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A Priori Multiobjective Self-Adaptive Multi-Population Based Jaya Algorithm to Optimize DERs Operations and Electrical Tasks

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ABSTRACT A smart grid (SG) is an emerging technology that provides electricity in a cost-efficient and eco-friendly way. SG combined with distributed energy resources (DERs) plays a crucial role in extending the existing grid's capacity while mitigating carbon emissions. The potential sources of DERs include solar, wind, and tidal energy. Usually, these DERs are located far away from the grid and not necessarily tied to the grid system. However, the energy trading capabilities of a grid-tied DERs are getting attention, both from academia and industry. This bonding of grid-tied DERs helps to decrease the loss of surplus energy, build an energy storage capacity, and other operational charges. Energy-consuming flexible home tasks can be optimized coordinately with the operations of DERs to minimize the economic cost and CO_2 emissions. In this work, our problem is multi-objective and we aim to reduce both electricity price and CO_2 emission. We proposed a multi-objective self-adaptive multi-population based Jaya algorithm (PMO-SAMP-Jaya) to schedule the operations of flexible home tasks. Different pricing schemes have been applied to uncover the correlation between CO_2 emission, economic cost, and pricing schemes. We assume a smart building, including 30 smart homes with PV and energy storage system (ESS) as DERs. Promising results have shown the effectiveness of our proposed scheme.

INDEX TERMS Smart grid, distributed energy resources (DERs), demand side management, environmental scheduling, renewable energy, meta-heuristic optimization.

I. INTRODUCTION

Energy cost and pollution mitigation are two major concerns of global warming and fossil fuel reduction [1]. Presently, electricity generation systems are mostly based on power plants that use coal, natural gas, oil, etc., as a primary source and run in intermediate positions. These plants produce electricity and then dispatched to the consumers through transmission and distribution networks. Several economic,

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environmental, political, social, and technical factors prompt the modern grid. A centralized generation system refers to a large-scale power generation at centralized facilities. These systems are normally positioned far away from the end-consumers and connected with the high voltage transmission lines. Due to high distance, the overall energy losses in a centralized generation system are about 65% or more [2]. However, DERs are considered as an alternative to centralized generation systems because they have economic advantages to avoid long-distance transmission of power. Further, DERs also has environmental advantages of generating fewer

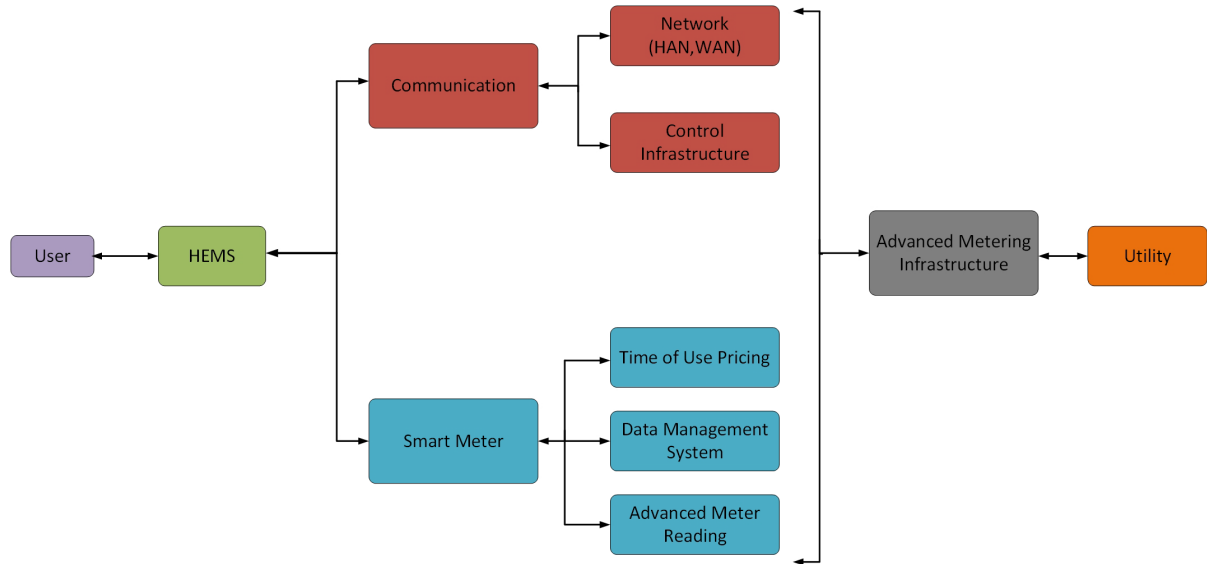


FIGURE 1. Components of SG infrastructure.

carbon emissions [3]. A DER system having renewable energy sources can be conceived as a special case of SG if it participates in demand-side management.

Researchers have addressed the recommendation of upgrading the existing grid network with the SG to meet the future energy demand. SG offers a substantial development in the power delivery systems incorporating advanced sensing and communication technologies at transmission and consumer ends. SG is regarded as self-healing, resilient to electrical faults, and a consumer-friendly system; equipped with advanced metering and communication technologies such as advanced metering infrastructure (AMI), home area network (HAN), and wide area network (WAN). Information flows in bidirectional mode simultaneously with the interoperability among the homes with the grid. This entire system comes-up with the probability to optimize the users' electricity consumption, and improve the operations of the entire system through a peak power reduction [4]–[6], smoothing the demand curve. It is unrealistic to ask the users to schedule their electricity usage optimally without providing them incentives. Therefore, a load management technique is required with a little awareness of users for setting-up and managing the load and let them estimate the costs and profits with different schedules. In building up the DSM algorithm three steps are largely considered such as data possession, load building, and finally the load scheduling. In the first steps, as the name suggested the power demand information is accumulated via the HAN or local network and established the load demand profiles. After that, load forecasting information is obtained from existing and historical trends. After getting data, the demand outline is generated, and the load demand is forecasted. In the last step, smart appliances automatically modify their time schedules to decrease the energy demand in peak-times based on pricing signals.

Homes utilize 40% energy of the world [7], so, home energy management system (HEMS) plays an active role in decreasing both: air pollution and energy price globally. Due to the rapid advances in communication technologies, smart homes are considered promising solutions, which further strengthens the idea. A smart home contains the home HEMS, AMI, and HAN system. AMI measures and collects the data from utility or service providers through an advanced communication medium, such as broadband over power line, power line communication, or fixed radio-frequency as shown in Figure 1. HEMS is an essential part of the smart home connected at the consumption side. It receives a pricing signal from smart meter also communicates with home appliances via HAN [8]. HEMS schedules the appliances at an optimal time slot in response to the pricing signal to decrease the consumption cost. Energy consumption can be further decreased by 30% by modifying the customer's living style via demand-side management [9]. Different dynamic pricing schemes for the domestic customer have been presented in [10] to decrease the power demand at peak times by modifying the users' electricity consumption pattern such as day-ahead pricing (DAP), critical peak pricing (CPP), time-of-use (ToU), including block rate (IBR) and real-time pricing (RTP).

