increase waiting time and vice versa. The research emphasizes the importance of minimizing the waiting time for consumers and identifies it as a critical factor in evaluating user comfort concerning load switching between on-peak and off-peak timeslots; user comfort is

$$waiting\ (Delay) = \frac{\sum_{t=1}^{T} |(T_{unsch}(t) - T_{sch}(t)|}{\sum_{t=1}^{T} T_{sch}(t)} \tag{15}$$

The User Comfort (UC) is calculated in terms of waiting time/delay that an appliance faces due to scheduling and unscheduling periods and the status of an appliance.

F. STORAGE SYSTEM

This section will go through the suggested energy storage systems and their formulae. Because ESS has specific limits, such as charging, the lowest and maximum charging levels are represented by ESmin and ESmax, respectively. The state of charge (SOC) is thought to be between 20% and 80% of its maximal value. The stored energy of ESS is denoted by:

$$\mathrm{SE}\ (\mathrm{t}) = \mathrm{SE}\ (\mathrm{t}-1) + \tau \cdot \eta^{\mathrm{ESS}} \cdot \mathrm{EE}^{\mathrm{char}}\ (\mathrm{t}) - \frac{\tau \cdot \mathrm{EE}^{\mathrm{discharg}e}\ (\mathrm{t})}{\eta^{\mathrm{ESS}}} \tag{16}$$

where SE indicates energy stored and measured in (kWh) at time t, η^{ESS} implies ESS efficiency, τ defines the period in hours, EE^{char} represents power provided by the solar and wind systems to batteries and $EE^{dischar}$ means power supplied from batteries to load. The following constraints have been imposed to keep charging/discharging within limits and to prevent deep discharge/overcharge.

$$EE^{char} \leq EE^{char}_{max}, EE^{dischar} \leq EE^{dischar}_{min}, \text{ and } S \leq SE^{char}_{max} \tag{17}$$

We will detail the approaches we suggested in our study in this part. zxvvvTo mimic optimization challenges, a non-dominated genetic sorting algorithm (NSGA-II) is utilized. The decision-making technique was used to choose the best choice from among the non-dominated alternatives. We will also go through the approaches that have been used in the past. Three alternative scenarios demonstrating the optimal value of operating cost and energy usage were presented for the proposed algorithm's outcome analysis. The NSGA-II algorithm with renewable energy resources without RES was the first scenario, while the same method with RES only is the second scenario and optimum scheduling of RES and ESS was the last scenario to reduce expenditures and energy usage.

VI. PROPOSED ALGORITHM

A. NSGA-II

In our proposed model to obtain Pareto fronts, we have used non-dominating sorting genetic algorithm II (NSGA-II). Using the concept of crowding distance and non-dominated sorting, an optimal solution from the obtained Pareto fronts is generated by NSGA-II.

The overall algorithm is illustrated in Figure 2.

B. BPSO ALGORITHM

The PSO algorithm is another approach for identifying the best solutions within a given search area. While it is typically used in a continuous area, it can be adapted for use in a discrete domain, which is known as BPSO. The four primary determinants of BPSO are the particle's initial position, starting velocity, own best position, and global best position. BPSO begins by creating a search space and randomly distributing a population throughout the space. In each step of the algorithm, the particle speeds are updated using Equation (18),

$$\begin{aligned}\sum_{t=1}^{C24}\sum_{i=1}^{I}\sum_{t=1}^{C24}\sum_{i=1}^{I} U_1^{t+1} &= \sum_{t=1}^{C24}\sum_{i=1}^{CI} UV_1^t\ (j) + Z1K1(Xibest, i(j)) \\ &\quad + Z2K2(Xigest, i\ (j) - X_{i1}^t(j))\end{aligned} \tag{18}$$

where U is the inertia factor, U_j^t is current velocity. U_i^{t+1} is the velocity of a particle. Random numbers are k1 and k2, while z1 is the local pull and z2 is the global pull. X_i^t is the particle's current position, $Xigest$ is the local and $Xigest$ is the global best position. Equation (19) is used to map the velocities of particles between 0 and 1.

$$sim\left(U_i^{t+1}\ (j)\right) = \frac{1}{1 + \exp(-U_i^{t+1}\ (j))} \tag{19}$$

C. BFO ALGORITHM

Bacterial foraging optimization (BFO) is a program that takes inspiration from natural processes. This algorithm has become popular among researchers due to its success in solving practical problems. In the natural world, bacteria swim towards the best sources of nutrients and optimize their energy, and the BFO algorithm models this process by considering several solutions, or ''nutrients''. BFO follows a four-step process that is similar to the WDO algorithm: reproduction, movement, elimination-dispersal, and chemotaxis. BFO uses specific criteria to guide its search process. Under the chemotaxis step, the system initializes the parameters and examines the initial positions of the particles, before calculating new positions of the bacteria in the solution matrix. The swimming cycle is started in the second phase to determine the appliances' present best state. Following this action, the reproduction cycle iterates, selecting only the fittest options to create the new population. The final step is to remove the least fitting solutions and replace them with fresh random samples that have a reduced likelihood. This is a crucial stage because it eliminates the least fit options and reduces the likelihood of recurrence.

