Optimizing residential energy usage patterns in smart grids using hybrid metaheuristic techniques

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Introduction. *This study applies hybrid metaheuristic optimization techniques to intelligently schedule household loads, ensuring a balance between cost reduction, comfort and grid stability in smart homes.* ***Problem.*** *The growing gap between energy demand and supply leads to high electricity costs, increased appliance waiting times, a higher peak-to-average ratio (PAR) and reduced user comfort. Efficient management of residential energy consumption remains a major challenge for sustainable smart grid operation.* ***Goal.*** *This study aims to minimize electricity costs, reduce PAR and enhance user comfort by optimally scheduling household appliances and shifting loads from peak hours to off-peak hours.* ***Methodology.*** *A demand-side management approach is implemented using 5 metaheuristic optimization algorithms: harmony search algorithm (HSA), flower pollination algorithm (FPA), hybrid harmony flower pollination algorithm (HFPA), multiverse optimization algorithm (MVO) and cuckoo search algorithm (CSA). Real-time pricing is employed as the pricing model. MATLAB simulations were conducted for 10, 30 and 50 smart homes, each comprising 15 residential loads categorized as controllable or base appliances.* ***Results.*** *Simulation results demonstrate that the proposed HFPA consistently outperforms HSA, FPA, MVO and CSA across all tested scenarios, achieving notable reductions in electricity cost and PAR while minimizing appliance waiting times.* ***Scientific novelty****. The hybrid HFPA effectively combines the strengths of HSA and FPA, balancing exploration and exploitation to deliver superior performance in multi-objective optimization for home energy management systems.* ***Practical value.*** *The proposed HFPA achieved up to 19.86 % reduction in electricity cost and 81.03 % minimization in PAR, significantly enhancing user comfort and operational efficiency. The method can be further extended for integration with renewable energy sources and machine learning-based predictive control systems.* References 32, tables 6, figures 5.

Key words: **home energy management system, energy consumption pattern, meta-heuristic optimization, hybrid optimization technique, demand side management.**

Вступ*. У роботі застосовуються гібридні метаевристичні методи оптимізації для інтелектуального планування навантаження побутових приладів, що забезпечують баланс між зниженням витрат, комфортом та стабільністю мережі у «розумних» будинках.* ***Проблема****. Зростання розриву між попитом і пропозицією енергії призводить до високих витрат на електроенергію, збільшення часу очікування приладів, підвищення відношення пікового навантаження до середнього (PAR) і зниження комфорту користувачів. Ефективне управління споживанням енергії у житлових будинках залишається серйозною проблемою для сталої роботи «розумної» мережі.* ***Мета****. Дане дослідження спрямоване на мінімізацію витрат на електроенергію, зниження PAR та підвищення комфорту користувачів шляхом оптимального планування роботи побутових приладів та перенесення навантаження з пікових годинників на непікові.* ***Методика****. Реалізовано підхід до управління попитом з використанням 5 метаевристичних алгоритмів оптимізації: алгоритму пошуку гармонії (HSA), алгоритму квіткового запилення (FPA), гібридного гармонійного алгоритму квіткового запилення (HFPA), алгоритму оптимізації мультивсесвіту (MVO) та алгоритму пошуку зозулі (CSA). У якості моделі ціноутворення використовується ціноутворення у режимі реального часу. Проведено симуляції у MATLAB для 10, 30 та 50 «розумних будинків», кожен з яких включав 15 побутових навантажень, класифікованих як керовані чи базові прилади.* ***Результати*** *моделювання показують, що запропонований HFPA перевершує HSA, FPA, MVO та CSA у всіх протестованих сценаріях, досягаючи помітного зниження витрат на електроенергію та PAR за мінімізації часу очікування приладів.* ***Наукова новизна****. Гібридний HFPA ефективно поєднує у собі переваги HSA та FPA, балансуючи дослідження та використання для забезпечення високої продуктивності у багатоцільовій оптимізації систем управління енергоспоживанням у будинку.* ***Практична значимість****. Запропонований HFPA дозволяє знизити витрати на електроенергію до 19,86 % та мінімізувати PAR на 81,03 %, значно підвищивши комфорт користувача та ефективність роботи. Метод може бути додатково розширено для інтеграції з відновлюваними джерелами енергії та системами прогнозуючого керування на основі машинного навчання.* Бібл. 32, табл. 6, рис. 5.

