

# Home Appliances in the Smart Grid: A Heuristic Algorithm-Based Dynamic Scheduling Model

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## Abstract

Customers and power utilities alike will benefit from smart grid technology by lowering energy prices and regulating generating capability. The accuracy of information sharing between main grids and smart meters is critical to the performance of scheduling algorithms. Customers, on the other hand, are expected to plan loads, respond to electricity demand alerts, engage in energy bidding, and constantly track the utility company's energy rates. Consumer loyalty can be improved by strengthening the connectivity infrastructure between the service provider and its customers. We suggest a heuristic demand-side control model for automating the scheduling of smart home appliances to optimize the comfort of the customers involved. Simulation findings show that the suggested hybrid solution will reduce the peak-to-average ratio of overall energy demand while still lowering total energy costs without sacrificing consumer convenience.

## Keywords

Demand-side management, appliance scheduling, critical peak pricing, household energy management.

## INTRODUCTION

Demand-side management (DSM) is a term that refers to decisions made by energy providers at their customers' homes [1]. DSM systems are designed to make better use of existing electricity without the need for the new generation, storage, or distribution facilities. Demand response services, fuel replacement programs, productive energy efficiency programs, and above all, industrial or residential load control programs are typically included in DSM programs [2]- [4]. One of the core architectural aspects of the residential load control platform [5] is to reduce and transfer usage. This can only be accomplished if consumers are motivated to build energy-efficient structures and to be mindful of their energy usage habits. High-power appliances can be shifted from peak to off-peak hours with a measurable decrease in the peak-to-average ratio (PAR) in load demand, as part of this realistic initiative. Because of the fast penetration of plug-in hybrid electric vehicles, load shifting is projected to become much more significant (PHEVs).

For one mile of driving, PHEVs usually need 0.2-0.3 kWh of charging power [6]. This adds a lot of additional load to the current delivery grid. It doubles average household demand, particularly during charging hours, worsening the already high PAR. A high PHEV penetration, in the absence of a properly reinforced device, may result in an unbalanced state, jeopardizing power quality requirements, voltage control problems, and even potential harm to utility and consumer equipment.

Another approach for residential load management is direct load control (DLC) [7]-[9]. The utility provider can remotely monitor electricity usage and the operation of some household equipment by using DLC systems. DLC programs include, for example, thermal comfort devices such as heating, ventilating, and air conditioning (HVAC), refrigerators, generators, and light control. When it comes to home automation and residential load management in particular, consumers' satisfaction is a high priority and a stumbling block in the implementation of DLC programs [10].

DLC program functions are being phased out in favor of competitive pricing. Users are empowered to handle their loads independently voluntarily through a competitive pricing mechanism, such as shutting down and moving heavy loads from peak to off-peak hours [11]-[13]. Critical-peak pricing (CPP), real-time pricing (RTP), inclined block cost (IBR), time of use pricing (ToUP), and day-ahead pricing (DAP) are some of the most common and widely utilized dynamic pricing schemes. Users are advised to switch appliances from peak to off-peak hours with the aid of these programs. This leads to a lower PAR and lower consumer prices [14].

## RELATED WORK

In the smart grid, researchers have recently developed and deployed several cutting-edge algorithms. These algorithms performed well when it came to evaluating the load consumption profiles of commercial, residential, and industrial buildings. Researchers have optimized energy regulators and schedulers to keep energy costs to a minimum.

All other equations are measured, and the relationship is identified by a number in [1] that refers to the IEEE reference numbering system and is written with a comparison system. Price schemes, energy market priorities, and consumer preferences must all be weighed to maximize value for all stakeholders.