The overall proposed model of the Microgrid operation system is represented in Figure 3.

VII. SIMULATIONS AND RESULT ANALYSIS

In this part, we provided the simulation results of the suggested NSGA-II approach, along with comparisons to the other two met heuristics methods (PSO, and BFA).

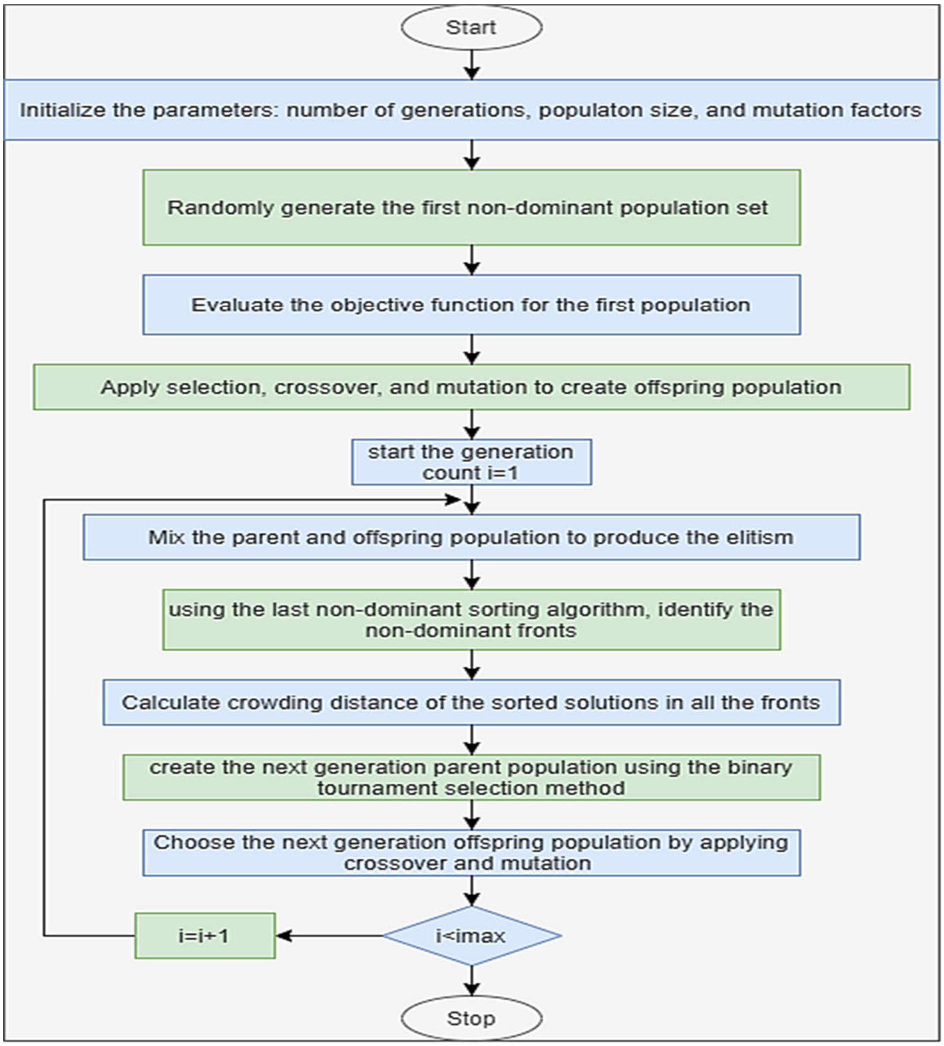

FIGURE 2. NSGA-II algorithm steps.

This system evaluates the integration of RESs, ESS, and the performance of the NSGA-II algorithm in three situations. The first scenario includes neither RES nor ESS, whereas the second includes just RES and the third includes both RES and ESS where the first objective function, is the system's operational cost, and the second objective function, energy consumption in a smart grid with ESSs, is investigated. A user with 6 passive appliances and an ESS is regarded as a source to implement the proposed NSGA-II. To support the load of the prosumers, we have made the power supply of the electric utility companies (EUCs) accessible 24 hours a day. To fulfill the needs of residential customers, the suggested model includes MTs, PVs, WTs, and batteries. The suggested model is simulated using the MATLAB 2021b software version, and the simulation time is varied depending on the case under study. The day-ahead 24-hour values of wind speed and solar irradiance are shown in Figure 4. Figures (5)-(8) illustrate the eruptive grid signals (forecast temperature, Purchased energy cost (RTP), battery charging levels, and overall load demands) utilized in the proposed study. PV system power production is mostly determined by solar irradiation and ambient temperature. As shown in Figure 9, we examined 90% of the total RE in any scheduling time window. In addition, of the 90% of RE utilized for charging the ESS, 30% is consumed in each time slot. Figure 10 displays the NSGA-II algorithm solutions for this situation, with iteration 110 picked as the best response by the decision-making process since it is the closest to the ideal point.

At a certain time and by utilizing only the NSGA-II, it can reduce the energy consumption from 0.976KWh to 0.937kWh with 0.1$/kW average operating cost.

VIII. SCENARIO 1

We will not employ RES and ESS in this case; instead, we will schedule the appliances using the scheduling algorithms. As a consequence, the cost, PAR, carbon emissions, and UC are calculated below.

