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RESEARCH ARTICLE

Enhancing Grid-Connected Microgrid Power Dispatch Efficiency Through Bio-Inspired Optimization Algorithms

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ABSTRACT This work tackles the scheduling challenge of microgrids for smart homes, aiming to optimize energy management with both renewable and non-renewable sources. A power control center orchestrates the microgrid, coordinating distributed energy resources (DERs) for peak demand fulfillment and excess energy utilization. We propose a proportional-integral control system for efficient demand response, achieving reduced post-scheduling costs and a peak-to-average ratio. Comparative analysis reveals Ant Colony Optimization outperforms Binary Particle Swarm Optimization in cost and peak-to-average ratio reduction. Simulations explore two scenarios: Case 1 integrates with the main grid for reliability, while Case 2 utilizes solely renewable energy sources. Although Case 2 exhibits superior performance, Case 1's dependence on the main grid offers greater real-world feasibility. Therefore, Case 1 with optimized DER scheduling emerges as the recommended solution for enhancing microgrid efficiency and ensuring reliable power supply in smart homes.

INDEX TERMS Microgrid, real-time pricing, renewable resources, PV systems, wind energy systems, demand-side management, mixed integer linear problem, supply-side management, chance constrained optimization.

I. INTRODUCTION

Microgrids (µGs) have become integral components of energy infrastructure in many nations globally, including the United Arab Emirates, Canada, and California. These microgrids play a crucial role in electricity generation, primarily leveraging distributed energy resources (DERs). DERs encompass both renewable energy resources (RESs) and non-RESs energy sources. RESs tap into renewable natural resources like the sun, geothermal energy, wind, tides, and rain, including hydroelectric, geothermal, solar, and wind turbine (WT) energy. On the other hand, non-RESs, such as fuel cells, diesel engines, and microturbines (FC), are known to emit pollutants harmful to the environment, including large amounts of nitrogen oxide (NO_x), carbon dioxide (CO_2), sulfur oxide (SO_x), highlighting the environmental trade-offs associated with different energy sources.

In this context, the authors introduce an incentive-based program [1] that illustrates effective Macro Grid (MG) utilization. Under this program, users are given incentives to reduce their load demand in response to bids, receive additional incentives, or face penalties for non-compliance.

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During excess power situations, storage devices are charged, and surplus power is sold to the MG. This approach aligns with the broader objective of sustainable and efficient energy consumption. Similar to [2], the research examines different hierarchical, decentralized, and centralized control systems for microgrids. Instead of concentrating on a single method or ideal outcome, the study offers a thorough analysis of various microgrid control strategies.

Multiple algorithms are employed due to the complexity of unit commitment and economic dispatch issues. These algorithms use a variety of optimization methods. The most promising algorithmic methods for resolving these problems include binary particle swarm optimization (BPSO), genetic algorithms (GA), and ant colony optimization (ACO). However, the study also focuses on other programming paradigms, such as mixed integer non-linear programming (MINLP), integer linear programming (ILP), and MILP (MINLP).

This study employs two heuristic techniques ACO and BPSO, to schedule tasks while reducing costs and peak-to-average ratios (PAR). With MG and the batteries, SSM uses both non-RESs and RESs to satisfy the load requirement. The research classifies WT and PV arrays as RESs while classifying DE, MT, and FC as non-RESs. However, the chance-constrained optimization (CCO) method is used to handle the resource scheduling problem on the SSM by converting the problem into a MILP. The MILP branch and bond (B&B) approach is also used to solve the issue.

The use of different bio-inspired optimization algorithms for microgrid energy management is covered in detail in the thorough review [3]. In the context of microgrid power dispatch, the authors discuss the benefits and drawbacks of several algorithms, including ant colony optimization, particle swarm optimization, and genetic algorithms. Additionally, another paper explores techniques and algorithms targeted at enhancing power dispatch efficiency with a particular focus on grid-connected microgrids. In addition to highlighting the importance of optimization strategies in attaining dependable and effective power dispatch, it examines the difficulties related to grid integration [4].

The difficulties presented by high levels of renewable energy penetration in grid-connected microgrids are discussed in the paper [5]. In order to reconcile the intermittent nature of renewable sources, it looks into the best power dispatch mechanisms, offering insights into effective grid integration. Therefore, For scheduling purposes, many authors used meta-heuristic techniques to tackle the energy management problems of generation systems. Whereas, the roulette wheel-based distribution method is applied over PSO-based power balance in [6]. WTs, MTs, PV arrays, battery banks, residential loads, and utility grids are considered hybrid generation systems (HGS). However, the penalty mechanism is developed to check the effect of battery degradation in terms of discharge on a daily basis. Also, three power dispatching methods are used for result comparison. However, by using the roulette wheel (RW) redistribution mechanism, a great difference exists between the actual value and the expected value.

Optimal usage of DERs with power dispatch is a challenging task. They are used to reduce the burden of MG. As in [7], a market structure is proposed and stochastic scheduling of µG is explored, where the µG operator makes day-ahead power exchange commitments with MG. When deviating from commitments, µG should pay penalties. The authors did not consider the emission of MTs, however, minimum chances of commitment violation occur due to the maximum use of DERs and taking more financial benefits. Instantaneously, the power balancing needs to be maintained between generation and consumption.

A. CONTRIBUTIONS

In this study, the scheduling issue for demand-side appliances and supply-side generators is resolved. For this, a number of smart houses in residential areas are taken into consideration. The region has its own µG to handle load demand; MG is only used in extreme instances or in an emergency. For electricity generation, µG includes both RESs and non-RESs. The energy that will be used later is thought to be stored by the storage system.

1) DSM

Fifteen homes are considered from a residential area and to solve the scheduling problem of appliances, two heuristic algorithms are used which are the following:

- We propose two heuristic algorithms for scheduling demand-side appliances in a residential area with fifteen smart homes.
- The algorithms optimize the supply-demand structure of the residential smart grid's energy consumption, aiming to reduce overall expenses while adhering to peak-to-average ratio (PAR) constraints.
- Our innovative approach establishes an optimization problem to determine the best response strategy, operation times, and energy consumption of appliances.

2) SSM

In this paper, a µG which is connected to MG for power exchange has been considered and a scheduling technique is used for different aspects, which are the following:

- A µG connected to the main grid is introduced for power exchange and present a scheduling technique addressing various aspects.
- Our contribution involves the adoption of objective functions that optimally combine economical µG operation with efficiency improvement requirements.
- We developed a model to ensure optimal µG operation during unscheduled periods, considering uncertainties in load, non-renewable energy sources (non-RESs), and renewable energy sources (RESs).

- The proposed model employs a Mixed-Integer Linear Programming (MILP) technique based on the Continuous Cuckoo Optimization (CCO) method, effectively incorporating power generation restrictions.

The rest of the paper is organized as; literature review is discussed in Section II, the proposed DSM in Section III, the proposed SSM in Section IV, simulation results and discussion in Section V, and the conclusion in Section VI.

II. LITERATURE REVIEW

µG is vital to the development of a smart society. It is a mechanism for supplying power that includes DER and load. DERs include controllable loads, storage systems, non-RESs, and RESs. It operates in a regulated and planned setting.

The author proposes a multi-objective optimization algorithm based on PSO and an improved binary dragonfly algorithm (IBDA) [8]. The optimal result was achieved by comparing the proposed algorithm with a traditional PSO algorithm. Therefore, the proposed algorithm can achieve a better solution with higher accuracy and faster convergence. The paper does not provide a specific optimal result. Therefore, The algorithm used in the paper [9] is the improved extremum seeking algorithm (IESA) for power sharing control strategy of the microgrid. The optimal result of the IESA was demonstrated through simulations, showing improved tracking performance and robustness compared to the conventional extremum-seeking algorithm.