The term "dynamic price" is used in comparison [9]. RTP is used to schedule smart home equipment in the most efficient way possible. They are mostly concerned with reducing uncommon power consumption, decreasing prices, and optimizing the advantages of energy storage. As compared to the usual pricing system, the cost of electricity is lowered by 22.6 percent, and the peak price is reduced by 11.7 percent. Writers, on the other hand, do not pay heed to the optimization scheme in their work. The DSM model's writers purchase electricity during off-peak hours and store it in a storage bank for use during peak hours. Their main focus is on the price reduction and holding energy in a battery reserve. Even though a lead to the formation of an optimum scheduling paradigm is proposed, the goals are not fulfilled. [12] explains a non-deterministic polynomial-time (NP) hardness-based energy optimization model. The publishers use greedy following the ideas to complete the task of the home schedule. They use given in equations and artificial intelligence optimization methods in their practice to achieve optimization. The phenomenon of lower peak load and lower peak fluctuation is often discussed. The problem is described not only by the load demand of the customer but also by the cost of generation. For scheduling home appliances, the authors propose a mixed-integer linear programming-based algorithm. The real-time pricing tariff is used to schedule home appliances to save money and reduce peak demand.

References [12]-[14] use a cost-minimization approach based on a Genetic Algorithm (GA). Renewable energy sources (RESs) and battery storage are built into the current structure in these articles. When power costs are high and the energy consumption is high, RESs are expected to charge a battery bank for later use. A controller is designed to track the charging and discharging thresholds associated with the battery bank to increase battery performance and life. Furthermore, batteries are expected to charge when power costs are light. As costs increase, some high-priority appliances are handled from a battery supply to save the consumer money.

In this article, we suggest a genetic algorithm, grey wolf optimization (GWO), and a mixed grey wolf and genetic algorithm meta-heuristic optimization models. (hybrid  $G^2$ ) for the control of 12 household appliances. Instead of one-hour time slots, each day is split into 96-time slots (every 15 minutes) for appliance service. This is important since certain appliances, such as electric cattle and dishwashers, need less than an hour to complete their tasks. In this way, consumers have a lot of flexibility and options for lowering costs, PAR, and overall energy demand. Finally, the unscheduled, GA plan, GWO, and hybrid simulation findings are presented.  $G^2$  are shown to demonstrate the efficacy of the proposed hybrid  $G^2$  model for DSM appliance scheduling.

## PROPOSED ARCHITECTURE

Smart home with multiple smart appliances is considered in this job. End users have also provided reports on the length of operating time (LoTs) and power rating (PR) of all appliances. The supply-side management layer (SSML), connectivity management layer (CML), and demand-side management layer (DSML) are the three sub-layers that make up the whole structure (DSML). All information about electricity generation is included in SSML. The energy management controller (EMC) and the appliance scheduler are used by DSML (AS), and schedules smart appliances based on the end users' specified LOTs. The aim of a load balancer (LB) is to prolong appliance service to reduce the demand-supply gap and prevent breaching the customer demand cap. Energy forecaster (EF) and demand response manager (DRM) communicate real-time demand-supply data with SSML and DSML via CML. Wi-Fi, Z-wave, and Zig-Bee networking protocols are used by the Home Area Network (HAN) to communicate easily between EMC. Smart appliances are often classified into three categories: baseline loads, daily loads, and controllable loads, based on whether or not their service may be disrupted when triggered. EMC employs an appliance interface (AI) that manages the on/off operations of all smart appliances connected to the device. It's worth noting that, to improve convenience, EMC uses AS to stop all scheduling operations of the appliances if the interrupt is caused by the user. To plan these smart appliances in a home energy management scheme, this paper uses three meta-heuristic techniques: GA, GWO, and hybrid  $G^2$  (HEMS). Scheduling is done to save end consumers money on their utility bills. The Knapsack problem is used to create run-time coordination among smart appliances. This allows each user the ability to manage appliance activity according to their preferences.

## APPLIANCE CATEGORIZATION

Based on their organizational activity, home appliances are divided into three subcategories. Interruptible machines are those whose service may be disrupted or postponed while in use, but whose operating period cannot be changed. Uninterruptible machines, on the other hand, are those whose service cannot be stopped or disrupted while they are in use. These appliances, on the other hand, maybe moved to various time slots

before they begin running.

To hold total energy usage under reasonable limits, it's vital to switch interruptible and non-interruptible equipment to separate time slots. To save money on power, it's best to use interruptible equipment during off-peak hours. Base equipment, on the other hand, is those that cannot be disrupted or delayed in a home energy management scheme (HEMS). Refrigerators, air conditioners, lighting, and microwave ovens are examples of machines whose operating patterns do not alter. Table 1 lists all of the equipment used in this report, along with their length of operating time (LOT), power rating, and category.