Although, several studies are present in the literature, however, there are still certain challenges. Most of the literature cited above shows that most of the studies deal with one problem at a time i.e., optimization of CO_2 emission or users' bill. Some of the work devoted to handle both the objectives is based on mathematical techniques, providing exact solutions at the cost of high computational complexity. For instance, mixed-integer linear programming (MILP) [11] is applied for optimizing the operations of home tasks and DERs operation, to minimize users' bill and CO_2 emissions. Heuristic techniques can find a near-optimal solution with

lower computational complexity [12]. Heuristics algorithms have been successfully applied for solving optimization problems, however, their performance highly depends on parameter tuning. In our research, we have applied PMO-SAMP Jaya [13] which is an enhanced version of the Jaya-algorithm [14] with no algorithm-specific parameters. To gain financial and environmental objectives both flexible home appliances and DERs operate in coordination with multiple smart homes sharing a common microgrid. However, the pricing scheme and CO_2 intensity profile are not always directly correlated, and sometimes both are conflicted with each other.

There are mainly two methods to solve multi-objective optimization problems, and these are the priori and posteriori methods. In a priori method, a multi-objective optimization problem is converted into a single objective problem by giving suitable weight to every objective. This eventually leads to a single optimum solution. In a priori method, the predilections of the decision-maker are asked and the most suitable solution according to the given predilections is found. A posteriori method gives multiple trade-off solutions for a multi-objective optimization problem in a single simulation run. The designer can choose one solution from the multiple Pareto-optimal solutions based on the requirement of the objectives.

In our research, we address a multi-objective optimization problem (i.e., decreasing the everyday electricity cost and CO_2 emissions simultaneously). To measure the potency of our algorithm, we considered a smart building consisting of 30 homes with an installed PV system and ESS. The major contributions of this study are summarized here:

- We presented a PMO-SAMP Jaya algorithm with an aim to minimize cost and CO_2 emissions simultaneously.
- Analyzed the impact of pricing schemes on environmental scheduling (i.e., CO_2 minimization). Three separate pricing schemes are applied to assess the correlation of pricing schemes on CO_2 emissions.
- For validation of our scheme, we have considered a smart building with 30 households having its own domestic micro-grid.
- Reduce the peak to average ratio (PAR) and decrease the peak power consumption by applying peak demand change.

The remainder of the paper is coordinated as follows: Section II reviews state-of-the-artwork of existing approaches and methodology. Problem description is presented in section III and problem formulation is addressed in section IV. Section V discusses the proposed method. Simulations and discussions are given in section VI and finally, section VII includes the concluding observations of our work.

II. RELATED WORK

HEMs perform a significant role in mitigating the CO_2 and consumer electric bill. References [15], [16] proposed a HEMS model to handle the operation of home appliances to reduce the electricity bill. Various energy management

techniques with the integration of DERs have been examined in quite recent times. To meet the energy requirements of a building, a model predictive control (MPC) technique is proposed by Dagdougui *et al.* in [17]. The author aims in this study is to manage the energy of smart homes with various DERs and the energy storage capacity. A grid-tied micro-grids system is proposed in [18]. The author utilizes the MILP technique to schedule the operation of the grid-tied micro-grids system. The gain is maximized by keeping diversifying and scheduling the electricity generation, storage, and energy trading to the conventional grid. A genetic algorithm (GA) is proposed in [19] to find the optimal schedule for minimizing the consumer's bill for both microgrids and domestic applications. A multi-agent system proposed in [20] schedules every microgrid exclusively to meet its total demand. Kriett and Salani [21] proposed a general MILP scheme intending to minimize the running charges of both thermal and electrical power in a domestic microgrid.

The approach in [22] finds the optimal consumption pattern for home usage to restrict the peak power demand. Appliances are categorized as time-triggered and event-triggered by considering their physical models such as a washing machine and refrigerators. A pricing scheme RTP with DSM is presented to find the optimal power consumption schedule households [23], considering fixed, flexible and interruptible appliances. Stochastic and robust optimization techniques are adopted for the scheduling of home tasks. Furthermore, the authors also measured the performance of both techniques with each other. In [24], the authors proposed a heuristic algorithm for the resource constraint-scheduling problem. The authors designed and implemented an energy-efficient smart home having a remotely controlled facility. The appliances are scheduled on priority-basis considering overall cost and power consumption limits at any time slot. Derin and Ferrante [25] model considers appliances operating time, counting electric vehicle batteries, washing machine, and a dishwasher as the home appliance. The exhaustive search takes relatively less time for these three appliances in a time slot of 7 hours. Table 1 summarises the state-of-the-artwork with their strengths and limitations.

Adika and Wang [26] technique creates a cluster of home appliances, depending on their usage time by tracking the accumulated loads with similar time-schedules for other time slots having specific power limits. Sianak *et al.* proposed a fuzzy decision-making approach [27] by applying the RTP scheme to best control the usage of appliances. The fuzzy approach is employed to support societies for evaluating their energy consumption and making judgments about their energy flow pattern. This approach can rank the appliances in a house area. To flatten the voltage curve, an interruptible load is scheduled and reshaped by using binary particle swarm optimization in [36], [37]. The voltage profile and the requirements of the users are considered in interruptible load reduction. This methodology works better for user power demands in achieving a flatter voltage profile along with the distribution feeder.

TABLE 1. State-of-the-art works.

Technique	Objective	Features	Remarks
MPC [17]	Operational management of energy	Integration of different RES and energy storage equipment	High computational complexity
MILP [18]	Operational cost minimization	Time constraint to purchase and sale the electricity to grid	System complexity
GA [19]	Minimize the cost while satisfy the users demands	Electricity sale-back mechanism to grid	Several variables such as weather conditions and emissions can effect the performance
MILP [21]	Reduce the operational cost of microgrid	Considered models of both; electrical and thermal power demand	Annual operating cost is reduced by 4.7% up to 7.6%
Stochastic optimization techniques [23]	Minimize the consumers' electricity bill	Compare the performance of both techniques	Provides better solution at the cost of high computational time
A clustering based technique [26]	Minimization of energy cost	Roof top PV system is used to meet the consumer's demand	Hard deadlines devices do not participate in demand response program
A fuzzy TOPSIS decision-making approach [27]	Optimize the energy flow pattern	Proposed approach can be used to rank the appliances	Consumers' preferences are compromised
Artificial immune network [28]	Minimize the peak load	The performance of the algorithm is tested on real data presented by the electric distribution company	Proposed scheme required minimum communication infrastructure
Game theory [29]	Cost reduction	Energy management without compromising customer privacy	High computational complexity
A two-stage robust optimization model [30]	Minimize the energy cost	SRDSM handles the high number of users	SRDSM is more efficient and scalable
Artificial neural network [31]	Minimize the electricity price	Integration of PV and energy storage equipment	PV input data contains uncertainties and errors
Game theory approach [32]	Reduce the expense and peak to average ratio	Integration of RES and storage components to reduce the stress on conventional grid	3% cost savings and 17% minimization in peak to average ratio
Linear programming and MPC method [33]	Minimize the operating cost	ESS and RES Integrated with energy trading mechanism	Consumers' frustration
Particle swarm optimization [34]	Minimize the power consumption	Handle the load in customer defined budget	13.97% power reduction achieved
Genetic algorithm [35]	Consumers' bill reduction	Batteries are used as a storage system	PAR is improved