The survey investigates the integration of bio-inspired methodologies with other optimization methods for microgrid energy management, with a particular focus on hybrid optimization algorithms [10]. It provides a thorough summary of the most recent developments in hybrid techniques and how well they work to increase power dispatch efficiency. Thus, this study explores the relationship between machine learning and microgrid power dispatch and how machine learning techniques might be applied to optimise dispatch tactics. The authors emphasise how machine learning can be used to increase overall dispatch efficiency and adjust to changing grid conditions [11].

In [12], without categorizing the appliances, the authors suggested a method for scheduling appliances to meet the load requirement using RESs for one day. To reduce electricity bills, RESs are used to their fullest potential and it is reduced using Binary linear programming (BLP). After scheduling, the cost is reduced by 48% while the use of RESs is increased by 65%.

The authors [13], described an energy ecosystem that included demand response (DR) programs, hierarchical agents, and optimization. They make judgments to store energy based on DR, they used a vanadium redox battery. Utilizing energy ecology, intelligent hierarchical agents, and micro combined heat and power systems (*mu*CHPs) management approaches, these are employed to minimize overall electricity costs while maximizing user preferences. The authors developed a program called the gravitational search algorithm (GSA). The Gravitational Field Theory (GFT), which is based on the laws of mass interaction and gravity, is used. The outcomes of GSA are compared with those of real GA (RGA), central force optimization (CFO), and PSO in order to assess how each mass behaves utilizing a few common standard functions and highly effective search agents [14].

Two case studies from various nations were explored by the writers in [15]. The goals are achieved by employing MILP, and the goals include cost minimization, PAR, and load reduction while taking into account the DSM and SSM domains. To provide the load demand for SSM, RESs are utilized. Results from case studies in the Netherlands and Burundi are contrasted. therefore, the objective function is described to obtain a better cost. In [16], the bacterial foraging algorithm is hybridized with GA. By focusing on user comfort, the hybrid strategy achieves the goals of energy management which helps to reduce the cost and the load from off-peak hours to peak hours. Real time pricing (RTP) behavior in a real-time setting is not taken into consideration in this study.

The multiple environment dispatch problems (MEDP) are proposed in [17]. By comparing the outcomes of two case studies with and without RESs, this problem is resolved using ACO. Additionally, the gradient method is contrasted with the provided method. While reducing the overall running cost of RESs, the main goal is to reduce emissions. Results showed that RESs saved 6.20 percent of the cost over the gradient approach, whereas MEDPACO and techniques without RESs saved 4.50 percent. In [18], a control method for μ G is presented that utilizes RESs and distributed generators connected to the grid to completely reduce harmonic disruption. Two case studies are used to compare the active power filters (APFs) with the proposed techniques, which are smaller, and cheaper but more complex. Additionally, the authors consider quick dynamic reaction, straightforward design, and analysis stability. To enhance the power quality and lessen harmonic disruption, the power of common connection (PCC) is used.

The suggested system in [19] is measured against the traveling salesman problem (TSP). Whereas, TSP and the mobile robot optimization were applied using an ACO algorithm with an interval type-2 fuzzy system without modifying their parameters. The amount of research on fuzzy systems using optimization approaches and μ G is constantly growing. The authors in the article [20] suggested an adaptive neural fuzzy interference system (ANFIS) to improve the efficiency of power transfer between the load and source sides. Instant energy from the load demand and the available sources are used as training inputs for the approach. To meet the load demand for SSM, the authors intended to use WT, PV, ultracapacitors, fuel cells and batteries. The results show that μ G strives for better outcomes when used on various case studies. Furthermore, the power flow is expertly controlled.

Using enhanced BCO (EBCO), the economic dispatch issue of the μ G system is resolved [21]. The suggested model is based on the given limitations and time of use (TOU) price tariff. In two scenarios, energy management in both grid-connected and islanded modes is used. Different tests are conducted to evaluate the efficiency and performance of low-voltage distribution systems. The findings demonstrate that the suggested method is reliable, doable, and more efficient than existing algorithms.

Financial incentives are employed in [22] for unforeseen situations where the use of battery storage, powered by RESs and non-RESs, significantly reduces the load. Users must pay a fee when energy needs are high and it must be bought from the utility by paying a fee. The aggregator gathers the penalty data and sends it to the system operator, who uses it to calculate the consumer cost. The goal is to maximize the utility of the demand side while minimizing the cost and penalty of generation. An appliance schedule optimization problem was presented by the authors in [23]. The mathematical approach is utilized to maximize UC while minimizing the electricity cost and PAR reduction for thermostatically controlled appliances. For SSM, the objective is to reduce the fuel cost of generators.

Authors in [24] hybridized PSO with the pattern search (PS) algorithm in order to combine gas and power networks. By establishing an appropriate relationship matrix, the elements of key performance indicators (KPI) and μ G are connected. For two cities in a country, two different case studies have been explored. For the purpose of enhancing power quality, dependability, economic efficiency, and environmental preservation, a hybrid PSO-PS is used to identify the best KPI. The authors used both the grid-linked and islanded forms of μ G when creating [25]. The authors of this paper presented a hybrid cuckoo optimization algorithm (COA) and linear programming (LP) for the optimization of coordination protection of directional overcurrent relays (DORs), with the goal of determining the optimal value for the fault current limiter (FCL) at PCC. PCC is used to locate the best FCL solution. Enhance DORs' coordination of protection. The COA is suggested to enhance the cuckoo's behavioral pattern. To assess the efficiency and effectiveness of the proposed hybrid COA-LP, the results are compared with GA and PSO. This comparison reveals that the suggested technique has higher computational efficiency in terms of overall operating time and cost. To manage scheduling with unpredictable parameters, a par BPSO and ILP approach is suggested in [26]. In order to handle uncertain hot water demand and ambient temperature, the study aims to minimize costs while maximizing thermal comfort while using interval number analysis. The paper does not, however, include a waiting time calculation. In contrast, the authors suggested multi-objective mixed integer nonlinear programming (MO-MINLP) [27]. With the aim of minimizing the trade-off between energy conservation and UC, this method is suggested for the complete scheduling of appliances.

In the analysis that follows, it is determined that optimization approaches are crucial for real-world solutions. Heuristic algorithms are frequently utilized for scheduling appliances and aid in managing energy consumption through RESs in numerous studies. The load requirements of buildings, households, and commercial spaces are managed in the real world using RESs.

In this study, RESs and non-RESs are combined so that the resulting power fulfills the load requirement. Following the completion of the load, the battery storage and excess electricity are sold to MG.

List of Symbols

Symbol	**Decription**
E_Pr_{hour}	Electricity price
P_r^{ap}	Power rating of appliances
ζ	Appliances on/off status
ω_1 & ω_2	Inertia weights
χ	PAR
γ_T	Load for each hour
ϵ_T	Total cost
p_{ij}^d	Pheromone probability
$\tau_{ij}(t)$	Pheromone between i and j
α and β	Coefficients for τ
$\eta_{ij}(t)$	Heuristic factor
$J_{d(i)}$	Routes that ants could select
v	velocity
v_{min}	Minimum velocity
v_{max}	Maximum velocity
n	Number of ants
$c_1 and c_2$	Acceleration constant
p_{best}	Local best
g_{best}	Global best
$V(t)$	Velocity update
$X(t)$	Position update
$Sig_{(i,j)}$	Sigmoid function for appliance status
$\exp^v(t)$	Exponent of velocity
λ	Total load consumed
P_{PV}	Output power of PV
G	Insolation on surface of PV panel
ρ_r	Rated power for PV
η_{PV}	Efficiency
$P^m in_{PV}$	Minimum power of PV
$P^m ax_{PV}$	Minimum power of PV
P_{WT}	Output power of WT
ψ_r	Rated power for WT
$v(t)$	Wind speed at time 't'
v_{in}	Cut-in speed
v_r	Rated speed
$P^m in$	Minimum power
$P^m ax$	Maximum power
P_{Buy}	Power buy from MG
P_{Sell}	Power sell to MG
P_G	MG power exchange
$P^m ax_{Buy}$	Maximum power bought

List of Symbols

P^max_{Sell}	Maximum power sold
P^{ch}_{max}	Maximum power to be charged
η_{ch}	Charging efficiency
P^{disch}_{max}	Maximum power to be discharged
P^{min}_{B}	Minimum power stored in the battery
η_{disch}	Discharging efficiency
P_{ch}	Power charged
P_{disch}	Discharged power
$P_{(hour,G)}$	Power generated
$Cost_G$	Generation cost

III. DSM

DSM plays an important role in making SG reliable and efficient. It provides benefits to consumers and utilities for efficient energy management. For DSM, the residential area is under consideration, where each home contains a smart meter. The smart meter is connected to a central controller to ensure effective and rapid response and better decisions for optimized power consumption between consumers and the utility.