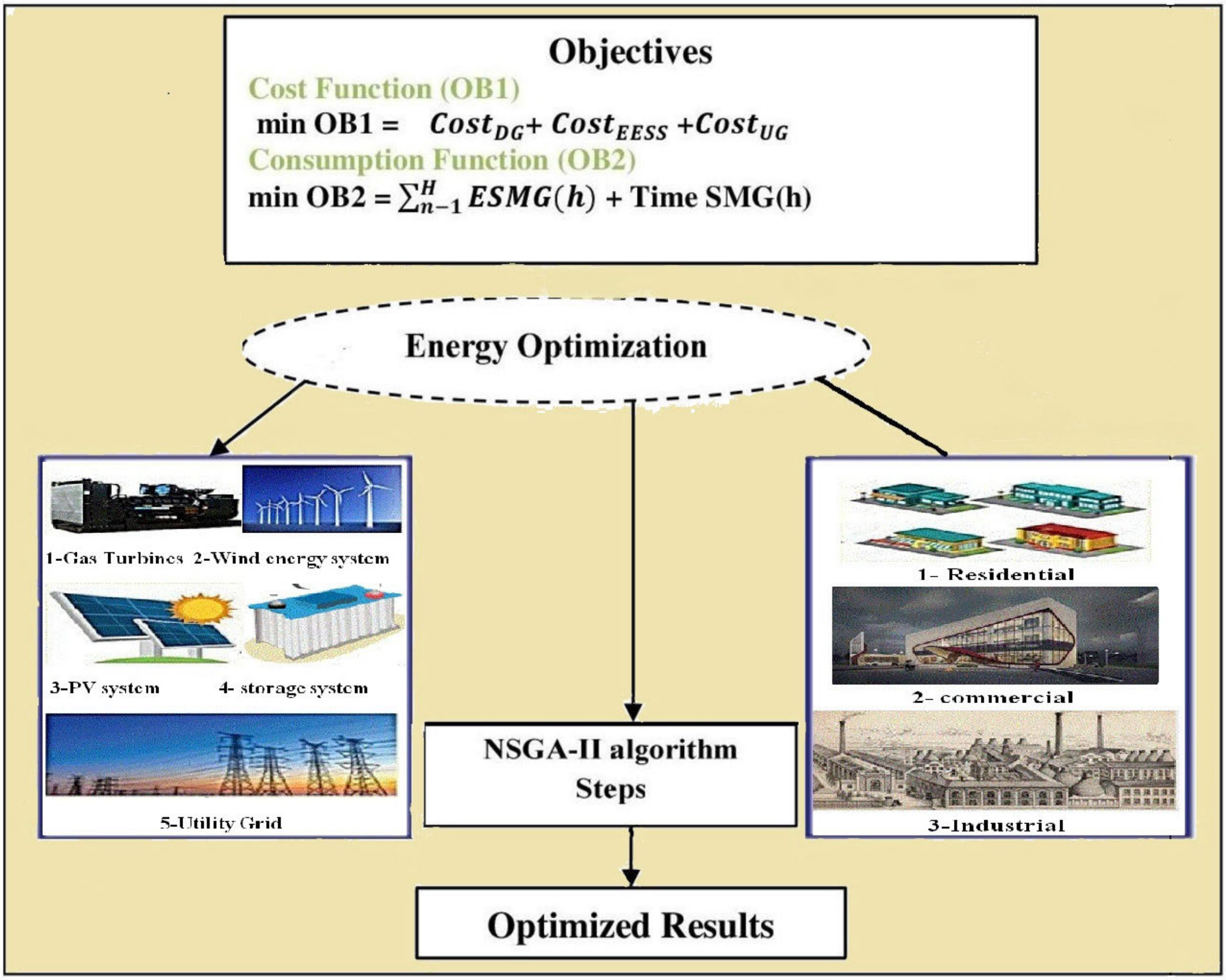

FIGURE 3. The proposed model of the microgrid operation.

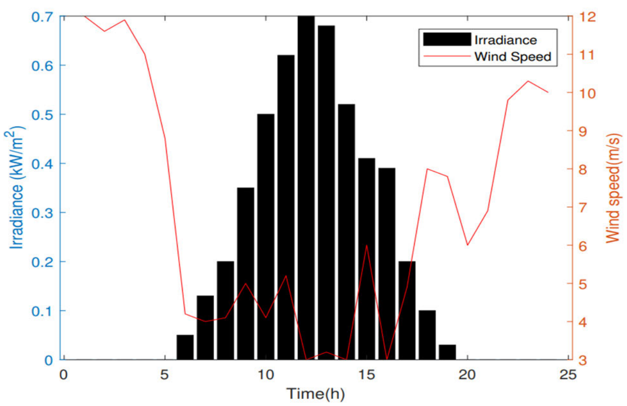

FIGURE 4. Solar intensity and speed of wind.