We will analyze the power grid, energy cost, and load control model for residential use in this segment. In the following section, we will formulate three design optimization problems based on these definitions.

#### A. Power System

We consider a smart power system with multiple load users and a single energy source, which may be a generator or a step-down transformer connected to the main grid. Furthermore, we presume that each user has an EMC capable of scheduling multiple appliances (12 in our model) at varying intervals of time (96 intervals in a complete day, i.e., 15 minutes each). Different smart meters are interconnected not only with the grid but also with each other by exchanging updated information using relevant communication protocols.

Let  $U$  be the set of users, where for each user  $u$ , let  $l_u^t$  denotes the total load at time slot  $t \in T[1 \dots \dots \dots T]$  where  $T = 96$ . Daily consumed load by a specific user  $u$  is denoted by  $t \in [l_u^1 \dots \dots \dots l_u^t]$  This leads us to calculate the total load of all users in a single time slot across the whole day  $t \in T$ . It is represented as

$$L_t = \sum_{u \in U} l_u^t \quad (1)$$

Similarly, daily peak load and average load can be calculated as

$$\text{Load}_{\text{peak}} = \text{maximum}_{t \in T} L_t \quad (2)$$

$$\text{Load}_{\text{average}} = \frac{1}{T} \sum_{u \in U} l_u^t \quad (3)$$

From equations (2) and (3), PAR can be calculated as below

$$\text{PAR} = \frac{\text{Load}_{\text{peak}}}{\text{Load}_{\text{average}}} = \frac{T \text{ maximum}_{t \in T} L_t}{\sum_{u \in U} l_u^t} \quad (4)$$

#### B. Energy Cost Model

For each time slot  $t \in T$  energy cost for electricity generation or distribution is represented by  $C_t(l_t)$ . Generally, for the same load, the cost may differ in the different time slots of a day. It mostly depends upon the electrical price maintained by the utility at the generation site. It is worth mentioning here that the cost function is considered in this paper can represent either the original cost of thermal generators or artificial cost tariffs maintained by the utility for the proper execution of the load control programs. The actual energy cost function can be represented in terms of a quadratic function in equation (5)

$$C_t(l_t) = a_t L_t^2 + b_t L_t + c_t \quad (5)$$

Where  $a_t$ ,  $b_t$  and  $c_t \geq 0$  For each time slot  $t \in T$

#### C. Residential Load Control

For an individual user  $u \in U$ , let  $=U_A$  denotes the different set of appliances, including base, interruptible and uninterruptible appliances in a home. For scheduling purposes, we initially define a schedule vector for each appliance  $a \in A_n$  of the individual user, where  $n$  is the number of the appliances.

$$K_{u,a} = [K_{u,a}^1 \dots \dots \dots K_{u,a}^T] \quad (6)$$

where  $K_{u,a}^t$  represents scheduled energy consumption in one-time slot for appliance  $a$  by user  $u$ . We can then calculate the total load by  $u$ th user.

$$l_u^t = \sum_{a \in A_n} K_{u,a}^T, t \in T \quad (7)$$

In our proposed model, the main task of AS is to determine an optimum time slot in  $uth$  user's smart meter for the individual appliance  $a$ . In this way, user  $u$  can shape its daily load profile by making use of equation (7). It is important to mention here that the energy scheduler does not aim to reduce the power consumption of different appliances rather it shifts to other different time slots for minimization of PAR and energy cost. Initially, a user needs to initiate a start and end time slot in which a particular appliance is supposed to complete its task. Let the beginning time slot be represented by  $\alpha_{u,a} \in T$  and end time slot is represented by  $\beta_{u,a} \in T$  and  $\alpha_{u,a} < \beta_{u,a}$

TABLE I  
APPLIANCE PARAMETERS

Appliances	Lot (slots)	Power rating (kWh)	Category
Washing machine	20	1.0	Uninterruptible
Clothes dryer	16	1.6	Uninterruptible
Electric vehicle	36	2.0	Interruptible
Water pump	32	2.0	Interruptible
Humidifier	12	0.5	Interruptible
Vacuum cleaner	24	1.5	Interruptible
Water heater	48	2.0	Interruptible
Dish washer	16	1.2	Interruptible
Refrigerator	96	1.4	Base
Air conditioner	40	1.5	Base
Light	50	0.8	Base
Microwave oven	16	2.0	Base