A. PROPOSED MODEL FOR DSM

To provide incentives to consumers, DSM enables efficient and effective scheduling of the appliances. Figure 1 illustrates the structure of the DSM to reduce electricity bills and to provide reliable operations between the utility and the consumers. With the help of this structure, both consumers and the utility can lower PAR for the ongoing running of SG. All appliances ask the central scheduler to perform the task, and the scheduler determines the state of the appliances at a specific time.

Proposed system model consists of fifteen homes. The model is based on three main stakeholders. These are residential areas, μ G and MG. There are fifteen homes with appliances, these appliances are; fans, lights, water pumps, vacuum cleaners, air conditioners, and refrigerators. The second component is μ G, which contains DERs. DERs include both RESs and non-RESs. RESs used in this study are WT and PV. However, non-RESs include DE, MT, and FC.

In this work, base appliances are considered to manage the load demand of multiple homes. The objective of the paper is electricity cost reduction.

1) LOAD

Energy consumption is determined by the power rating and on/off status (1 for on and 0 for off) of appliances. The appliances are scheduled for 24 hours a day. It is calculated as given in equation (1):

$$\gamma_T = \sum_{ap=1}^{n} (P_r^{ap} \times \zeta) \tag{1}$$

In this equation ζ represents the on and off status of the appliances.

B. PROBLEM FORMULATION

Problem formulation is carried out using multiple knapsack problem (MKP), which is an NP-hard problem. It is a resource allocation problem, there is a set of resources that are considered as knapsacks, with a number of objects. The resources should lie within the capacity limit of the sack. The Multiple Knapsack Problem (MKP) is an extension of the classical Knapsack Problem, which is a combinatorial optimization problem. In the Multiple Knapsack Problem, there are multiple knapsacks or bins, each with its own capacity constraint, and a set of items with associated weights and values. The goal is to determine the optimal way to allocate the items to the knapsacks in a manner that maximizes the total value while adhering to the capacity constraints of each knapsack. MKP is used to formulate the scheduling problem, where appliances are scheduled for a day.

1) COST

The cost is determined according to the load consumed. It is calculated as given in equation (2):

$$\epsilon_T = \sum_{hour=1}^{T} (\sum_{ap=1}^{n} (E\_Pr_{hour} \times \ldots P_r^{ap} \times \zeta)) \tag{2}$$

Cost is calculated by multiplying the electricity price with the power rating and on/off status of appliances, as shown in equation (2).

2) PAR

To maintain the stability between demand and supply, PAR is used as a parameter of utility. PAR is calculated as given in equation (5). It is calculated by taking the ratio of the maximum peak of energy consumption and average energy consumption. Peaks are evaluated as shown in equation (3) and the average is taken as given in equation (4).

$$Peak_L = maximum(\gamma) \tag{3}$$

$$Avg_L = \frac{\sum_{t=1}^{T}(\gamma)}{T} \tag{4}$$

$$\chi = \frac{Peak_L}{Avg_L} \tag{5}$$

3) OBJECTIVE FUNCTION

MKP is a resource allocation problem, where multiple set of resources is considered as sacks with a number of appliances as items. MKP is mapped in this scenario as given below:

- Number of sacks is considered as 24. Each sack is represented as 1 hour or 60 minutes.
- 6 appliances are considered as items.
- Weights of items are the power consumed by each item with power ratings that exist within the minimum and maximum limit.
- Allowable power is considered as the capacity of the sack.

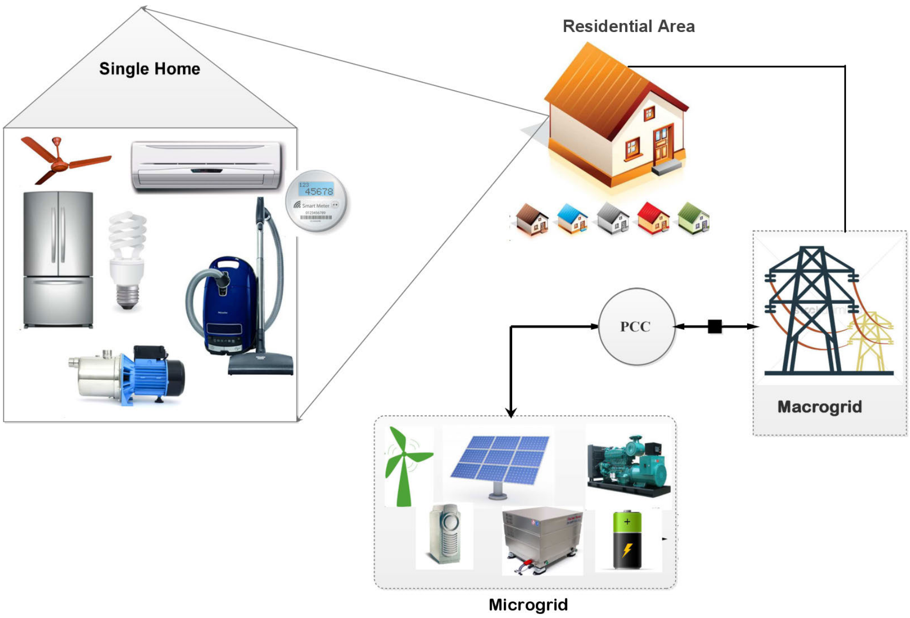


FIGURE 1. Proposed DSM model.

The knapsack problem is defined in equation (6) with the capacity limits of sacks as discussed in the equations below. Equation (8) shows the status of the appliances that should be 1 or 0, where "1" for "on" and "0" for "off". PAR should be minimum from the maximum peak load as shown in equation (9). The objective function is designed for a day as [31]:

Minimize:

$$\sum_{i=1}^{T}\left(\sum_{j=1}^{n}(E\_Pr_i \times \zeta_{ij}) + \chi\right) \tag{6}$$

subject to (7)

$$\sum_{i=1}^{T}\left(\sum_{j=1}^{n}\zeta_{ij} \in [0, 1]\right) \tag{8}$$

$$\chi \leq Peak_L \tag{9}$$

$$0 < hour \leq T \tag{10}$$

C. OPTIMIZATION TECHNIQUES

Two optimization strategies are used in this research to schedule appliances and evaluate the effectiveness of the suggested system. Below is a discussion of them:

1) ACO

Using an extensive search space and an ideal path, ACO is utilized to locate the best solution. The ants follow the pheromones of their partner ants to obtain food while searching for the shortest route.

Ants move from one node to another as the probability to select the next node is maximum from a large search space. The probability of pheromone is calculated by using equation (11) [32]:

$$p_{ij}^{d} = \frac{(\tau_{ij}(t))^{\alpha} \times (\eta_{ij}(t))^{\beta}}{\sum s \in J_{d(i)}(\tau_{is}(t))^{\alpha} \times (\eta_{is}(t))^{\beta}} \tag{11}$$

In algorithm 38, initially, system parameters are initialized. Here, each appliance is represented by the number of ants. On the basis of pheromone, the pattern considering the status of the appliances is selected. This pattern defines the optimal solution in appliance scheduling problems. This algorithm runs for 24 hours and the fitness of the pheromone is evaluated for each timeslot i.e. 24 times within a day.

To solve the problem, objective function constraints are applied. In peak hours, it makes sure that the hourly load demand of each residence should not exceed a predefined threshold. G_{best} value is returned in each hour which is in the form of an array representing appliance scheduling. Parameters of ACO are given in Table 1.