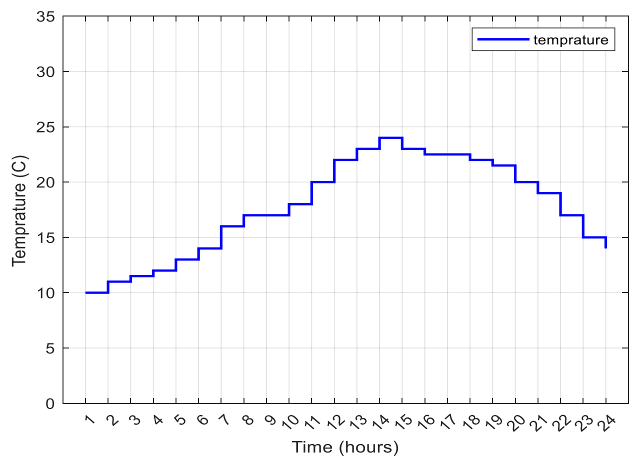

FIGURE 5. Daily forecast temperatures.

A. ELECTRICITY COST

Figure 11 illustrates the power cost of planned and unscheduled loads in the absence of RES and ESS. In time slot 9, the maximum cost of the unscheduled is 70 cents. The highest cost of power in PSO is 66 cents in time slots 19, 21, and 23. In BFA, the maximum cost of power in time slot 9 is 58 cents. In the instance of NSGA, the time

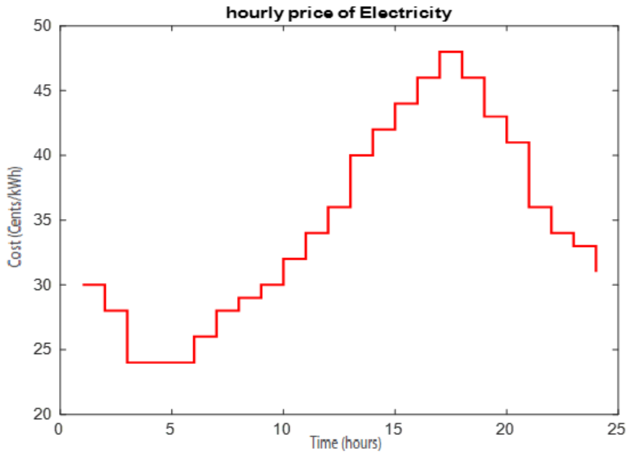

FIGURE 6. Purchased energy cost.

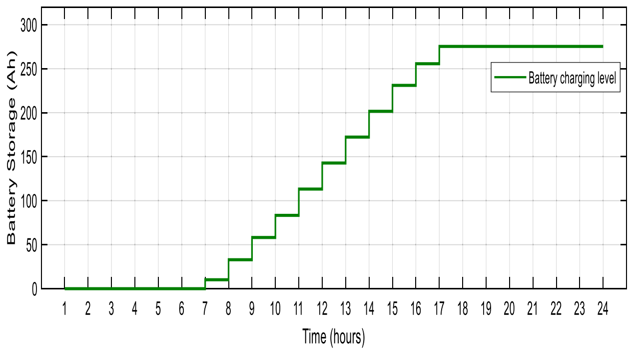

FIGURE 7. Daily battery storage.

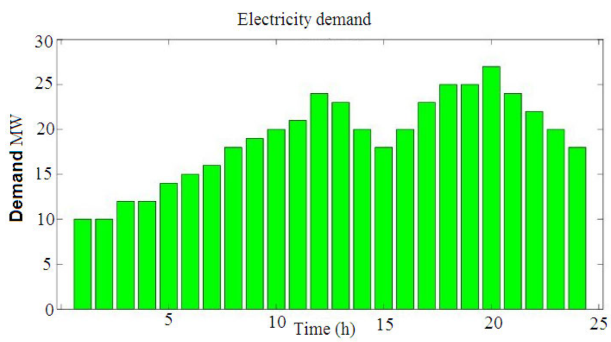

FIGURE 8. Overall load demand.

slot 19 is 56 cents. In terms of electricity bill minimization, the suggested NSGA algorithm outperforms previous heuristic methods. The total cost of power in unplanned load is 740 cents, whereas the costs of BFA, PSO, and NSGA are 705, 683, and 672 cents, respectively. Overall, power costs demonstrate that BFA, PSO, and NSGA each save 4.7%, 7.7%, and 9.18%, respectively. Nevertheless, when total cost reduction is involved, the NSGA method offers the best results when compared with other algorithms in this circumstance. Table 2 shows the cost comparison for Scenario 1.

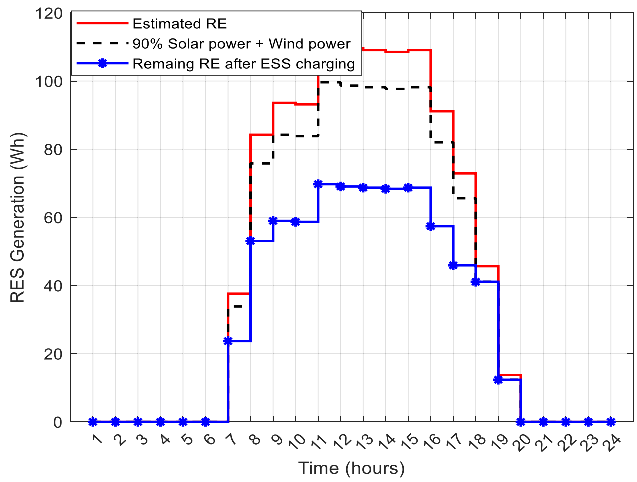

FIGURE 9. The expected RE and ESS charging level.