Ключові слова: **система керування енергоспоживанням у будинку, структура енергоспоживання, метаевристична оптимізація, гібридний метод оптимізації, керування попитом.**

Introduction. The rapid growth in global power demand, driven by technological advancements, highlights the urgent need for efficient energy management. Traditional electricity networks are increasingly unable to meet these growing needs, prompting the development of a new concept known as the Smart Grid. Smart Grid integrates cutting-edge components such as smart devices, clean energy sources, smart meters, and energy-saving appliances. Smart meters, for example, are used to monitor energy flow importing, exporting, or both. They are also critical in ensuring communication between customers and utilities, offering efficient, reliable, cost-effective, and dynamically controllable energy solutions [1, 2].

Many demand-side management (DSM) solutions have been suggested in the literature to optimize power consumption patterns by shifting loads on a priority basis, reducing loads to off-peak levels, and filling valleys by utilizing energy during low-demand periods. These approaches help balance supply and demand effectively [3]. The objectives of DSM techniques are to minimize electricity cost, energy consumption, and the peak-to-average ratio (PAR). Demand response programs, which play a pivotal role in DSM, encourage customers to modify their power consumption habits depending on price signals. Demand response is typically classified into 2 types: price-based and incentive-based programs, both aiming to induce energy-efficient behaviors [3, 4]. For example, users shifting their loads during off-peak hours benefit from lower power bills, increasing user satisfaction.

The major objectives of electricity management include lowering PAR, electricity costs, and energy use, along with the integration of renewable energy sources. To fulfill these objectives, several DSM strategies have been devised; some involving scheduling algorithms that optimize demand through demand response programs. These initiatives use smart appliances, smart metering infrastructure, and two-way communication to ensure effective energy use in multiple load sectors such as homes, plazas, towns, cities, and industries. Dynamic pricing systems also play a vital role: real-time pricing (RTP) provides current data and prices; variable peak pricing manages multiple peak periods; and time-of-use pricing accounts for devices operating at different times [4, 5].

Given that residential areas contribute significantly to overall energy consumption, this research focuses on optimizing the usage of smart appliances in single and multiple homes. Appliances are categorized as controllable or base appliances to facilitate effective scheduling.

The main challenges in Smart Grid include minimization of energy consumption, electricity bill reduction, PAR reduction, minimization of waiting time (equivalent to maximizing user comfort), and renewable energy source integration. Several heuristic and mathematical approaches have been proposed to address these optimization challenges. Most crucially, waiting time – used as a proxy for user comfort is often overlooked in efforts to mitigate rising power expenses. Furthermore, the unpredictable nature of consumer demand complicates optimal scheduling at the residential level. DSM also faces challenges such as communication, load shifting, security and privacy, and fairness. To address these limitations, various meta-heuristic optimization strategies have been applied. Previous studies have employed binary particle swarm optimization (BPSO), genetic algorithm (GA), bacterial foraging optimization (BFOA), wind-driven optimization (WDO) and hybrid methods such as GA–BPSO.

This study **aims** to minimize electricity costs, reduce PAR, and enhance user comfort by optimally scheduling household appliances and shifting loads from peak hours to off-peak hours. To accomplish these aims, 5 metaheuristic optimization algorithms are implemented to optimally shift household loads from peak hours to off-peak hours within a smart grid environment: harmony search algorithm (HSA), flower pollination algorithm (FPA), hybrid harmony flower pollination algorithm (HFPA), multiverse optimization algorithm (MVO) and cuckoo search algorithm (CSA).

Analysis of the related work. In recent years, a variety of optimization strategies have been presented to enhance Smart Grid optimization utilizing DSM and demand response. Cost minimization, PAR reduction, and load optimization have always been the primary objectives for achieving an ideal solution. In this part, a literature review on various optimization strategies is presented. In [6], the authors proposed an empirical pattern and real-time mutli-period artificial bee colony (MABC) technique type cardinal electrical power management scheme for home microgrids to maximize system overall performance and decrease power expenditures. To regulate unit pricing in real time, this system employs real-time scheduling in conjunction with day-ahead scheduling points, as well as a localized energy marketplace structure based on single-side auctioneer. The recommended approach’s performance is compared to that of the mixed integer non-linear programming (MINLP) method. The results show a considerable increase in efficiency and accuracy across a variety of circumstances. An experimental approach to energy management systems (EnMS), focusing on reducing energy consumption through advanced techniques is discussed in [7].