TABLE 1. ACO parameters.

Parameters	Values
Number of ants	6
Visibility factor	6
Pheromone factor	2
Stoping criteria	Max. Iteration
Trail factor	0.5
Evaporation rate	5
Max. iteration	200

2) BPSO

PSO is a population-based method used to optimize the problem by improving the solution iteratively as in [33]. Therefore, BPSO is a binary variant of PSO, it is also a nature-inspired algorithm and has the same features as PSO.

Algorithm 1 ACO

ACO parameters initialization: pheromone, routes, iterations
for users = 1:15 **do**
  For all appliances ap $\in$ n
  For all timeslots t $\in$ T
  Randomly generate population
  Pheromone Initialization
  for it=1:Maxit (Iterations) **do**
    for ai=1:Nants **do**
      For no. of tours
      For each ant to update pheromone trails using equation (11)
      Evaluate objective function for each ant using equation (6)
      for t=1:T **do**
        Calculate the load consumed using equation (1)
        Calculate Electricity cost using equation (2)
        Calculate χ using equation (5)
        locally update pheromone for each ant
        Choose P_{best}
      end for
      Globally update the pheromone for each ant
    end for
    Repeat the steps till maximum iterations
  end for
  Record the demand of users
  Get supply from DERs
  if $Demand < Supply$ **then**
    Calculate surplus power
    Charge the batteries
    if $surplus! = 0$ **then**
      Sell power to MG (Incentive)
    end if
  else if $Demand > Supply$
    Calculate insufficient power
    Check Power in batteries
    if $Insufficient\_power! = 0$ **then**
      Buy electricity from MG (Penalty)
    end if
  end if
end for

In BPSO, parameters are initialized as shown in table 2. To evaluate the fitness of particles, a random number is defined as the probability for the on and off status of appliances as '1' or '0'. The initial velocity of particles is calculated as given in equation (12):

$$v = v_{min} + (v_{max} - v_{min}) \times (rand(swarm, n)) \tag{12}$$

The initial position is updated after scheduling and the on or off status of appliances is updated. 'pbest' is the local best solution of particles in the current iterations and 'gbest' returns the global best solution, where cost and PAR are minimized. The velocity is updated using the defined equations in [34].

$$V(t) = \omega \cdot v(t) + c_1 r_1 \cdot (p_{best}(t) - X(t)) + c_2 r_1 \cdot (g_{best}(t) - X(t)) \tag{13}$$

$$X(t) = X(t) + V(t) \tag{14}$$

Equations (13) and (14) are used to update the velocity and position of each particle. The sigmoid function is used to convert the status of appliances in the binary form [35]. It is formulated as:

$$Sig(i,j) = \frac{1}{1 + e^{v}(t)} \tag{15}$$

D. PCC

PCC is the point, where, μ G is connected to MG and manages the power flow between them. In this paper, power exchange is managed by PCC among the stakeholders of

Algorithm 2 BPSO

```
BPSO parameters initialization (particles, inertia weight, initial and final velocity, acceleration constants, and iterations)
for users = 1:15 do
    For all appliances
    For all timeslots
    Randomly generated population
    Initialize particle velocity
    Initialize position of particles to P_best
    Initialize on/off status of appliances
    for it=1:Maxit (Iterations) do
        for t=1:T do
            Evaluate objective function
            Update particle velocity using equation (13)
            Update particle position using equation (14)
            if v <v_min && v >v_max then
                v = v
            else if v <v_min then
                v = v_min
            else if v >v_max then
                v = v_max
            end if
            Apply sigmoid function using equation (15)
            For each bit
            if rand < Sig then
                bit = 1
            else
                bit = 0
            end if
        end for
        Global best (g_best) is saved
    end for
    Return best schedule
    for hour = 1:T do
        Record the demand of users
        Get supply from DERs
        if Demand < Supply then
            Calculate surplus power
            Charge the batteries
            if surplus! = 0 then
                Sell power to MG (Incentive)
            end if
        else if Demand > Supply then
            Calculate insufficient power
            Check Power in batteries
            if Insufficient_power! = 0 then
                Buy electricity from MG (Penalty)
            end if
        end if
    end for
end for
```

the proposed system model. It acts like a switch to allow the power exchange with MG when demand is high and buy power from MG or sell power in case of excessive power.

IV. SSM

The sources used in this paper are RESs and non-RESs. These generators are PV, WT, MT, FC, and DE. Moreover, batteries are used to store surplus energy generated by DERs. PV and

TABLE 2. BPSO parameters.

Parameters	Values
Number of iterations	100
wf	1
wi	0.4
c1	1
c2	1
Swarm	10
v_{min}	-2
v_{max}	2
n	6
Stopping criteria	Max. Iteration

WT both face uncertainties while generating power. Contrary to the intermittent nature of RESs, generators give reliable and stable power.

A. PROPOSED MODEL FOR SSM

To meet the load demand of an area–which could be residential, commercial, or industrial μ G includes DERs and the storage system. A μ G mainly uses the grid-connected and islanded modes of operation. With the aid of MG, μ G runs in linked mode to the grid. However, in islanded mode, μ G operates independently without the help of MG.

Energy trading for SSM is made possible through the usage of the μ G's grid-connected mode. A residential area load demand is met by μ G. The proposed SSM is illustrated in figure 2.

1) PV

Solar radiation is the only source of power for PV systems. Equation (16) is used to compute the output power of PV.

$$P_{PV}(t) = \frac{G(t)}{1000} \times \rho_{rated} \times \eta_{pv} \tag{16}$$

2) WT

When the wind blows, WT's rotors turn, creating power. The output power of WT is determined using the below equations:

$$P_{WT}(t) = \begin{cases} 0 & if\ v \leq v_{in}, \\ \psi_r \times \dfrac{v(t) - v_{in}}{v_r - v_{in}} & if\ v_{in} \leq v(t) \leq v_r, \\ \psi_r & if\ v_r \leq v(t) \leq v_{out}. \end{cases} \tag{17}$$

3) MT

On a comparatively limited scale, MT is utilized for power generation to create heat and electricity. The generator's advantages include being lighter, more efficient, and emitting fewer emissions. It has low capital, maintenance, and operating costs because of its modest size.

4) DE

Electrical generators known as DEs come in a variety of sizes and characteristics and are used in residential, commercial, and industrial settings. DEs of a smaller size are adequate for usage at home. In this study, power generation for residential areas is limited to a small-scale DE.

5) FC

FCs emit large amounts of x. FCs are utilized as a backup option to generate power because of their high emission. A 2.8 megawatt FC plant is utilized as California [30] and is taken from the real world. Using the constraint specified in the equation (24), the FC's output power is determined.

6) ENERGY STORAGE SYSTEM

There is a requirement to store extra energy provided by DERs because the power supplied by WT and PV is entirely reliant on the weather. Batteries are utilized for effective energy storage to hold the extra power produced by DERs. Batteries are used to store energy generated in excess. The amount of energy stored must not exceed the battery's maximum capacity. To compute the charging and discharging of batteries, the equation (18) as presented in [7] is used.

$$P_B(t) = P_B(t-1) + P_{ch}(t)\eta_{ch} - \frac{P_{disch}}{\eta_{disch}}, \ \forall t \in 24 \tag{18}$$

7) MG POWER EXCHANGE

The power exchanged with MG is determined by using equation (19). When more power is needed or when the current level is too high, MG is used to swap it.

$$P_G(t) = P_{Buy}(t) - P_{Sell}(t) \tag{19}$$

B. PROBLEM FORMULATION

The economic dispatch problem optimization is the goal of SSM. The scheduling of DERs thereby minimizes cost. The CCO and MILP approaches are used to formulate the problem in this research, but the B&B approach is used to find the solution.

1) CCO

It is used to find solutions to issues with a variety of uncertainties [36]. By limiting the feasible zone while locating the ideal solution, the confidence level is raised. Therefore, limitations are created by taking potential uncertainties into account.