In [28], the authors utilize the adaptive, distributed, and auto-regulated capacity of artificial immune network algorithms for peak load shaving. The performance of the algorithm is tested in four different scenarios, including one with realistic-data from the electric distribution company. The algorithm shows excellent performance in all the scenarios, keeping the load somewhat higher than the pre-defined consumption limit. The cognitive radio-based communication network is proposed in [29] to schedule the greenhouse energy and handles several home appliances, electricity generation, and storage systems. The game theory technique is applied to schedule the electricity storage system. Consumer's bill reduction and comfort maximization, both are considered in the objective function. The proposed algorithm achieves the desired objectives without compromising consumers' privacy. In [30], the authors proposed a two-stage robust optimization model to minimize the energy cost. In [30], the authors proposed a robust optimization technique to minimize the energy price. The model considers multiple smart homes with PV and battery storage units at each users' house. PV generated energy is utilized to fulfill the users' power demand and charge the battery storage unit. However, the model fails as the number of users increases. The authors in [31] applied an artificial neural network to reduce the electricity consumption charges, by maximizing the utilization of PV generated energy, and energy storage units in peak hours.

A game theory approach presented in [32] includes storage elements, particularly in the environments with energy supply limitations. The proposed model flattens the load profile by reducing the peak-to-average ratio. A case study is demonstrated to measure the feasibility of the proposed scheme; a variety of household demand prototypes are estimated within a microgrid to increase the payoff of both; the single consumers and the whole system. [33] proposed a linear programming based load scheduling algorithm and MPC method to minimize the operating expense of a microgrid system and optimize the loads by considering renewable energy sources (RES) and time-of-use tariff. The proposed algorithm modifies the load pattern and enhances the performance of the microgrid system by decreasing the running expense to 6.06%. The authors of [34], [38] used a PSO to schedule the load at an optimal time slot to lessen the power expense while respecting the end-user comfort. Results showed 13.97% achievements in power consumption. In [35], the authors proposed a multi-objective optimization problem to reduce the electricity bills and improve the peak to average ratio. The authors also considered the comfort of end-users. DSM model based on a stochastic approach to deal with contingencies [39] combined with RES and DR programs. This study aims to reduce the operating costs of the distribution grid.

Although, several studies have been presented in the literature, however, most of the studies deal with one problem at a time i.e., optimization of CO_2 emission or users' bill.

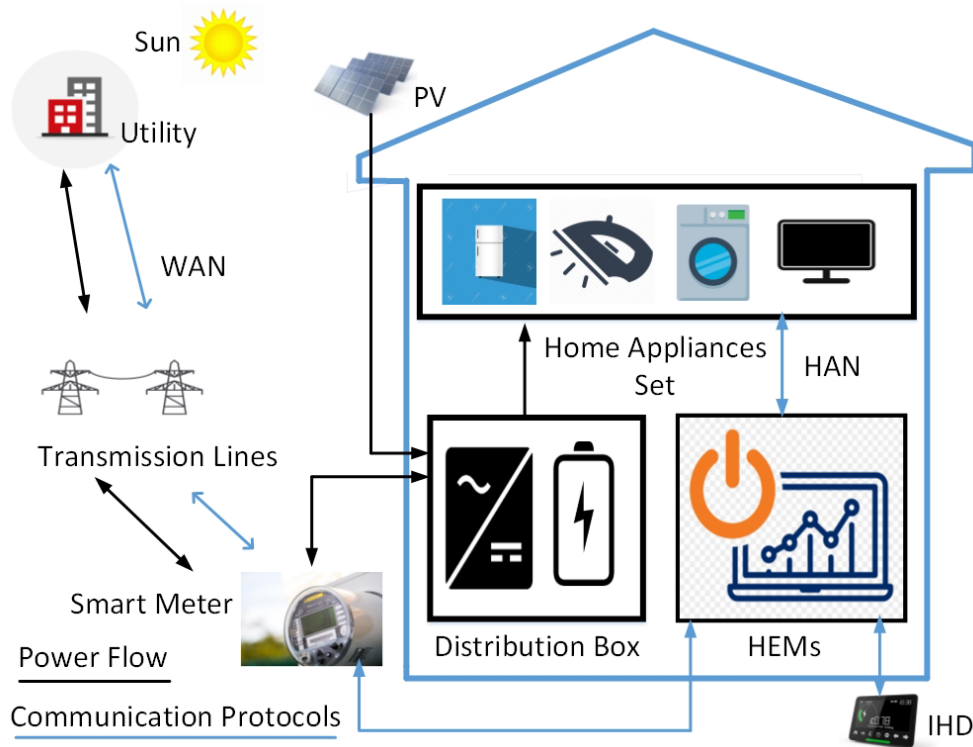


FIGURE 2. System model.

Some of the work devoted to handle both the objectives, based on MILP [40] which has high computational complexity. Motivated from literature, we have proposed a PMO-SAMP-Jaya algorithm for achieving our objective efficiently and effectively. Jaya algorithm has an advantage over other heuristic algorithms that it has no algorithm-specific parameter, therefore it doesn't require any parameter tuning.

III. PROBLEM DESCRIPTION

In this work, we consider a smart building equipped with PV and ESS as local DERs (see in Figure 2). The smart building consists of 30 smart houses, whereas all the houses share a common DERs. Smart building is also tied to the traditional power grid to fulfill the energy demand when demand can't be fulfilled by DERs. The ESS is utilized to store the excess energy generated by PV, however, all the excess energy can't be stored in ESS. In this case, selling the excess energy back to the utility is the only choice, regardless of price. So, we considered a mechanism for selling the surplus energy back to the utility. All smart homes have their own energy consumption pattern and power demand curve. The total power demand depends on the tasks of residential appliances including fixed and flexible appliances.

Table 2 shows the different types of appliances adopted from [40]. Power demand depends on the time period of operation of these appliances. In this work, we considered the day-ahead RTP (DA-RTP) scheme and peak demand charge (PDC) and DC pricing schemes to charge the consumers' bill. Carbon dioxide (CO_2) emissions are also

forecasted one day ahead. We intend to reduce the total economic cost and CO_2 emissions. We have developed a SMAP Jaya algorithm to achieve our objectives. Moreover, we investigated our model on three pricing schemes, i.e. DA-RTP, critical peak pricing (CPP) with PDC, and CPP with DC (DC). CPP with PDC is adapted from [41], whereas CPP with DC is adapted from [42]. The overall problem can be explained as below:

A. GIVEN ARE

(a) DA-RTP pricing signal, (b) forecasted PV power generation, (c) time slots divided into equal intervals, (d) ESS storage capacity, CO_2 emission intensity, efficiency of technologies, (e) PDC for over-threshold amount, (f) DC based on maximum power demand, (g) storage capacities, (h) request time and end time or electrical task and (i) time duration of a task.