For example, an electrical vehicle (EV) having  $E_{u,a} = 2KWh$  needs 4 hours to complete its charging cycle for a 50 km driving range in a single day. For compiling tasks, a user must select a larger time slot because, in case of any interruption, the scheduler completes the task by its end time. For example, the user may select  $\alpha_{u,a} = 12 am$  and  $\beta_{u,a} = 8 am$  Mathematically, it is represented as

$$\sum_{t=\alpha_{u,a}}^{\beta_{u,a}} x_{u,a}^t = E_{u,a} \quad (8)$$

where  $x_{u,a}^t$  represents energy consumption vector of appliance  $a$  during  $t$  time slot by  $u$ . Also, from equation (8), it is concluded that appliance  $a$  schedules balances according to daily consumption requirement. Similarly, total energy consumption by all appliances and by all users can be summed up.

$$\sum_{t \in T} L_t = \sum_{u \in U} \sum_{a \in A_n} E_{u,a} \quad (9)$$

Since electronic devices are divided into base, interruptible, and uninterruptible smart appliances, so in case of uninterruptible appliances, strict energy consumption needs to be adopted. In our case, the washing machine (WM) and clothes dryer (CD) have constraints that once WM task ends, CD must start its operation immediately. In that case,  $\alpha_{u,a} = 1$  for WM and  $\beta_{u,a} = 0$  for CD. Similarly, a refrigerator is on all the time, so in that case  $\alpha_{u,a} = 1$  for WM and  $\beta_{u,a} = 96$ . Generally, a scheduler has no active impact on the operation of non-interruptible appliances. For a complete energy consumption profile, the standby power of interruptible appliances needs to be calculated. It is the power that is consumed by interruptible appliances when they are in idle mode.

We need to calculate the minimum ( $\gamma_{u,a}^{minimum}$ ) and maximum ( $\gamma_{u,a}^{maximum}$ ) standby power level for interruptible appliances. Standby power can be assumed to be such power that a device is consuming when it is in non-operation mode but ready to start its operation. We can assume it as:

$$\gamma_{u,a}^{minimum} \geq x_{u,a}^t \geq \gamma_{u,a}^{maximum} \quad (10)$$

We are now ready to calculate different optimal energy scheduling models by considering equations (1)-(10) in our proposed hybrid DSM model.

## OPTIMIZATION METHODS

Integer linear programming (ILP), mixed integer programming (MILP), and mixed-integer nonlinear programming (MINLP) are traditional optimization approaches that cannot manage a large number of appliances. Furthermore, these approaches are computationally unreliable, making them unsuitable for deterministic real-time optimization. The meta-heuristic optimization strategy, on the other hand, will offer the best solution by taking into account user-defined constraints. We are applying a genetic algorithm (GA), grey wolf optimization (GWO) method, and a hybrid of both techniques to achieve real-time optimal results.

GA is based on genes found in living organisms. Binary coded chromosomes are initially initialized at random. The length of chromosomes represents the total number of smart appliances, and the ON/OFF state of smart appliances is determined by the binary-coded pattern of chromosomes. The fitness function of GA is assessed once the initial population has been created, which is an objective function of this analysis. To create a new population, mutation and crossover are used. The produced population fitness function is then compared to the previous one, producing the best results. The GWO algorithm, on the other hand, is based on grey wolf hunting and a leadership hierarchy mechanism. In the leadership hierarchy, there are four types of wolves: alpha, beta, delta, and omega. Prey phases are used to execute optimizations such as hunting, scanning, encircling, and attacking. As a result, the search agents' positions are changed in the form of a location vector against prey. The location of search agents is updated before they achieve an optimum position in the n-dimensional search space.