EnMS is a technique created by UNIDO that is used to minimize greenhouse gas emissions [8] into the environment by conserving energy. This strategy would be used for commercial and office buildings that utilize a lot of power on a regular basis. Simulation and results indicate that installing EnMS can cut power usage by up to 30 %. The distributed optimization algorithm for microgrids energy management (MEM-DOA) was first put out in [9]. The authors of this paper contend that the contributions of distributed energy generation and distributed energy storage to DSM cannot be overestimated. A DSM-connected grid consists of large-scale central energy storage, electric vehicles, and a variety of smart consumers, both active and passive. MEM-DOA is being implemented by the authors according to the type of customer. According to the results, the suggested approach is more successful in reducing PAR, power costs, and user comfort. The authors [10] presented a hybrid method for residential area load scheduling called teaching learning genetic optimization (TLGO), which blends the teaching learning-based optimization (TLBO) algorithm with GA.

In [11] was proposed a metaheuristic optimization strategy for residential areas. This study work employs 3 metaheuristic optimization techniques: tabu search algorithm, particle swarm optimization (PSO) and simulated annealing. The authors of [12] describe a home energy management system (HEMS) that is based on 4 heuristic algorithms: WDO, GA, BFOA and BPSO. Additionally, a hybrid method called genetic BPSO (GBPSO) is suggested. The RTP model is used to get updated time base prices of energy units for load optimization. The simulation and findings illustrate that GA out runs in PAR, BPSO outruns in cost minimization, and GBPSO out runs in cost and PAR reduction. Based on the RTP price structure, work [13] suggests a simple DSM model for residential clients. It seeks to lower electricity bills, PAR and appliance wait times. The GA heuristic technique is used in this study. The authors explore 2 test systems for validation of simulation results, one is of one user or home and other one is 20 users. The results show that the proposed system perform well in both cases. A heuristic-based evolutionary method has been developed in [14] with the primary goal to minimize electricity costs and PAR. In this research, the authors look at 3 sorts of users: residential load, industrial load and commercial load. The results demonstrate that the suggested method can handle several types of devices and achieves the desired PAR and cost.

The authors proposed a successful DSM paradigm for residential areas in [15]. The authors employ 2 pricing methods, time-of-use and inclining block rate and 3 optimization approaches: GA, ant colony optimization (ACO) algorithm and BPSO. The results of the study illustrated that GA outperform from ACO and BPSO in cost and PAR minimization. In [16], employs consumer demand response with dynamic price rates. The goal of this strategy is to enhance the user experience by shift the loads from high demand period to low demand period. The authors provide self-organizing home energy networks that are controlled by appliance control interfaces and interact with smart appliances. In [17], the authors provide a real-time information-based energy management system for balancing the household load in microgrid. For this objective, the authors employ GA to reduce power costs while increasing user comfort. In this study, daily utilizing loads are divided into 5 categories: elastic, inelastic, thermostatically controlled, user aware, and normally used loads. The results reveal that the proposed algorithms lowered costs by up to 22.63 % and reduced PAR by up to 22.77 %. The authors employ RTP to encourage consumers to engage in load scheduling [18]. The authors employ an intelligent decision support system (IDSS) for load scheduling. High-performance scheduling is used to establish time of use pricing, on/off peak pricing, RTP, two-tier pricing and combinations of the above.

In [19], a multi-objective optimization framework is suggested for the optimized operation of a stand-alone combined cooling, heating, and power microgrid. The study employs a modified chaos particle swarm optimization (MCPSO) algorithm to enhance convergence speed and search performance for complex optimization problems. In [20] was proposed a strategy to tackle global warming and increasing carbon emissions. The authors assess their goal by utilizing GA, effective differential evolution (EDE), the suggested improved differential teaching learning algorithm, and the TLBO method to control energy usage and user comfort. The authors of this study utilize RTP. For the HEMS in DSM, the authors [21] proposed a heuristic optimization method. For residential load control, this study employs the conventional dynamic programming approach in addition to 2 heuristic optimization techniques: GA and BPSO. In [22], the authors suggest a realistic scheduling mechanism (RSM) to cut power costs and achieve equilibrium amongst appliance utilities. In this study, the authors suggest a BPSO-based optimization approach to cut power costs and improve user pleasure. PAR is ignored in this article. Table 1 gives a summary of the most recent study, including the research purpose, recommended methodology, and constraints.