B. TO DETERMINE

(a) Energy plan, (b) Request time of the task, (c) storage plan and (b) energy selling plan.

Our objective is to determine the optimal power consumption schedule, selling the excess energy back to the utility and DERs operations with minimum economic cost and environmental impacts. Reduce the power demand from the grid when the price is high or there is a higher CO_2 emission.

IV. MATHEMATICAL FORMULATION

We formulate our problem as a multi-objective optimization problem to address economic and environmental

TABLE 2. Electricity consumption task [40].

Task	Power (kW)	Request time (h)	End time (h)	Time window (h)	Actual Operation time (h)
Dish washer	-	9	17	8	2
Washing machine	-	9	12	3	1.5
Spin dryer	2.5	13	18	5	1
Cooker hob	3	8	9	1	0.5
Cooker oven	5	18	19	1	0.5
Microwave	1.7	8	9	1	0.5
Interior lighting	0.84	18	24	6	6
Laptop	0.1	18	24	6	2
Desktop	0.3	18	24	6	3
Vacuum cleaner	1.2	9	17	18	0.5
Fridge	0.3	0	24	-	24
Electrical car	3.5	18	8	14	3

sustainability. Power consumption tasks are scheduled based on electricity price, CO₂ intensity and request & end time of the tasks. The objective is to minimize users' power consumption cost, CO₂ emissions and avoid the peaks. The constraints on capacities and maximum power generation are given below.

A. PV/SOLAR ENERGY

The building is furnished with a rooftop PV system. The proposed smart home management system tries to get the maximum advantage of the PV system to lessen the overall cost of the household customer and to reduce CO₂ emissions. The output power of PV unit is denoted by S_t [43]:

$$S_t = \eta^{PV} AR^{PV} R_t (1 - 0.005(TEM - 25)) \quad (1)$$

where, solar panel's efficiency is represented by η^{PV} and AR^{PV} is the area of solar panel. Sun irradiation is denoted as R_t and TEM is the air temperature.

B. CAPACITY CONSTRAINT

The output from both solar and electrical storage should not exceed by their designed capacities. S_t and E_t is represented the output from both solar and electrical storage units respectively.

1) SOLAR

$$S_t \leq C^S \quad \forall t \quad (2)$$

2) ELECTRICAL STORAGE

$$E_t \leq C^E \quad \forall t \quad (3)$$

C. ENERGY STORAGE CONSTRAINTS

Energy stored E_t at time period t is equal to the energy stored at time t - 1 plus the charging and minus the discharging. During the charging process at time δ, only ηδA_t is used in

charging. While during the discharging time, if δB_t energy is required to deliver then δB_t/η of energy is needed to supply.

$$E_t = E_{t-1} + \eta\delta A_t - \delta B_t / \eta \quad \forall t \quad (4)$$

η represents the loss factor during the discharging and charging process and δ represents time period.

At the end of every day, no electrical storage is permitted, so the storage must revert to its original state.

$$E_0 = E_T = E^I \quad (5)$$

The rates of charging and discharging of the electricity storage should not surpass its own capacity:

$$B_t \leq H^E \quad \forall t \quad (6)$$

$$A_t \leq P^E \quad \forall t \quad (7)$$

D. ENERGY BALANCES

The electricity requirement is accomplished by the power produced by the PV system plus the energy obtained from the ESS and main grid, minus the power supplied to the ESS.

$$\sum_j \sum_i \sum_{\theta=0}^{Q_{ji}-1} X_{i\theta} T_{ji,t-\theta} = S_t + B_t - A_t + G_t \quad \forall t \quad (8)$$

E. REQUEST AND END TIME

T_{jit} is the binary variable which shows the task i of home j executed at a time t. Therefore, tasks of every home are executed between the request time and the end time minus the tasks proceeding period.

$$\sum_t T_{jit} = 1 \quad \forall j, i \quad L_{ji}^S \leq t \leq L_{ji}^F - Q_{ji} \quad (9)$$

F. PEAK DEMAND CHARGE

The grid's electricity peak demand is decreased to curtail the requirement of the high demand from a microgrid,. For every period, when the electricity demand from the grid, G_t is under the accepted threshold m then the regular prices are applied. However, if G_t passes m, the consumption above the threshold γ_t is included and additional rate will be charged (see Eq. 10). Since, both the objective function and γ_t (Eq. (10)) are to be minimized, if G_t - m is positive then γ_t should be equal to G_t - m. If G_t - m is negative then γ_t should be equal to 0.

$$\gamma_t \geq G_t - m \quad \forall t \quad (10)$$

G. DC

The highest demand of power from the grid in each day is explained as follows:

$$G^{max} \geq G_t \quad \forall t \quad (11)$$

H. OBJECTIVE FUNCTION

The proposed energy management system attempts to maximize the advantage of solar energy to reduce the overall cost of the domestic customer. The ESS is employed to store electricity when there is an excess generation. It is essential

TABLE 3. Technical parameters and costs of the DERs [44].

	Capacity (kW)	Efficiency (%)	Maintenance cost
PV unit	80kwh	20	2.5p/kwh
ESS	10kwh	95	0.5p/kwh

for utilizing the PV output more effectively. When ESS is sufficient, we sell back to the grid. Our objective function is to minimize the power consumption price and CO₂ emissions. Following the DA-RTP scheme, this involves the functional and maintenance cost of the PV system, the electrical storage and the electricity purchased from the main grid. μ^E and r are the maintenance cost of ESS and PV respectively. b_t is the electricity price at time t .

$$Obj_1 = \sum_t [\delta(rS_t/\eta^{PV} + b_t(G_t - G_t^{sell,Grd}) + \mu^E B_t)] \quad (12)$$

Under the PDC, the everyday price is computed as in Eq. 13. Underneath the threshold, the electricity price follows the RTP price scheme while the additional charges are applied if the demand goes above the allowed threshold. p is the difference between peak and base electricity demand price from the grid.

$$Obj_1 = \sum_t [\delta(rS_t/\eta^{PV} + b_t(G_t - G_t^{sell,Grd}) + \mu^E B_t + p\gamma_t)] \quad (13)$$

If the DC is used for the everyday price, the penalty on maximum demand from the grid is also included in the objective function. q is the charge of maximum power demand from the grid.

$$Obj_1 = \sum_t [\delta(rS_t/\eta^{PV} + b_t(G_t - G_t^{sell,Grd}) + \mu^E B_t)] + qG^{max} \quad (14)$$

Our other objective also considers to reduce the CO₂ emission from the traditional electricity grid. ξ_t^G is the CO₂ intensity of grid electricity at time t .

$$Obj_2 = \sum_t \delta \xi_t^G G_t \quad (15)$$

The above both objective functions are modeled as a multi-objective optimization problem as;

$$Min (w1 * Obj_1 + w2 * Obj_2) \quad (16)$$

A weighted sum method is used for solving the multi-objective optimization. Weighted sum method converts the multi-objective function into single objective function and then solves the problem. We first normalized both the objective function values to the same range to avoid the function with the largest range to dominate the evolution. $w1$ and $w2$ are the weights assigned to the objective functions Obj_1 and Obj_2 respectively. Both of the weights have the same value equal to 0.5.