The hybrid methodology is being proposed to strike a balance between global and local search. In terms of discovery mode, GA excels. It also has a high degree of convergence when it comes to finding the best solution. The GA measures are initially used to produce an initial population of chromosomes. These chromosomes are potentially potential solutions to the problem. Furthermore, the ON/OFF status of smart appliances is represented by a few chromosomes. The fitness function is founded on GWO's objective function. Via GWO's velocity updating phase, the best population is regenerated. To begin, it seeks out the best in the area. The solution, and it achieves a global best solution based on this benefit. The cost minimization problem can be formulated using an optimum stopping law, and the best match value can then be chosen. A new stream is generated as a result of crossover and mutation. As a result, a new age demographic emerges, with entirely different traits from the previous one.

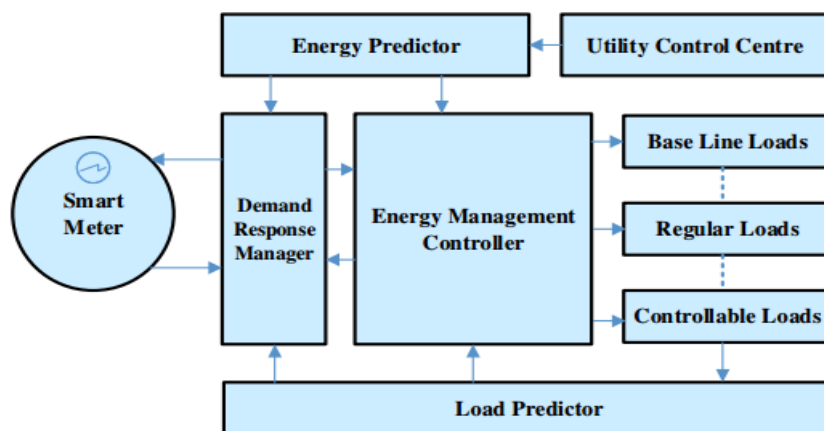


Fig. 1. The proposed system architecture

## SIMULATION RESULTS

In this part, we present simulation results and evaluate the proposed algorithms' accuracy. PAR elimination, cost minimization, and load balancing are all important features to consider when generating RTP signals for DSM. Each group's rate, load, and waiting time are expressed in cents, hours, and kWh. According to RTP, Fig. 2 depicts the load on the grid for a single home using all three methods. In RTP tariffs, the price of power fluctuates during the day.

Prices are higher in the afternoon, on hot summer days, and cold winter days, in particular. Figure 3 shows that while demand is heavy during high price rate hours, unscheduled load produces higher peaks than scheduled load. As a result, the cost of power for unscheduled loads is high. It also shows that, without impacting total load, the proposed exercise feature has the greatest cost and PAR reduction effectiveness.

In comparison, Fig. 4 represents the load profile over several time slots over a full day. It reveals that the suggested hybrid model outperforms the GA and GWO models in terms of moving load to off-peak hours, resulting in substantial PAR and cost savings. Figure 4 portrays the cost in multiple time slots during the day;

as opposed to the hybrid, GWO and GA's consumption trend at peak price is high.  $G^2$  approach. This affects the overall cost per day for the aforementioned approaches as shown in Fig. 5. It clearly shows that the price using hybrid is low as compared to GA and GWO. Using the hybrid  $G^2$ , the proposed approach reduces 20% cost, which is the best among all three used approaches

PAR results are shown in Fig. 6, where the unscheduled load is very high, and for the hybrid  $G^2$  it is commendable. This shows the adeptness of the proposed approach which is better than GA and GWO. In this case, about 50% PAR is reduced by hybrid  $G^2$ . While addressing the cost and PAR, the waiting time of different appliances cannot be overlooked; this is highlighted in Fig. 7. Waiting time has a direct relationship and impact on user comfort and it is an important parameter for efficiency measurement in any proposed scheme. It shows that waiting time for baseload appliances for GA and GWO is higher as compared to the hybrid  $G^2$ .