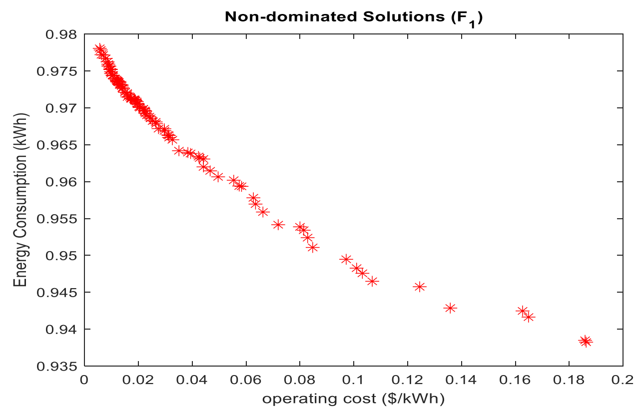

FIGURE 10. Scenario 1 By NSGA-II.

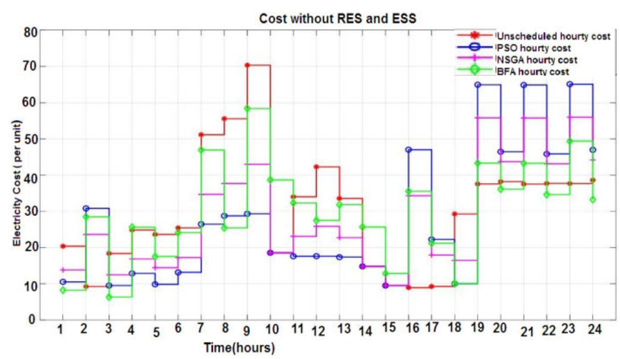

FIGURE 11. Cost reduction for scenario 1.

TABLE 2. Comparison of scenario 1 cost.

Algorithm	UnScheduled	PSO	BFA	NSGA
Cost	740	705	683	672
Reduction (%)	-	4.7	7.7	9.2

B. PAR

Figure 12 illustrates the PAR of the unscheduled and scheduled load. Results show that PAR for the unscheduled is 2.62 while PAR for the scheduled algorithms is: 2.34 by PSO, 2.26 by BFA, and 2.12 by NSGA respectively. As a result, the percentage reduction for the algorithms is 10% for the PSO, 13.1% for the BFA, and 18.4% for the NSGA. The comparison of PAR in scenario 1 is shown in Table 3.

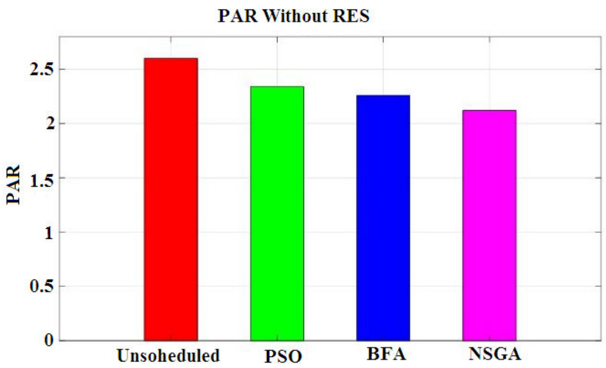

FIGURE 12. PAR reduction in scenario 1.

TABLE 3. Comparison of scenario 1 par.

Algorithm	UnScheduled	PSO	BFA	NSGA
PAR	2.6	2.34	2.26	2.12
Reduction (%)	-	10.0	13.1	18.4

C. CARBON EMISSIONS

Figure 13 demonstrates the comparable carbon emissions of planned and unscheduled loads without RES and ESS. The results reveal that carbon emissions from heuristic methods are lower than those from unplanned loads. Maximum carbon emissions in unplanned time slot 21 are 162 pounds. In the case of BFA, it is 156 pounds in time slot 21, whereas it is 152 pounds in time slot 21 for PSO. It is 150 pounds in time slot 21 according to NSGA schedule. In unplanned load, the total carbon emissions are 3206 pounds. It is 2904, 2890, and 2861 pounds for BFA, PSO, and NSGA, respectively. As a consequence, overall carbon emissions in BFA are decreased by 9.41%, in PSO by 9.85%, and in NSGA by 10.7%. However, in this circumstance, the NSGA algorithm produces the greatest results in terms of lowering carbon emissions. Table 4 compares carbon emissions in Scenario 1.

TABLE 4. Comparison of scenario 1 carbon emission.

Algorithm	UnScheduled	PSO	BFA	NSGA
Co2	3206	2904	2890	2861
Reduction (%)	-	9.41	9.85	10.7

IX. SCENARIO 2

In this particular case, the incorporation of exclusively Renewable Energy Sources (RES) without Energy Storage Systems (ESS) into the residential vicinity is assessed based on the factors of electricity costs, Peak-to-Average Ratio (PAR), and carbon dioxide emissions.