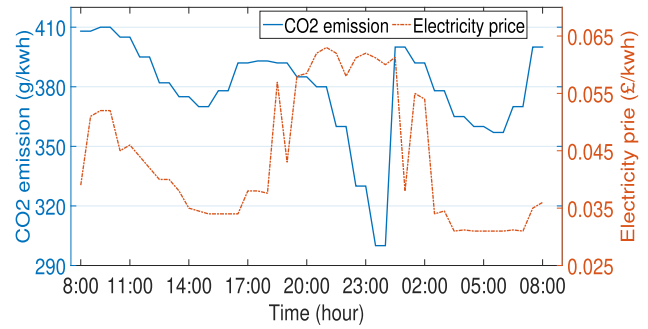


FIGURE 3. DA-RTP tariff and CO₂ emissions profiles for UK (August 17th, 2013).

V. PROPOSED METHOD

In our work, we have considered a smart building with 30 homes equipped with a rooftop PV unit and ESS. Each home has a similar power consumption pattern and the smart building is also connected to the main power grid. Smart meter, AMI, EMS, and HAN are considered to be present in each home. The overall architecture of our proposed system is depicted in Figure 2. Smart meter receives pricing signals and CO₂ intensities from the utility which are then passed to the HEMS. The in-home display (IHD) unit displays the current price, power demand, and appliance parameters. The user can interact with the HEMS via this unit. HEMS receives appliances parameters, their request and end times, energy demand, PV parameters, and the information from the smart meter (pricing signal and CO₂ intensity). Based on this information, HEMS schedules the tasks accordingly and communicates the schedule with appliances via the HAN. Furthermore, a mechanism for trading surplus energy is also considered. There is an agreement between the user and utility on the minimum amount of energy to sell and below the threshold, energy trading is not allowed. The user can sell back the surplus energy produced by PV as per agreement with the utility. Capacities of PV and ESS are assumed to be provided and other technical parameters are adopted from [44] (See Table 3). Total time is divided into 48 slots, each of half an hour for scheduling of the tasks. We considered 12 different tasks/ appliances in our works adopted from [40] (Table 2). The appliances are scheduled according to their operational time frame, earliest request, and end time. We considered three scenarios: CO₂ minimization, cost minimization, and the trade-off scheme. Trade-off schemes handle both the objectives simultaneously. For optimal scheduling, we applied three different pricing schemes: DA-RTP, PDC, and DC.

A. PMO-SAMP JAYA ALGORITHM

We proposed a PMO-SAMP Jaya optimization algorithm [13] for solving the problem, which is an improved version of Jaya algorithm. The algorithm is widely applied algorithm for solving the constraint and unconstrained engineering optimization problems. Jaya algorithm [14] was originally proposed by R. Rao in 2016, having no algorithm-specific

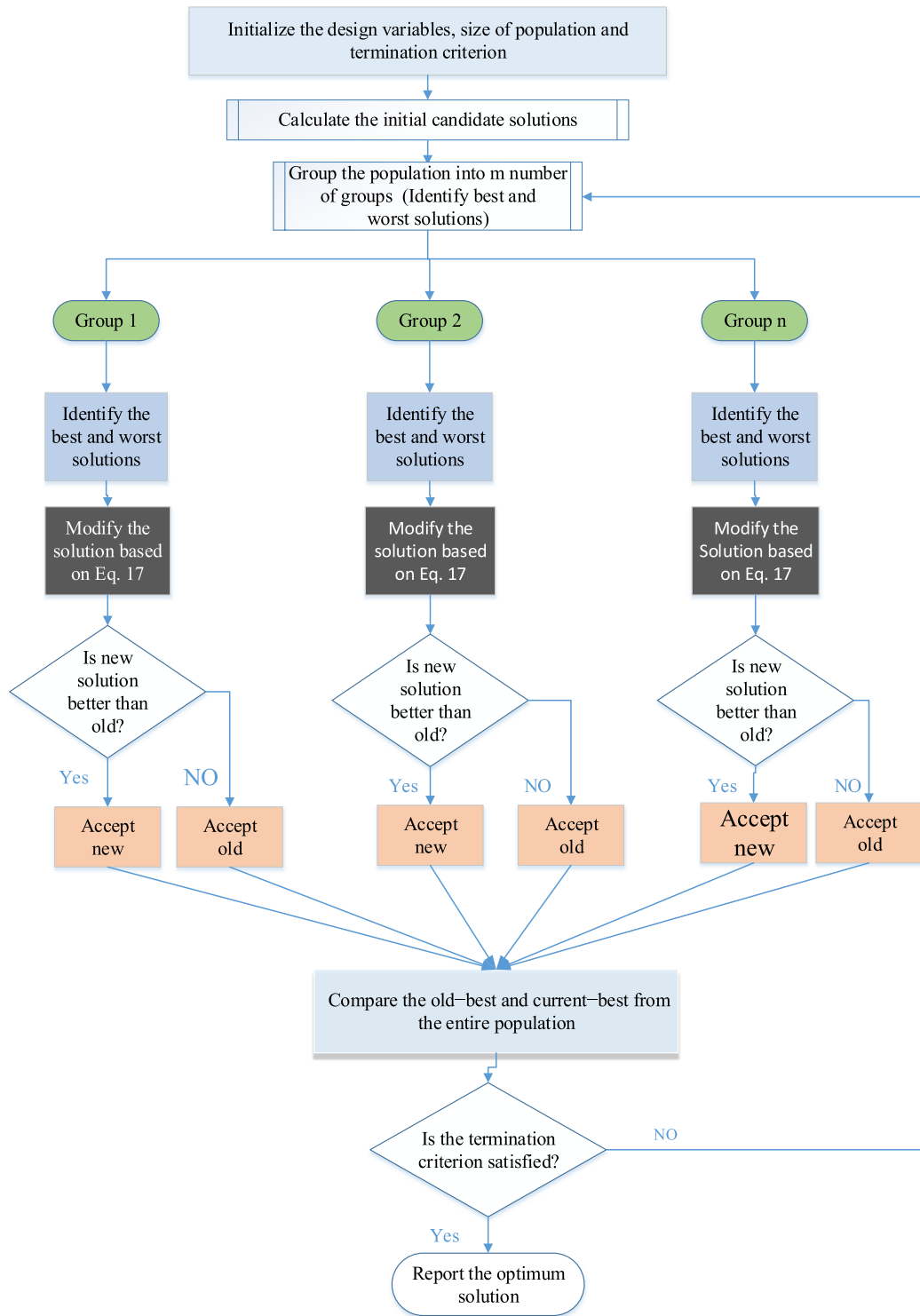


FIGURE 4. Flowchart of the SAMP-Jaya algorithm.

parameter to be tuned. The algorithm has only common control parameters; population size and the number of iterations. PMO-Jaya algorithm upgrades the search mechanism of Jaya algorithm and controls the exploration and exploitation rates of the search process.