The output power limitations for PV and WT, respectively, are shown in the formulae 20 and 21. The output power of PV and WT falls within the previously mentioned equations' upper and lower limits for power. The constraints for RESs are:

$$P_{PV}^{min} \leq P_{PV}(t) \leq P_{PV}^{max} \tag{20}$$
$$P_{WT}^{min} \leq P_{WT}(t) \leq P_{WT}^{max} \tag{21}$$

According to the limitations in equations (22), (23), and (24), the output power of FC, MT, and DE is represented in the defined threshold.

$$0 \leq P_{MT}(t) \leq P_{MT}^{max} \tag{22}$$
$$P_{DE}^{min} \leq P_{DE}(t) \leq P_{DE}^{max} \tag{23}$$
$$P_{FC}^{min} \leq P_{FC}(t) \leq P_{FC}^{max} \tag{24}$$

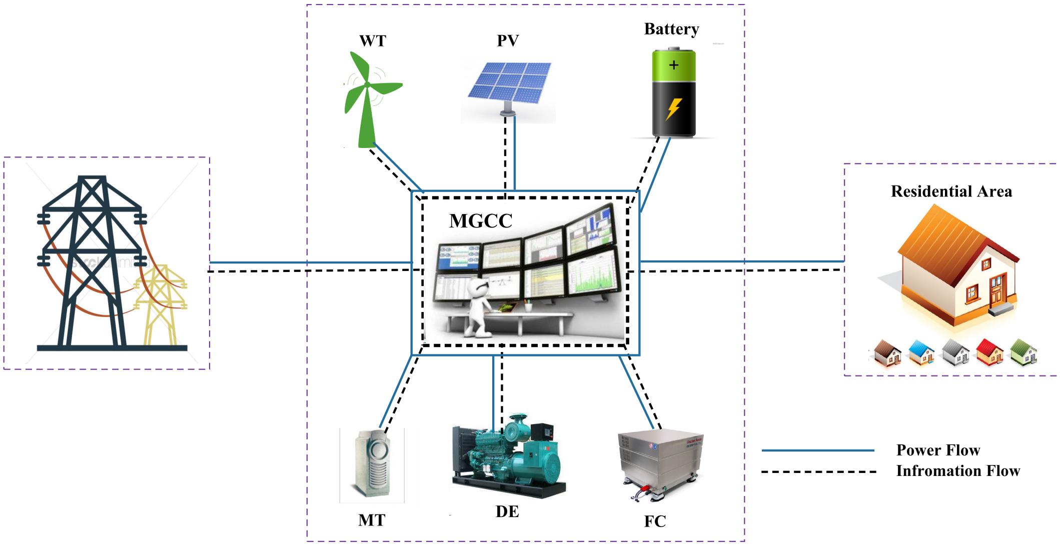


FIGURE 2. **Proposed SSM model.**

Equations (27) and (28) are used to determine the maximum charging and discharging of batteries. In contrast, the charging and discharging for a day are calculated using the equations (25) to (30).

$$P_{ch}^{max} \leq 0.1E_B^{max}(1-\zeta_B(t)) \tag{25}$$
$$P_{disch}^{max} \leq 0.1E_B^{max}\zeta_B(t) \tag{26}$$
$$P_{ch}^{max} \leq (P_B^{max} - P_B(t-1))\eta_{ch} \tag{27}$$
$$P_{disch}^{max} \leq \frac{(P_B(t-1) - P_B^{min})}{\eta_{disch}} \tag{28}$$
$$P_{ch}^{min} \leq P_{ch}(t) \leq P_{ch}^{max} \tag{29}$$
$$P_{disch}^{min} \leq P_{disch}(t) \leq P_{disch}^{max} \tag{30}$$

Power trading is managed by PCC. The limits for the purchase and sale of power are determined as shown in equations (31) and (32).

$$0 \leq P_{Buy}(t) \leq P_{Buy}^{max} \tag{31}$$
$$0 \leq P_{Sell}(t) \leq P_{Sell}^{max} \tag{32}$$

2) B&B

It depends on a search space's upper and lower bounds being effectively evaluated [37]. The B&B approach is similar to the divide and conquer strategy. Before computing, the candidate solution computed bound aims are examined to see if they are optimal; if not, they are ignored until better or optimal results are discovered. The branches indicate the solution set.

The proposed model includes the par B&B method because it is the most extensively used MILP technique. Equation (33) presents the objective function to reduce the overall generation cost, and equations (20)-(32)l specify the restrictions.

$$minimize \sum_{x=1}^{T}\sum_{y=1}^{ngen} TC_{xy} \tag{33}$$

$$s.t.$$

$$\sum_{y=1}^{ngen} P_y(t) + P_G(t) + P_B = Demand(t) \tag{34}$$
$$TC_{xy} \geq 0 \tag{35}$$

(20), (21), (22), (23), (24), (25), (26), (27), (28), (29), (30), (31), (32)

V. SIMULATION RESULTS AND DISCUSSION

The performance of the proposed solution is validated for appliance scheduling under DSM, simulations are conducted. Two optimization techniques are used for comparison in terms of cost and PAR. For SSM, CCO has applied MILP and B&B methods.

A. RESULTS FOR DSM

Two optimization techniques are used for comparison in terms of cost and PAR. The techniques compared are ACO and BPSO. For simulations, results are taken with and without MKP.

1) APPLIANCES

Six appliances are considered for fifteen homes and selected according to the basic needs of each home. These include lamps, fans, refrigerators, air conditioners, water pumps, and vacuum cleaners. Table 3 lists the appliances along with their power values.

2) RTP

In smart grids, RTP is a dynamic pricing mechanism wherein the price of electricity fluctuates according to the actual, real-time supply and demand situations within the power system. RTP, in contrast to conventional fixed-rate tariffs, takes into account the shifting dynamics of the market,

TABLE 3. Parameters of appliances.

Appliances	Power (kWh)	Rating
Fans	0.75	
Lights	0.60	
Refrigerator	0.725	
AC	3.517	
Water pump	1	
Vacuum cleaner	0.7	

enabling customers to react to price signals and choose their electricity usage wisely. Therefore, RTP tariff is defined by the network operator to set prices based on the demand and supply. In the RTP environment, prices are announced before the period starts. RTP tariff is used to calculate electricity bill which is represented in figure 3. Users have to set their day ahead schedule to get more incentives or comfort. Therefore, the RTP tariff is used to calculate the electricity bill for a day.

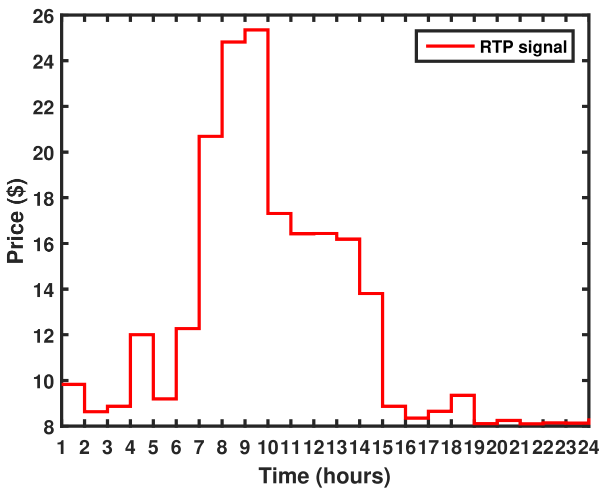


FIGURE 3. RTP price signal.

3) ENERGY CONSUMPTION

Figure 4 shows the energy consumption pattern of scheduled and base loads for a day. The base load pattern shows that user activities are high during 7-10 and 13-19 hours, which leads to high PAR and cost. The maximum consumption of ACO and BPSO scheduled load limit is 1.2 kWh to 2 kWh respectively. From the comparison, it is verified that the peak load after scheduling is minimum than the unscheduled load.

4) RESULTS WITHOUT MKP

The results without knapsack are different while comparing with MKP results. The PAR comparison between unscheduled, ACO and BPSO are presented in the table 4.