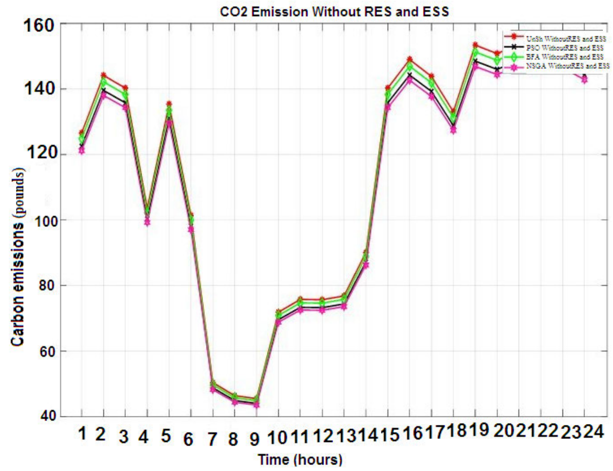

FIGURE 13. Carbon emissions reduction in scenario 1.

A. ELECTRICITY COST

Figure 14 illustrates the electricity expenses incurred by both scheduled and unscheduled loads using only Renewable Energy Sources (RES). Table 5 displays the evaluated costs and their comparison within scenario 2.

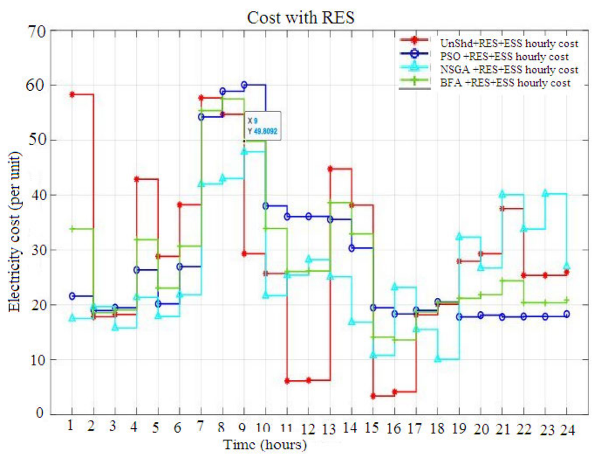

FIGURE 14. Cost reduction for scenario 2.

TABLE 5. Comparison of scenario 2 cost.

Algorithm	UnScheduled	PSO	BFA	NSGA
Cost	692	659	636	620
Reduction (%)	-	5. 2	8.1	10.4

B. PAR

Figure 15 illustrates the peak-to-average ratio (PAR) of unscheduled and scheduled loads, and the comparison of PAR in scenario 2 is presented in Table 6.

C. CARBON EMISSIONS

Figure 16 depicts the carbon emissions resulting from scheduled and unscheduled loads when only RES is integrated. The corresponding comparison of carbon emissions in scenario 2 is presented in Table 7.

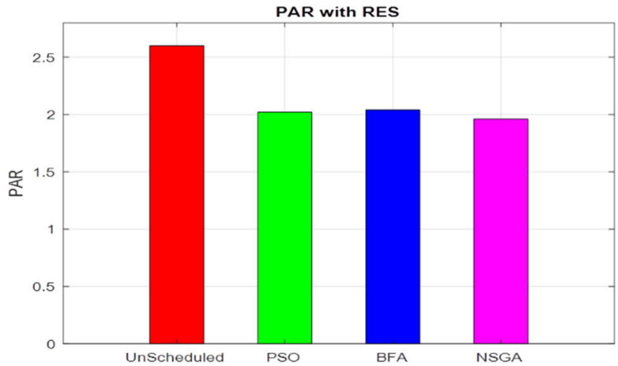

FIGURE 15. PAR reduction in scenario 2.

TABLE 6. Comparison of scenario 2 par.

Algorithm	UnScheduled	PSO	BFA	NSGA
PAR	2.6	2.02	2.04	1.96
Reduction (%)	-	22.3	21.5	24.6

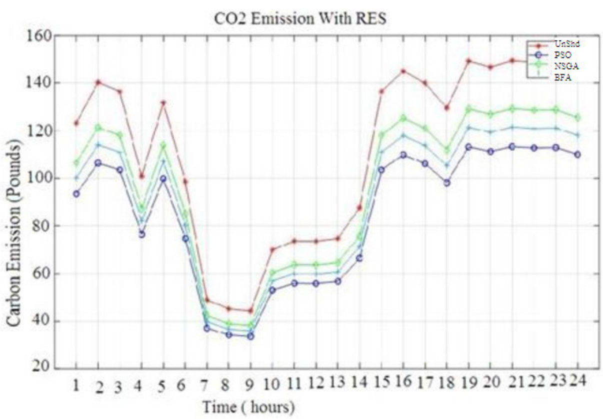

FIGURE 16. Carbon emissions reduction in scenario 2.

TABLE 7. Comparison of scenario 2 carbon emissions.

Algorithm	UnScheduled	PSO	BFA	NSGA
PAR	2717	2247	2400	2303
Reduction (%)	-	17.3	11.6	15.2

X. SCENARIO 3

In this particular case, the combination of renewable energy sources (RES) and energy storage systems (ESS) in a local area is assessed based on four factors: electricity bill, PAR, carbon emissions, and UC.