Jaya algorithm works by moving towards the best solution and avoid the worst solution for any given problem. It uses an adaptive scheme for dividing the population into sub-populations which control the exploration and exploitation rates of the search process based on the problem landscape.

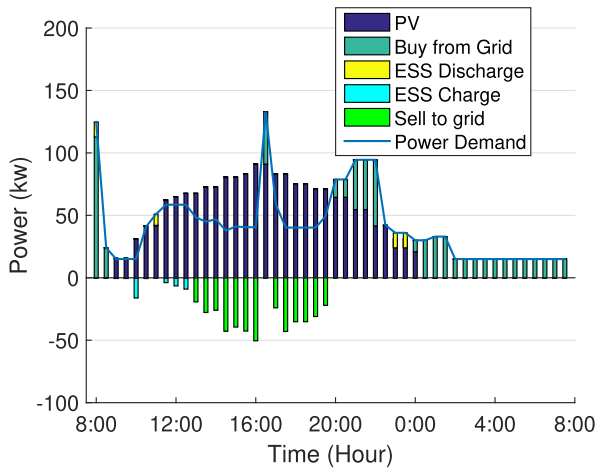


FIGURE 5. Results of proposed scheme for CO_2 minimization.

Flowchart of SAMP-Jaya algorithm is shown in Figure 4. Lets $f(x)$ be an objective function, which we want to optimize (minimize or maximize). In any i^{th} iteration, there are m design variables and n size of population. Let $X_{a,b,i}$ be the value of a^{th} variable for b^{th} candidate at the i^{th} iteration, then the value will be updated as given by the given equation,

$$X'_{a,b,i} = X_{a,b,i} + r_1(X_{a,best,i} - |X_{a,b,i}|) - r_2(X_{a,worst,i} - |X_{a,b,i}|) \quad (17)$$

where $X_{a,b,i}$ is the value of a^{th} best parameter for best candidate solution and $(X_{a,worst,i})$ is the worst solution in a population. $X'_{a,b,i}$ is the updated solution and r_1 and r_2 are the randomly generated numbers in the range of $[0, 1]$. $r_1(X_{a,best,i} - |X_{a,b,i}|)$ tries to move to the best whereas $r_2(X_{a,worst,i} - |X_{a,b,i}|)$ tries to avoid the worst solution. If the new solution is better, then the population is updated. New and old; both candidates are compared and the best solution is forwarded to the next iteration. The same process continues for the whole population. In this way, the algorithm tries to move to the best solutions and avoids the worst. PMO-SAMP algorithm divides the population into subgroups; however, unlike island-model, the PMO-SAMP algorithm decides the number of groups adaptively according to the problem landscape. PMO-SAMP algorithm considers the quality of the solution to divide the population into groups. The number of groups is distributed over the whole search space instead of a particular region, so expected to produce an optimal solution. The number of sub-populations is modified adaptively, according to the strength of change in the solution. This strategy improves the searching process for tracing the best solution and improves the diversification of the searching process. Also, newly generated candidates replace duplicate solutions to maintain diversity and enhance the exploration mode.

In our work, the length of the solution (or design variables) is equal to the number of appliances considered in our work. The number of iteration and population size is kept at 100. Design variables include appliances' parameters such as

power rating (PR_A), start time (St_A) and finish time (Ft_A), total operational time (OT_A), pricing signal (EP_S) and CO_2 emissions data (CE_S). Our algorithm tries to optimize the objective function as given by equation 16 subject to certain constraints discussed in IV section. The step by step working of PMO-SAMP-Jaya algorithm is shown below.

- 1) Initialize the design variables (PR_A , St_A , Ft_A , OT_A , EP_S , CE_S), Size of population and termination criteria.
- 2) Calculate the initial solution based fitness function (Equation 16).
- 3) Group the population into m numbers of groups according to the solution's quality (Identify best and worst solutions)
- 4) Modify the solution in each group as given by Equation 17.
- 5) If new solution is better, replace the existing solution with new solution.
- 6) Else keep the existing solution.
- 7) Merge the groups together into population. Compare the *Old - best* and *current - best* from the entire population.
- 8) Stop and iteration is stopping criteria has met and report the best solution.

In step 6, *Old - best* and *current - best* are best solution from entire population in previous and current iteration. if current value is better, then the m is increased by 1 to enhance the exploration mode, otherwise m is decreased by one, as algorithm need exploitation mode.

VI. SIMULATIONS AND DISCUSSION

This section discusses the simulation and results generated by our proposed model. The developed model is implemented in MATLAB 2016b on PC with an *Intel(R)Core(TM)i5 - 3230M* CPU, 3.40 GHz CPU with 8GB of RAM and Microsoft Windows 10 installed on it.

In our experiments, we applied three pricing schemes as discussed earlier in section IV. DA-RTP is adopted from [41], whereas the the data for CO_2 emissions is publicly available at [45] (Figure 3). For PDC, we conducted simulation for three threshold value. We considered three different scenarios: cost minimization, CO_2 minimization, and the trade-off scheme (both, CO_2 and cost are minimized).

In the scenario of CO_2 minimization, the multi-objective becomes the single objective, with zero weight assigned to the electricity cost, hence scheduling is only based on minimizing carbon footprints of the electricity. In the case of CO_2 minimization, the HEMS tries to minimize the CO_2 emissions by modifying the usage pattern regardless of the pricing scheme. Therefore, the results for CO_2 minimization schemes are shown only once. Figure 5 shows that tasks are scheduled within their scheduling window to minimize the carbon emissions. In this case, flexible tasks are scheduled to maximize the utilization of RES, except in the early morning and in the evening where the tasks are inflexible. Rest of the power demand is fulfilled by buying electricity from the