Figure 5 shows that peaks are reduced with respect to PAR after scheduling. The results of PAR in unscheduled is 1.66 and after scheduling costs with ACO and BPSO are 0.77 and 1.31 respectively. However, 54% PAR is improved with ACO and 21% with BPSO as compared to unscheduled cases. Thus, ACO performs better than BPSO.

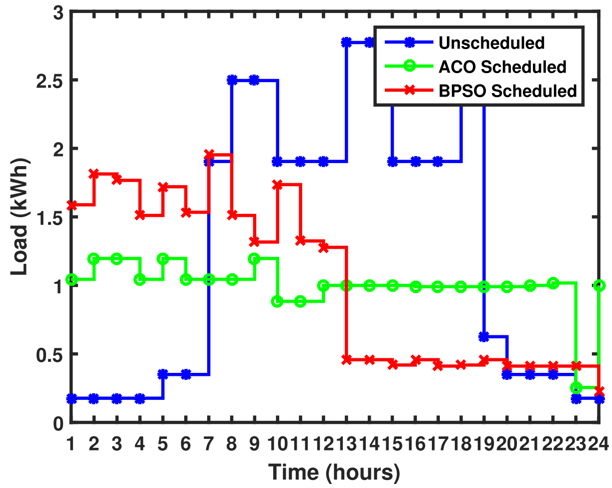


FIGURE 4. Energy consumption.

TABLE 4. Comparison of PAR (without MKP).

Techniques	PAR (kWh)	Difference	Difference Percentage (%)
Unscheduled	1.6651	– –	– –
ACO	0.77419	0.89091	54
BPSO	1.3082	0.35694	21

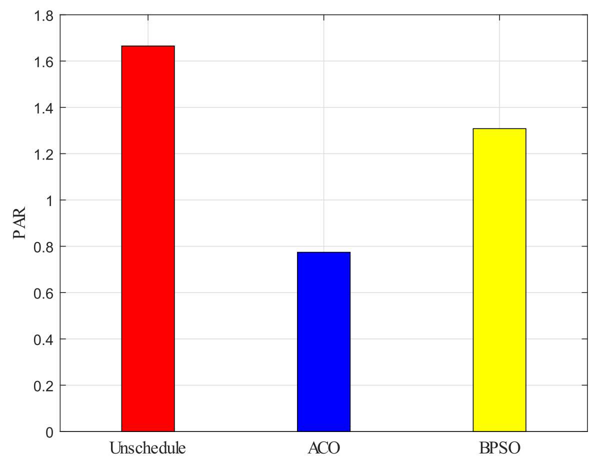


FIGURE 5. PAR of utility (without MKP).

TABLE 5. Comparison of cost (without MKP).

Techniques	Total Cost ($)	Difference	Difference Percentage (%)
Unscheduled	39.843	– –	– –
ACO	25.149	14.695	37
BPSO	30.408	9.4359	24

Table 5 shows the comparison of the total cost of one day without applying the knapsack problem, between ACO and BPSO-based energy management systems. Howewhenafter scheduling, 37% PAR is improved with ACO and 24% with BPSO as compared to base load PAR. Thus, ACO performs better than BPSO for cost and PAR as well. The cost comparison is given in figure 6.

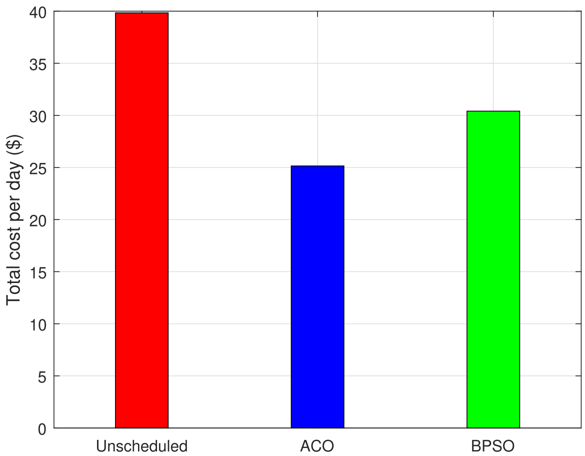


FIGURE 6. Cost profile (without MKP).

5) RESULTS WITH MKP

The results with MKP are shown in table 6 and illustrated in figure 7. After scheduling, ACO has minimum PAR then BPSO, and unscheduled. The difference between ACO with BPSO and unscheduled is 58% and 82%.

TABLE 6. Comparison of PAR (with MKP).

Techniques	PAR	Difference	Difference Percentage (%)
Unscheduled	5.41	−−	−−
ACO	1	4.41	82
BPSO	2.25	3.16	58

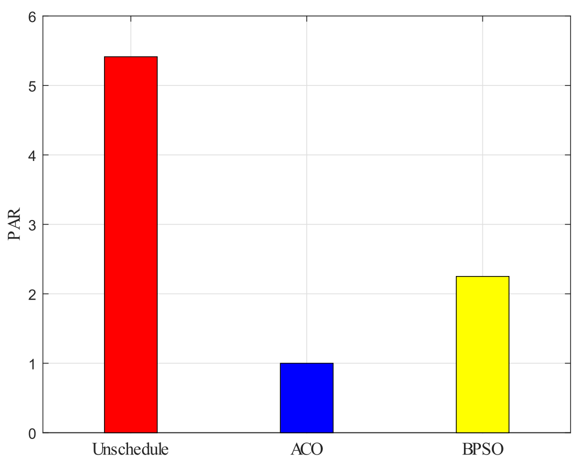


FIGURE 7. PAR of utility (with MKP).

By applying MKP, cost becomes high as compared to without MKP. After scheduling, ACO performs better in minimizing total cost. The economic difference between ACO with BPSO and unscheduled is 09% and 92%. Thus, the overall cost is high as compared to without MKP. The comparison of cost between ACO, BPSO, and unscheduled is given in table 7 and demonstrated in figure 8.

TABLE 7. Comparison of cost (with MKP).

Techniques	Total Cost ($)	Difference	Difference Percentage (%)
Unscheduled	349.72	−−	−−
ACO	28.38	321.33	92
BPSO	319.92	29.80	09

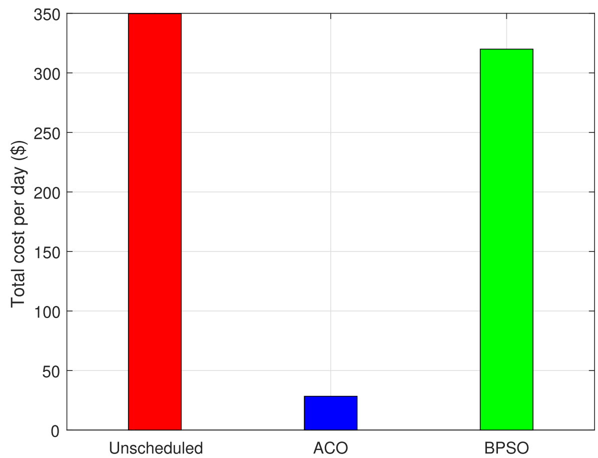


FIGURE 8. Cost profile (with MKP).