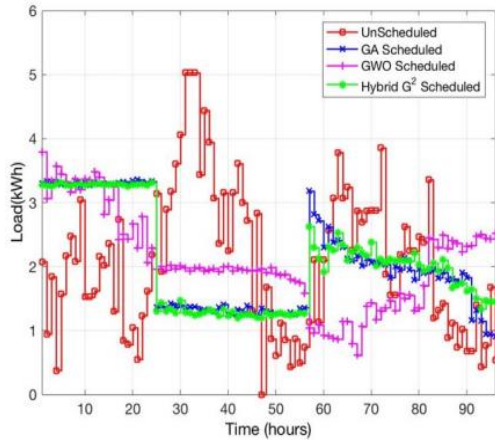


Fig. 2. Load profiles

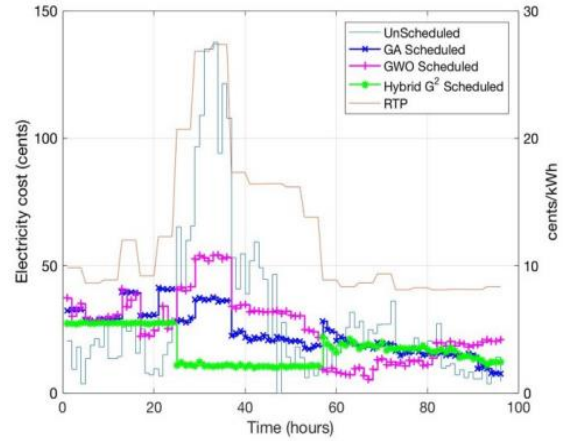


Fig. 3. Energy cost during the time slots

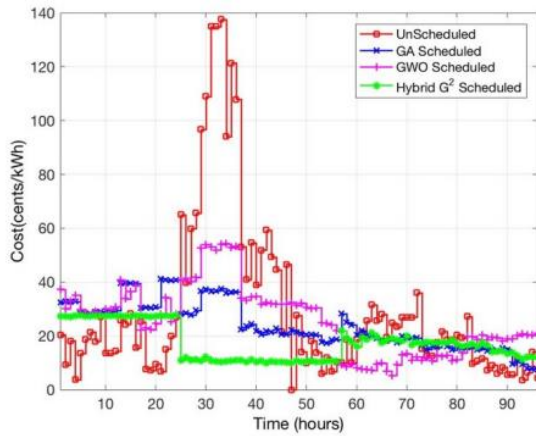


Fig. 4. Energy cost during the time slots

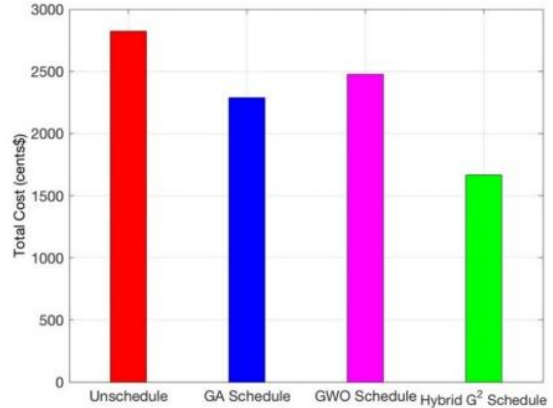


Fig. 5. Total cost under different

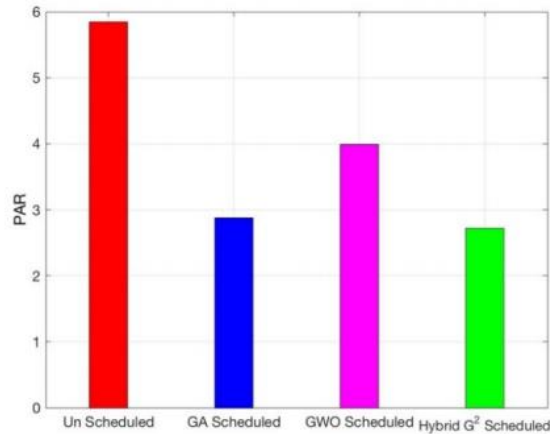


Fig. 6. PAR under different schemes

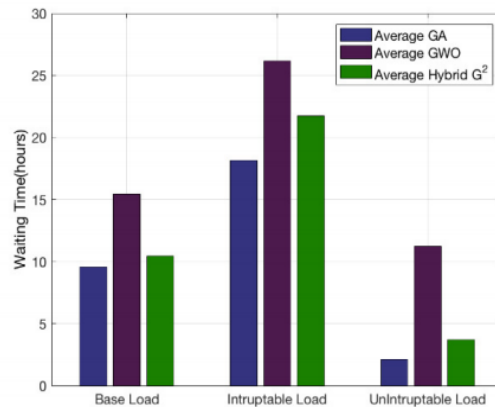


Fig. 7. Waiting time for the different approaches

During the simulation, we perceived that GA is best for a maximum number of populations. With the increase in the population and generation step, the difference between the lowest and highest point becomes negligible. On the other hand, GWO shows high performance for a small population under hundred intervals. Fig. 5 and Fig. 6 show that GA outperforms GWO in terms of cost reduction, peak reduction, and PAR. The hybrid  $G^2$  shows positive influence on both approaches by lowering PAR, cost, and peak load values.

## CONCLUSIONS

We also provided an efficient method for load control in this paper by optimally moving or managing home appliances. The key goal is to make it easier for people to save money on energy. Consumers will save a large amount of money on electricity bills, according to the simulation findings. Artificial intelligence-based optimization techniques are used to support customers. Users can provide a feasible approach to optimum power management for residential energy users by using a carefully planned appliance scheduling model, according to the findings. The suggested system is a combination of GA and GWO. The hybrid solution outperforms both the GA and the GWO. The load is calibrated such that not only are load peaks eliminated, but also user comfort is preserved. It's worth noting that there's a cost-parity tradeoff to consider. Since expense is reduced at some times, the proposed model shifts the load to off-peak hours, optimizing PAR. The suggested hybrid model's usefulness in terms of cost minimization is shown by the results. Integration and testing of RES, as well as a real-time pricing signal, will be part of future work.

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## REFERENCES

- [1] Wen, Zheng, Daniel O'Neill, and Hamid Maei. "Optimal demand response using device-based reinforcement learning." *IEEE Transactions on SmartGrid* 6.5 (2015): 2312-2324.