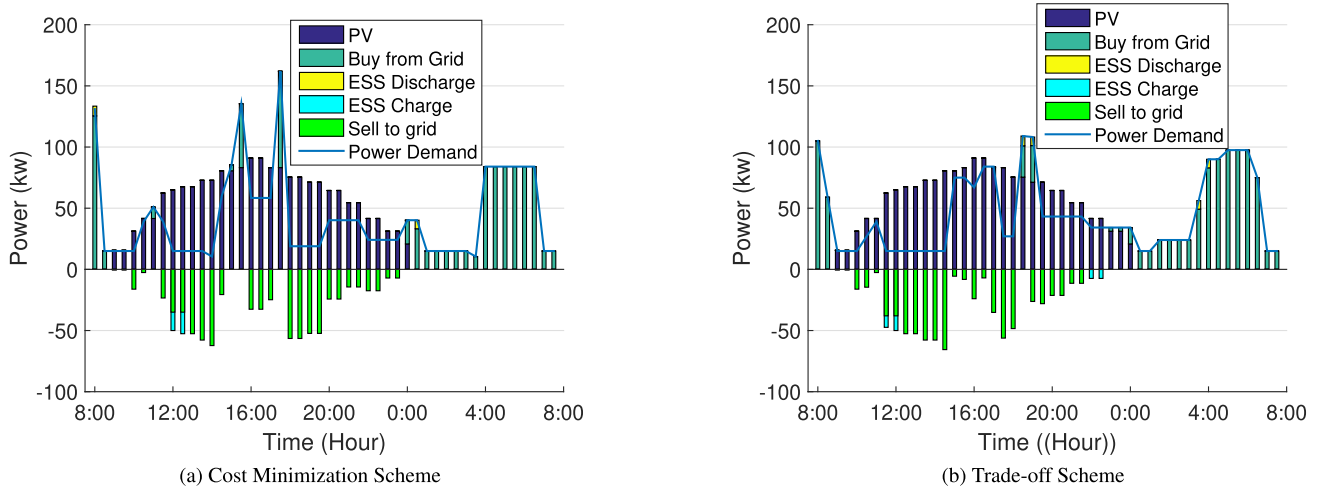


FIGURE 6. Results of proposed algorithm under DA-RTP.

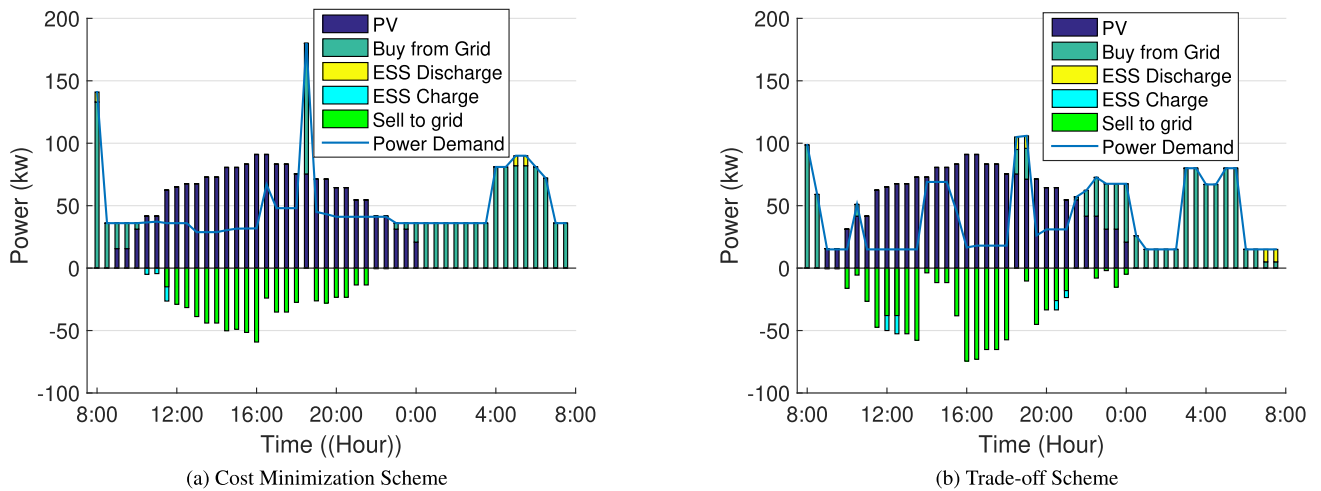


FIGURE 7. Results of proposed algorithm under DC.

main grid. ESS is charged from PV generated power and discharged at four different time stamps.

Figure 6 shows the results of the proposed algorithm under DA-RTP scheme. 6a shows the results of cost minimization scheme. HEMS schedule the tasks to minimize the electricity cost without caring about carbon footprints, while gaining maximum benefits from PV. As illustrated in Figure 6a, most of the tasks are scheduled between 4:00 and 7:00 because electricity price is low during these time slots. The other two peaks can be seen at 15:00 and 19:00. HEMS scheduled the tasks where electricity price is relatively low, or fewer benefits can be achieved by selling the surplus energy back to the grid. Energy generated from is PV is utilized in an efficient way to minimize cost and gain more benefits from PV by selling back the surplus energy to the grid where prices are high. Results for trade-off scheme (cost and CO_2 both) are illustrated by Figure 6b. Tasks are scheduled in such a way to minimizes both cost and CO_2 footprints. Peaks can be seen

at 14:00 and 23:00 which shows the trade-off of the scheme. And the other peak can be seen between 3:00 to 7:30 in order to minimize both, cost and CO_2 emissions.

Figure 8 depicts the results of the proposed method under PDC pricing. Figure 8 (a, c & e) indicates the results of our proposed method when only electricity cost is considered as an objective, with no weight given to CO_2 footprints. Results show that the total power demand is scattered over the day under peak demand threshold, showing more flattened curve except where the tasks are inflexible. As thresholds are applied, the total electricity demand over the agreed threshold can be reduced. HEMS tries to schedule the load in such a way to minimize the cost and reduced the maximum demand to avoid the peak demand penalty. The results for the trade-off scheme are shown in Figure 8 (b, d & f). As illustrated by the results, loads are moved between 18:00 to 22:00 compared to Figure 6b showing the trade-off between two objectives.