B. FEASIBLE REGION

A feasible region is an area in which results are satisfied by the objective function. The area is bounded by a set of points. In this work, a feasible region is identified for cost on the basis of load consumed. Fifteen homes are considered with the objective to minimize electricity costs by managing load consumption. The total cost is computed according to the load consumed by the consumers. The objective function is given in equation (36):

$$minimize(\epsilon_{hour}^{total}) \tag{36}$$

The electricity price is calculated using an RTP signal. The range of the RTP signal varies between 8.10 - 25.35 ($/kWh). To identify the boundary of feasible regions, four cases are considered:

$Case\ 1 : minimum(load), maximum(price)$
$Case\ 2 : minimum(load), minimum(price)$
$Case\ 3 : maximum(load), minimum(price)$
$Case\ 4 : maximum(load), maximum(price)$

Figure 9 shows the feasible region for electricity consumption cost. Trapezium shows the range of total cost by P1, P2, P3 and P4. The shaded area is the feasible region with the boundary points P1, P2, P5, P6, and P4. The cost that lies within the shaded area at any timeslot is feasible and electricity costs are minimized in that area. $P_1(0.67, 1.45)$

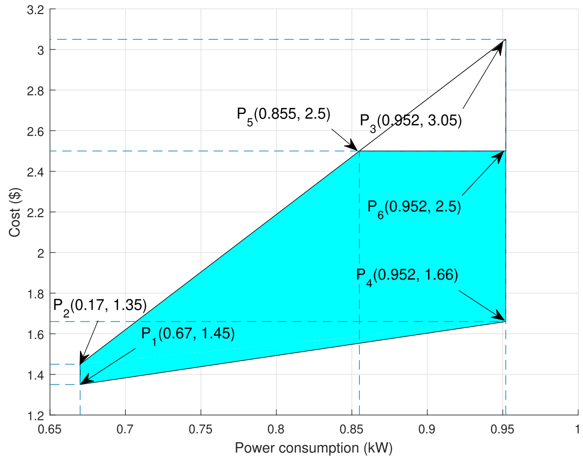


FIGURE 9. Feasible region of electricity consumption cost.

TABLE 8. Operating cost of each generator.

Generators	Operating cost ($/h)
Photovoltaic arrays	0.05
Wind turbine	0.007
Microturbine	0.08
Fuel cell	0.2
Diesel engine	0.022

shows the consumption cost in a timeslot with minimum price and $P_2(0.17, 1.35)$ shows the minimum cost in a timeslot when the load is minimal. $P_3(0.952, 3.05)$ represents minimum cost, and $P_4(0.952, 1.66)$ shows maximum cost when the load is maximum during on and off-peak hours.

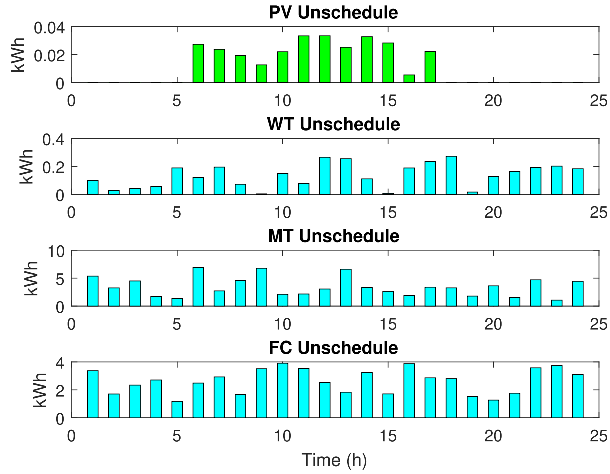
When the cost limits are applied, P3 is excluded from the feasible region. When the cost is 2.5 \$, $P_5(0.855, 2.5)$ and $P_6(0.952, 2.5)$ represents the maximum power consumption. Lines P5 and P6 show that consumers can increase power consumption at a low cost. However, P4 and P6 represent that a user can consume more energy by minimizing their consumption cost.

C. SSM

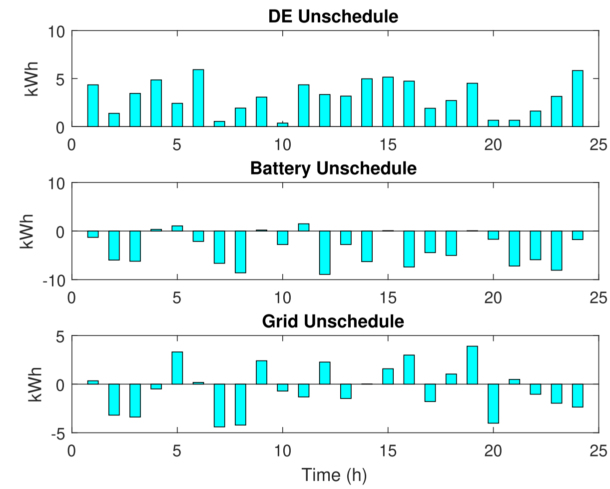
Scheduling the output power of DERs on SSM is a challenge. These are planned to reduce the cost of generation. By converting the scheduling issue into a MILP problem and solving it using the B&B approach, the scheduling issue is expressed using CCO. Hourly timeslots are used to schedule DERs for the entire day.

The running costs of each generator are shown in Table 8 which is taken from [6] and is considered to be fixed. Equation (16) and (ref)WT are used to compute the power of PV and WT, respectively. The FC, DG, and MT power profiles were extracted from [28] and [29]. Tables 9 and 10 display the parameters used for battery and MG swap, respectively.

Parameters used for battery and MG exchange are shown in tables.



(a) Power Profile of PV, WT, MT, and FC



(b) Power Profile of DE, Battery, and MG

FIGURE 10. Unscheduled power profile.

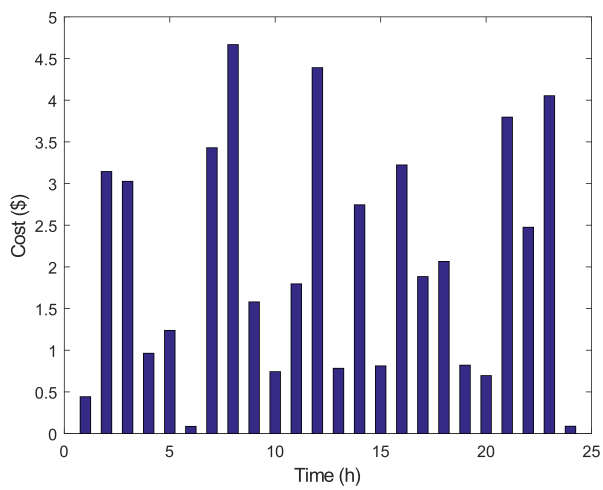
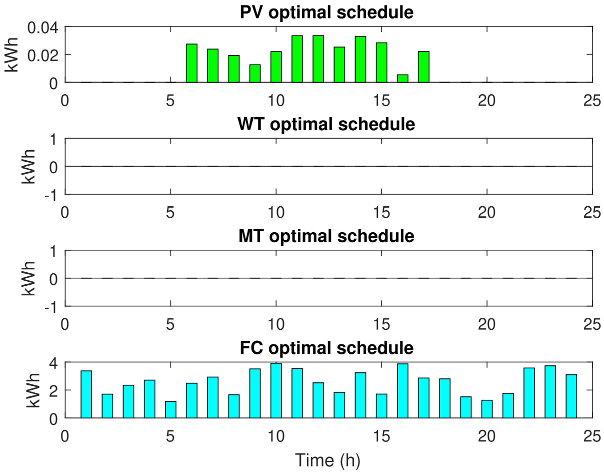
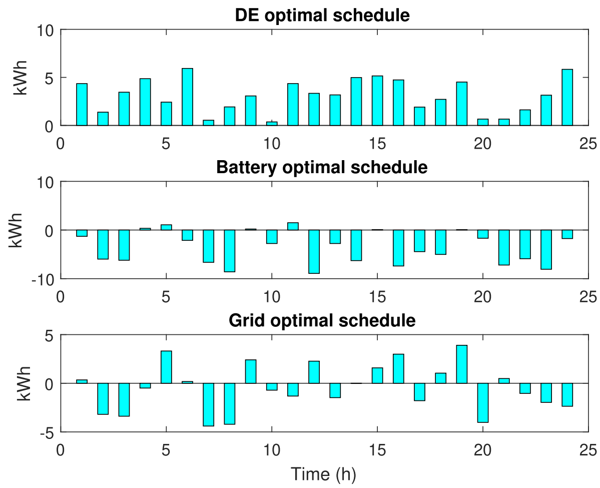


FIGURE 11. Unscheduled cost profile of DER.

In this work, the power generated from DERs before scheduling is shown in figure 10 and cost in figure 11. For scheduling purposes, two cases are considered for SSM.