- [2] Mohsenian-Rad, Amir-Hamed, et al. "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid." *IEE transactions on Smart Grid* 1.3 (2010): 320-331.
- [3] Shirazi, Elham, and Shahram Jadid. "Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS." *Energy and Buildings* 93 (2015): 40-49.
- [4] Rahim, Sahar, et al. "Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources." *Energy and Buildings* 129 (2016): 452-470
- [5] Mesarić, Petra, and Slavko Krajcar. "Home demand side management integrated with electric vehicles and renewable energy sources." *Energy and Buildings* 108 (2015): 1-9.
- [6] Deilami, Sara, et al. "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile." *IEEE Transactions on Smart Grid* 2.3 (2011): 456-467.
- [7] Azar, Armin Ghasem, and Rune Hylsberg Jacobsen. "Appliance scheduling optimization for demand response." *International Journal on Advances in Intelligent Systems* 9.1 & 2 (2016): 50-64.

- [8] Ramanathan, Badri, and Vijay Vittal. "A framework for evaluation of advanced direct load control with minimum disruption." *IEEE Transactions on Power Systems* 23.4 (2008): 1681-1688.
- [9] Ahmad, Adnan, et al. "An optimized home energy management system with integrated renewable energy and storage resources." *Energies* 10.4 (2017): 549.
- [10] Rasheed, Muhammad Babar, et al. "Priority and delay constrained demand side management in real-time price environment with renewable energy source." *International Journal of Energy Research* 40.14 (2016): 2002-2021.
- [11] Ma, Kai, et al. "Residential power scheduling for demand response in smart grid." *International Journal of Electrical Power & Energy Systems* 78 (2016): 320-325.
- [12] Marzband, Mousa, et al. "Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization." *International Journal of Electrical Power & Energy Systems* 75 (2016): 265-274.
- [13] Lee, Jae Yong, and Seong Gon Choi. "Linear programming based hourly peak load shaving method at home area." *Advanced Communication Technology (ICACT), 2014 16th International Conference on. IEEE, 2014.*
- [14] Nadeem, Zunaira, et al. "Scheduling appliances with GA, TLBO, FA, OSR and their hybrids using chance constrained optimization for smart homes." *Energies* 11.4 (2018): 888.