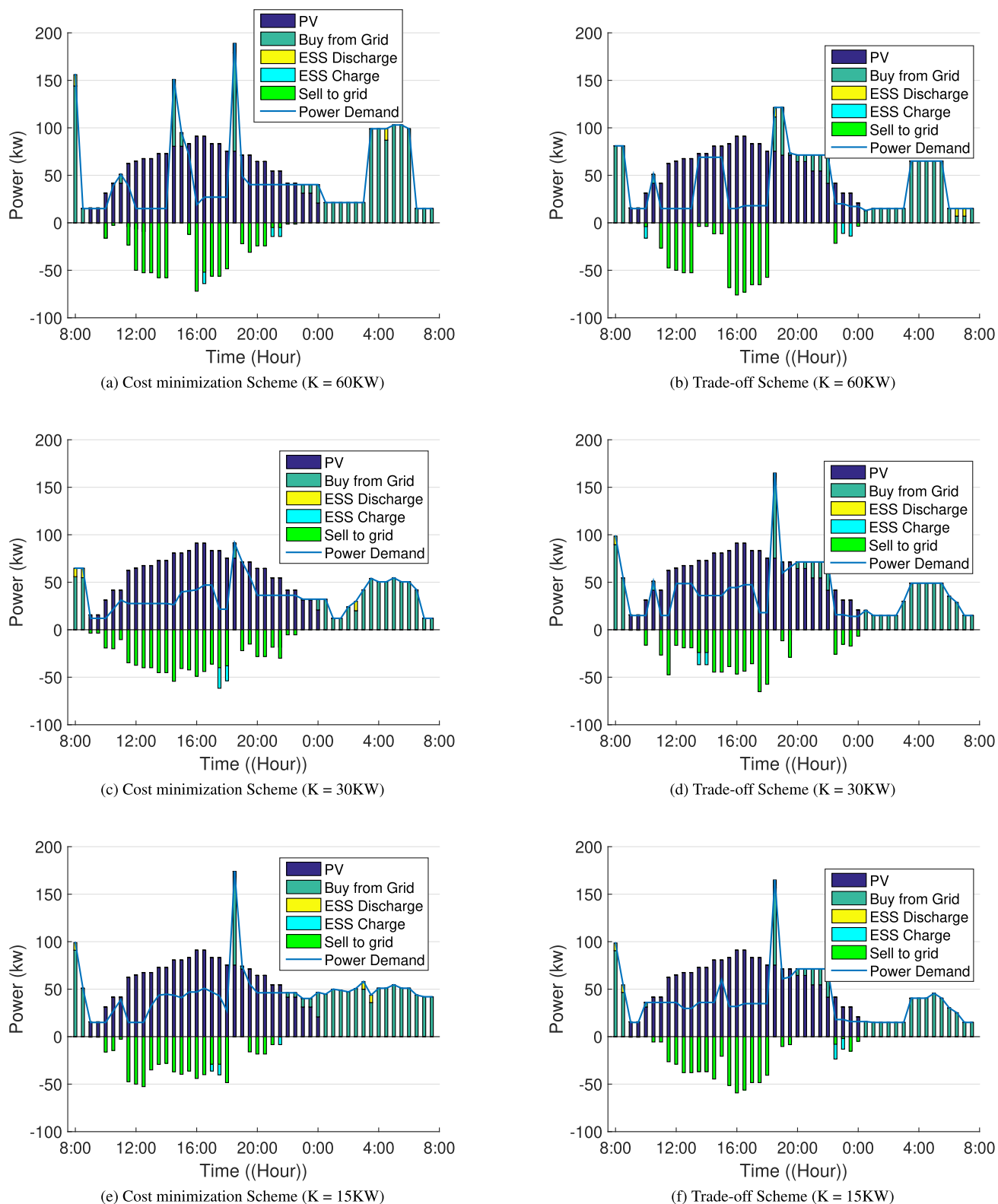


FIGURE 8. Results of proposed algorithm under PDC.

Results for DC scheme are presented in Figure 7a and 7b. In case of considering the only bill minimization as an objective, the scheduler scheduled the load where the prices are lower and maximizes the utilization of PV generated

power. When considering CO_2 as an objective, the electricity demand profile is reshaped according to CO_2 emissions. In trade-off scheme, the load is reshaped according to the trade-off between the two objectives. In all the scenarios,

TABLE 4. Total cost and total power demand from grid (* PDC = Peak demand charge).

Scheme applied	Pricing scheme	PMO-SAMP-Jaya (Proposed)			MILP [40]		
		Total demand from Grid (KWh)	Total Cost (£)	CO ₂ emissions (kg)	Total demand from Grid (KWh)	Total Cost (£)	CO ₂ emissions (kg)
Cost Minimization Scheme	DA-RTP	502.8	28.02	293.4	744.4	58.3	551.3
	PDC (K=60KW)	560.3	30.2	289.0	623.5	60.8	531
	PDC (K=30KW)	484.1	32.45	288.86	623.8	65.1	530
	PDC(K=15KW)	497.6	32.28	292	623.8	73.4	530.1
	DC	530.2	34.54	294.8	623.8	74.6	534.5
Trade-off Scheme	DA-RTP	496.3	31	292.64	624.4	58.5	526
	PDC (K=60KW)	536.1	34.45	285.3	623.8	64.9	520
	PDC (K=30KW)	470.2	36	287.4	623.8	74	519.6
	PDC (K=15KW)	487.0	39.32	288.07	623.8	80.8	520
	DC	512.4	37.75	291.5	623.8	77.1	521
CO ₂ minimization Scheme	DA-RTP	300.0	42.2	282.4	635.7	66.6	515.2

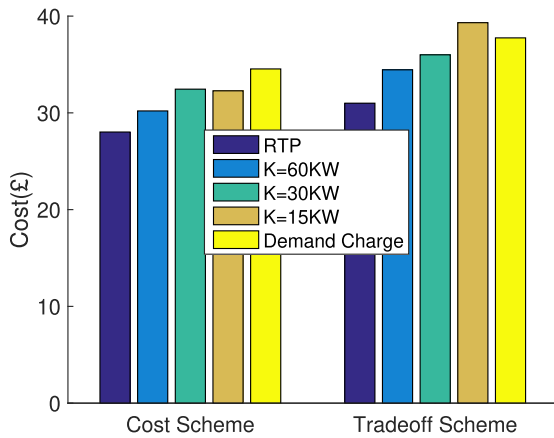


FIGURE 9. Total electricity cost under Cost minimization and trade-off scheme.

the ESS is charged from PV generated power and discharged when the electricity price or carbon emissions are higher. However, the ESS is not frequently charged, but only a 3 to 4 times a day. Due to the efficiency and maintenance cost constraints, ESS is not utilized if the maintenance cost or cost of energy loss is high during the charging or discharging.

Total cost for each pricing scheme under cost minimization and trade scheme is shown in Figure 9 and summarised in Table 4. Table 4 shows the comparison between our proposed algorithm and MILP. MILP is proposed in [40] where authors used combined heat and power and boiler as a DERs while we used PV energy. Cost minimization scheme incurs a total cost of 28.02£ under DA-RTP with a total power demand of 502.8KW, while the trade-off scheme under DA-RTP shows 31£ with 496.3KW. PDC shows the total cost of 30.2£ with 560.3KW total power demand from the grid while the same scheme incurs 31£ with 496.3KW. DA-RTP shows better results as compared to other schemes, whereas PDC with k = 30KW has good results as compared to the K = 60KW and K = 15KW constraints.

VII. CONCLUSION

We proposed multi-objective self-adaptive multi-population based Jaya algorithm to optimally schedule the energy consumption in a smart building. Both, electrical tasks and the operations of DERs are handled efficiently. The building has a rooftop PV installed and electricity tariff. Besides, CO₂ intensity profiles are considered to be available for optimal shifting of the tasks and DERs. Our Scheme optimally manages the electrical tasks and DERs to achieve the desired trade-off, while also considers energy trading to maximize the users’ profit. Scheduling heavily depends on power demand pattern, which may be affected by weather, electricity price, CO₂ intensity profiles and pricing scheme. PDC and DC pricing scheme limits the maximum power demand from the grid by applying the penalty, which distributes the load more smoothly and minimizes the peak to average ratio. The results depict that the proposed algorithm schedules the load in an efficient way to minimize CO₂ emissions and cost while maximizing PV generated power. Synchronization of DERs with the traditional grid is the biggest challenge which is not considered in this work. This can be considered as a potential future work.

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