(a) Power Profile of PV, WT, MT, and FC



(b) Power Profile of DE, Battery and MG

FIGURE 12. **Case 1: schedule power profile.**

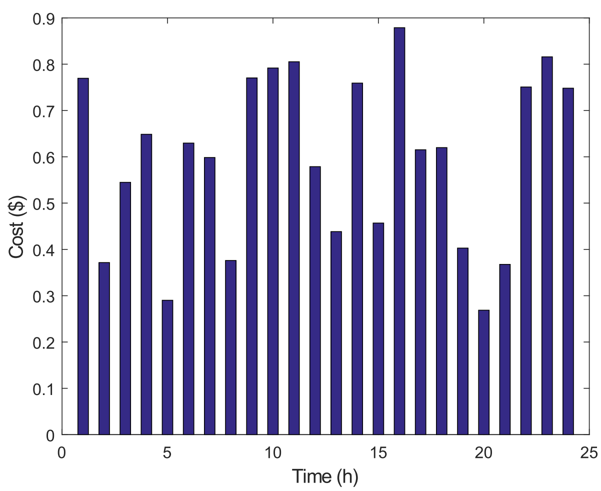
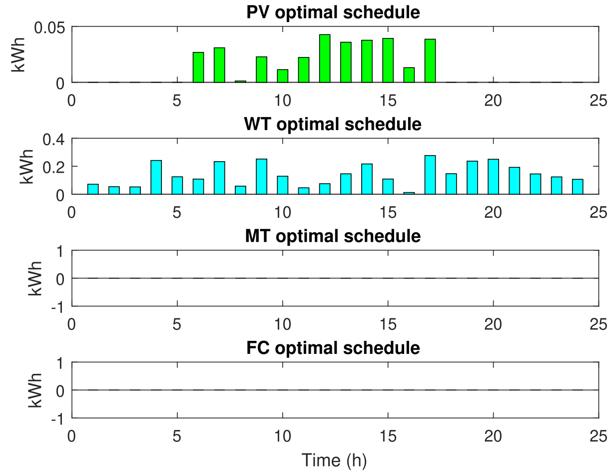


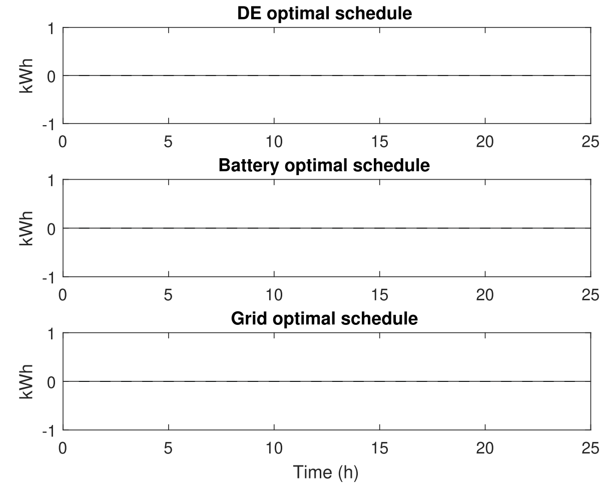
FIGURE 13. **Case 1: scheduled cost profile of DER.**

1) CASE 1

PV, DE, batteries, and FCs are used after scheduling by prioritizing them while MGCC helps to exchange power between the residential area and MG. Figure 12 presents the exchange's power to meet the load demand. However, in case 1, for the backup option, WT and MT are saved.



(a) Power Profile of PV, WT, MT and FC



(b) Power Profile of DE, Battery and MG

FIGURE 14. **Case 2: schedule power profile.**

TABLE 9. **Parameters for battery.**

Parameters	Value
η_{disch}	1
η_{ch}	0.80
Maintenance and operation cost	0.6 ($/kWh)

TABLE 10. **Parameters for MG.**

Parameters	Value
$Cost_{Buy}$	0.09 ($/kWh)
$Cost_{Sell}$	0.03 ($/kWh)
P_{Buy}^{max}	10 (kWh)
P_{Buy}^{min}	0
P_{Sell}^{max}	7 (kWh)
P_{Sell}^{min}	0

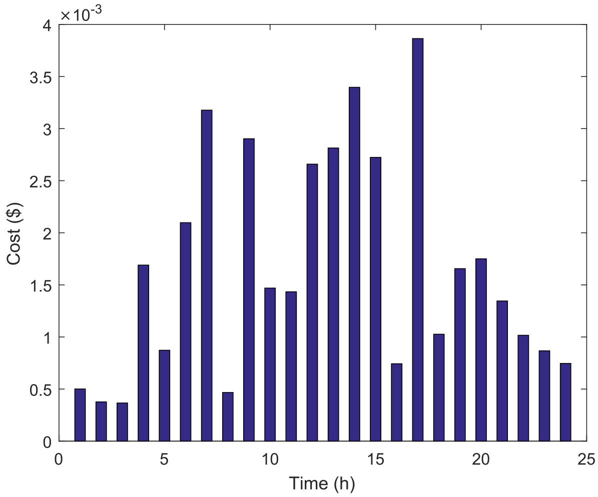


FIGURE 15. Case 2: scheduled cost profile of DER.

To minimize the overall operational cost, the generators are used presented in figure 13.

2) CASE 2

In this case, to further minimize the cost RESs are used to fulfill the load demand without the interference of MG. The RESs used are PV and WT. Power generated from these sources is given in figure 14.

Simulations proved that better and more economical results are found by using RESs while other generators are used for backup options as shown in figure 15. Results are also found better while using only RESs, but it is not suitable due to uncertainties in power generation by RESs.

VI. CONCLUSION

Our research effectively tackled the complex scheduling issues in demand-side management (DSM) and supply-side management (SSM). We developed a customised microgrid (μG) using both renewable and non-renewable energy sources (non-RESs), concentrating on a group of smart homes in a neighbourhood. During times of emergency or high demand, this μG smoothly connected to the Macro Grid (MG) and efficiently controlled load needs. We were able to manage extra energy and adjust to changes in demand by using a storage system. Through communication with the MG, coordination of Distributed Energy Resources (DERs) inside the μG optimised appliance scheduling, guaranteeing effective power management. The MG, μG, and residential sectors were able to interchange energy in a coordinated manner thanks to the Power Control Centre (PCC). The simulation findings, which showed a notable decrease in cost and PAR post-scheduling, proved the effectiveness of our approach. ACO performed better than BPSO in our comparison study in terms of cost and PAR. We were able to investigate the solution space by defining an area that the goal function may exist in under all circumstances. After DER scheduling was thoroughly examined, Case 2 produced better results; however, we suggested Case 1 for real-time implementation because of the uncertainties involved in depending just on RESs (PV arrays and WTs). Overall, our results highlight how well our suggested method works to improve the dependability and efficiency of microgrid operations in intricate urban environments.

A. SIGNIFICANCE AND CONTRIBUTION

Beyond technical innovations in scheduling, our research has broader implications for smart grid management. We contribute to the growing body of knowledge on microgrid optimization by comparing and evaluating different methodologies. Importantly, our recommendation of Case 1 for real-world implementation underscores the need to prioritize both reliability and practicality when integrating these solutions. This work establishes a comprehensive framework for efficient and dependable energy management in microgrids and smart homes. Our scheduling approach and detailed performance analysis further the conversation on resilient and sustainable energy solutions. Ultimately, the knowledge gained here can inform practitioners, academics, and policy-makers in designing effective microgrid management strategies for smart grids. We believe our approach both advances the development of intelligent and sustainable energy systems and tackles a specific scheduling challenge. We are proud of our contribution to this crucial field and remain committed to exploring further frontiers in smart grid technologies.

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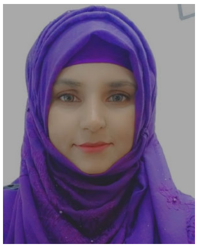

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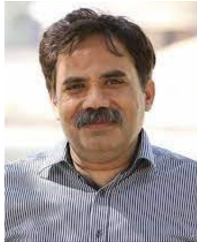

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