A. ELECTRICITY COST

To evaluate the impact of RES and ESS integration on electricity costs, Figure 17 displays the comparison of scheduled and unscheduled load costs with RES alone. The assessed costs and their comparison for scenario 3 are also presented in Table 8.

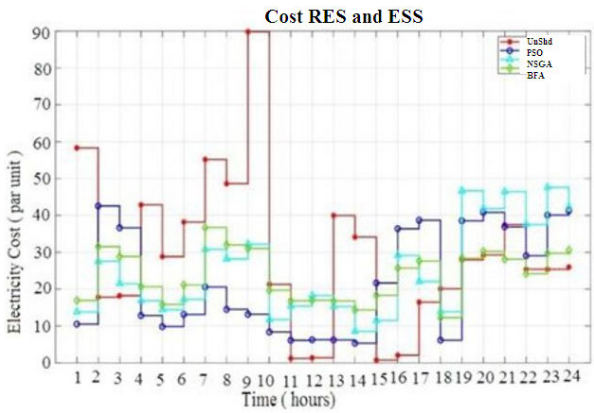

FIGURE 17. Cost reduction for scenario 3.

TABLE 8. Comparison of scenario 3 cost.

Algorithm	UnScheduled	PSO	BFA	NSGA
Cost	710	633	588	582
Reduction (%)	-	10. 8	17.1	19.0

B. PAR

The PAR comparison of scheduled and unscheduled load is illustrated in Figure 18. Additionally, Table 8 presents the PAR evaluation and comparison of scenario 3 which integrates both RES and ESS into the local area.

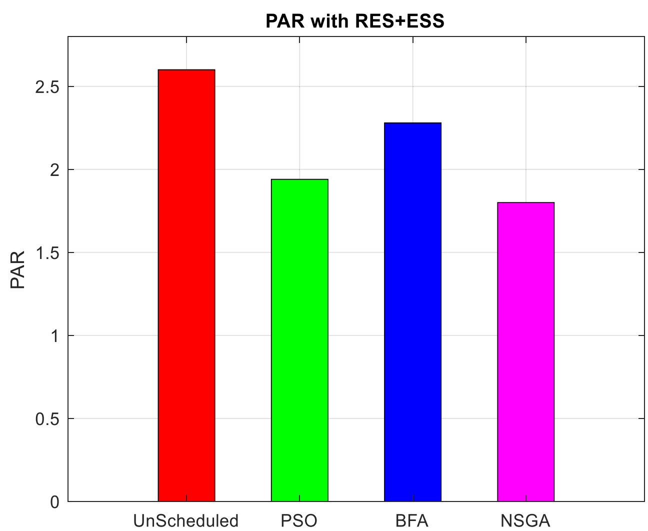

FIGURE 18. PAR reduction in scenario 3.

TABLE 9. Comparison of scenario 3 par.

Algorithm	UnScheduled	PSO	BFA	NSGA
PAR	2.6	1.91	2.28	1.8
Reduction (%)	-	26.5	12.3	30.7

C. CARBON EMISSIONS

Figure 19 depicts the carbon emissions associated with scheduled and unscheduled loads when integrating RES and ESS in the local area. The comparison of carbon emissions in scenario 2 is tabulated in Table 10.

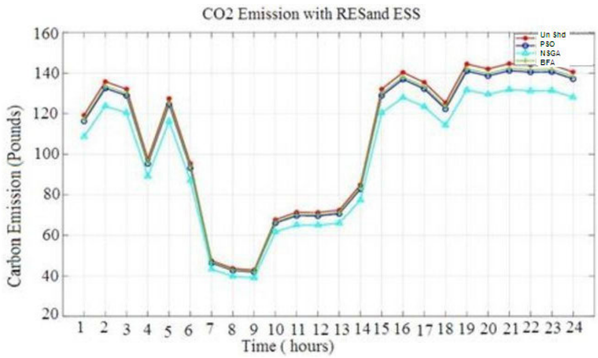

FIGURE 19. Carbon emissions reduction in scenario 3.

TABLE 10. Comparison of scenario 3 carbon emissions.

Algorithm	UnScheduled	PSO	BFA	NSGA
Co2	2612	2412	2389	2043
Reduction (%)	-	7.6	8.5	21.7

D. USER COMFORT

User Comfort is manipulated in terms of waiting time in this paper. Waiting time is the amount of time a user waits before turning on an appliance. For a reduced power cost, users must use their appliances according to the desired timetable. If a user is more concerned with saving money, he will have to sacrifice his comfort. Figures 20, 21, and 22 show the average waiting time for the PSO, BFA, and NSGA algorithms, respectively. The results reveal that NSGA has shorter waiting time than other algorithms. In certain instances, the PSO and BFA have short waiting periods, however the NSGA algorithm has the shortest waiting time in practically all situations.

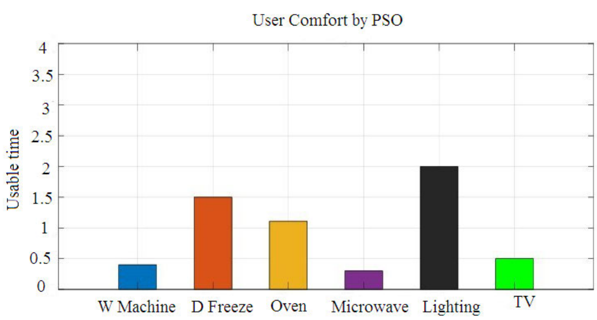

FIGURE 20. UC by PSO.

XI. COMPARAISON STUDY

As shown in Table 11 and in scenario involving both renewable energy sources (RES) and energy storage systems (ESS), the NSGA algorithm consistently outperforms PSO and BFA, providing optimal solutions with significant cost, PAR, and

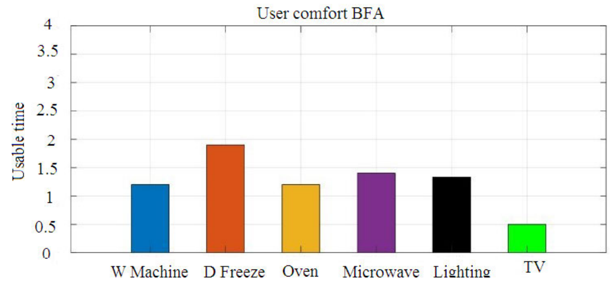

FIGURE 21. UC by BFA.

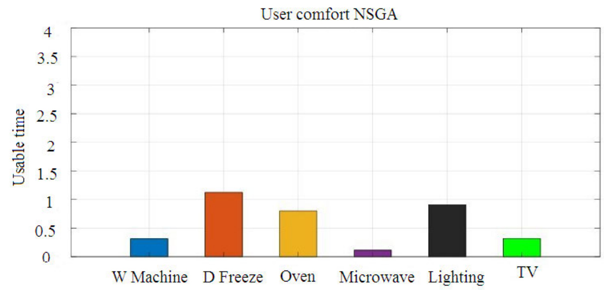

FIGURE 22. UC by NSGA.

TABLE 11. Comparison of all metric parameters.

Algorithm	Cost	Red. (%)	PAR	Red. (%)	CO2	Red. (%)	Scenario
UnSch.	740	-	2.6	-	3206	-	Scenario -1 (without RES and ESS)
PSO	705	4.7	2.34	10	2904	9.41	
BFA	683	7.7	2.26	13.1	2890	9.85	
NSGA	672	9.2	2.12	18.4	2861	10.7	
UnSch.	692	-	2.6	-	2717	-	Scenario -2 (with RES and without ESS)
PSO	659	5.2	2.02	22.3	2247	17.3	
BFA	636	8.1	2.04	21.5	2400	11.6	
NSGA	620	10.4	1.96	24.6	2303	15.2	
UnSch,	710	-	2.6	-	2612	-	Scenario -3 (with both RES and ESS)
PSO	633	10. 8	1.91	26.5	2412	7.6	
BFA	588	17.1	2.28	12.3	2389	8.5	
NSGA	582	19.0	1.8	30.7	2043	21.7	

CO2 reductions. The choice of algorithm depends on specific priorities, such as cost minimization, environmental impact reduction, or peak-to-average ratio improvement.

Scenario-1: (without RES and ESS)

NSGA demonstrates the highest cost reduction of 9.2%, with notable reductions in PAR (18.4%) and CO2 emissions (10.7%).

PSO and BFA also exhibit substantial improvements over the UnScheduled scenario.

Scenario-2: (with RES and without ESS)

NSGA continues to outperform other algorithms, achieving a 10.4% cost reduction and significant improvements in PAR and CO2 reduction.

BFA and PSO show competitive results, with BFA providing the highest CO2 reduction (21.5%).

Scenario-3: (with both RES and ESS)

NSGA maintains its superior performance, achieving the highest cost reduction (19.0%), PAR reduction (30.7%), and CO2 reduction (21.7%).

BFA follows closely, demonstrating substantial improvements in all metrics.

PSO exhibits competitive results, especially in cost and PAR reduction.

XII. CONCLUSION

This research has presented an optimized model for the effective management of energy in a smart grid, integrating renewable energy resources (RERs) such as PV arrays, Micro Turbines (MTs), electrical energy storage systems (ESSs), and a Utility grid (UG). The inherent unpredictability of renewable resources was characterized using the beta Probability Density Function (PDF). The primary objectives of the study were to minimize the operational costs and energy consumption within a smart grid, as outlined in three distinct scenarios. Following the optimization of objective functions by the NSGA-II algorithm, the decision-making process facilitated the selection of the most optimal solution.

Incorporating renewable energy resources and the optimal scheduling of ESSs, the NSGA-II algorithm was employed to achieve cost and energy consumption reductions in the specified scenario. Specifically, for NSGA-II, the operational cost was recorded at 0.15 $/kW, with an energy consumption of 0.939 kWh. The outcomes of the study demonstrate the superior performance of the proposed algorithm compared to benchmark algorithms, showcasing reductions in energy cost, carbon emissions, and peak-to-average ratio (PAR). For instance, in scenario-2, the electricity bill witnessed a decrease of 16.4%, PAR reduced by 24.6%, and carbon emissions reduced by 15.2%.

Through comprehensive simulation and results analysis, it can be concluded that the proposed model holds significant merit in optimizing operational costs and enhancing energy efficiency within an intelligent grid.

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