Table 1

Review of the most recent research

References	Techniques	Objectives	Limitations
Energy management systems for smart hybrid home [6]	MABC, MINLP	Cost, PAR reduction, user comfort	Increased system complexity
Energy management system on energy efficiency [7]	EnMS	Cost reduction and maximize user comfort	PAR is neglected
Distributed optimization algorithm for DSM [9]	MEM-DOA	Cost, PAR reduction	User comfort is ignored
Intelligent hybrid heuristic approach for smart metering [10]	GA, TLBO, TLGO	Cost and user comfort	PAR not considered, Increased complexity
Metaheuristic optimization techniques for residential energy management [11]	PSO, simulated annealing, tabu search	Cost, PAR reduction, user comfort	Increased system complexity
Heuristic algorithm based HEMS [12]	GA, BPSO, BFOA, WDO, GBPSO	Cost and PAR reduction	Increased system complexity
An improved system architecture for optimal DSM [13]	GA	Cost reduction	PAR is ignored
DSM of smart grid [14]	Heuristic based evolutionary algorithm	Cost reduction and minimization of PAR	Waiting time is ignored
Using heuristic methods to optimize energy management [15]	GA, BPSO, ACO	Reduce cost, PAR, execution time, and improve user comfort.	Increased system complexity
An intelligent HEMS to improve demand response [16]	ANFIS predictor	Energy consumption	User comfort is ignored
Real-time information-driven energy management [17]	GA	Minimize power costs while increasing user comfort	PAR not considered, increased complexity
Heuristic optimization of consumer electricity costs [18]	IDSS	Minimize electricity cost and execution time	PAR and user comfort is ignored
MCPSO based optimized operation model [19]	PSO, MCPSO	Convergence speed, environmental benefit	Increase system complexity
DSM in nearly zero energy buildings [20]	GA, EDE, TLBO	User comfort and energy consumption	PAR is neglected
Hybrid optimization for residential load [21]	BPSO, GA	Maximize user comfort, minimize electricity cost	PAR not considered
RSM for smart houses [22]	BPSO, RSM	Electricity cost and user comfort	PAR is neglected

System model. Energy management and end-user demand-side control are the two main goals of DSM, which increase its efficiency and dependability. Smart devices such as energy management controllers (EnMCs) and smart meters are installed in every smart home to facilitate consistent and reliable bidirectional communication between consumers and utilities. The EnMC receives data from sensors, storage devices, local generation, and all electrical equipment. Smart meter sends pricing signals to the EnMC after receiving them from the utility. After that, the EnMC organizes appliance data according to the utility's price signal. Smart meter and utilities can connect via wired protocols or wireless systems such as Z-Wave and ZigBee. All electric loads, EnMCs and smart meters interact over a home area network. This paper examined single and multiple homes equipped with 15 appliances. In the energy pricing model, the RTP tariff is used to generate an electricity bill. To achieve the aforementioned aims, operating time interval (OTI) of 5 min, 30 min and 1 hour are employed. A 1-hour time slot is broken into 12 equal-sized sub-time slots, each of which lasts 5 min. Because many appliances last less than an 1 hour, the remaining operating time of the appliance is squandered. As a result, a 5-min time interval saves power and makes the system more resilient than a 30-min or 1-hour OTI.

Load categorization. Load appliances are categorized according to their power consumption into 2 main classes: non-controllable appliances and base appliances. Figure 1 shows the model of the proposed system and Table 2 shows the parameters of all appliances. Burst load appliances are another name for non-controllable appliances. The time slots of these appliances can be adjusted to any available slot. It is impossible to change the equipment's overall running time or energy consumption pattern. These appliances can not be shut off once they are switched on. Examples of these items are a washing machine and a fabric dryer. Base appliances are also known as fixed appliances. The total operating duration and energy consumption pattern of these appliances cannot be altered. If the user wants to switch on these appliances at any time, they must do so during the specified time frame.

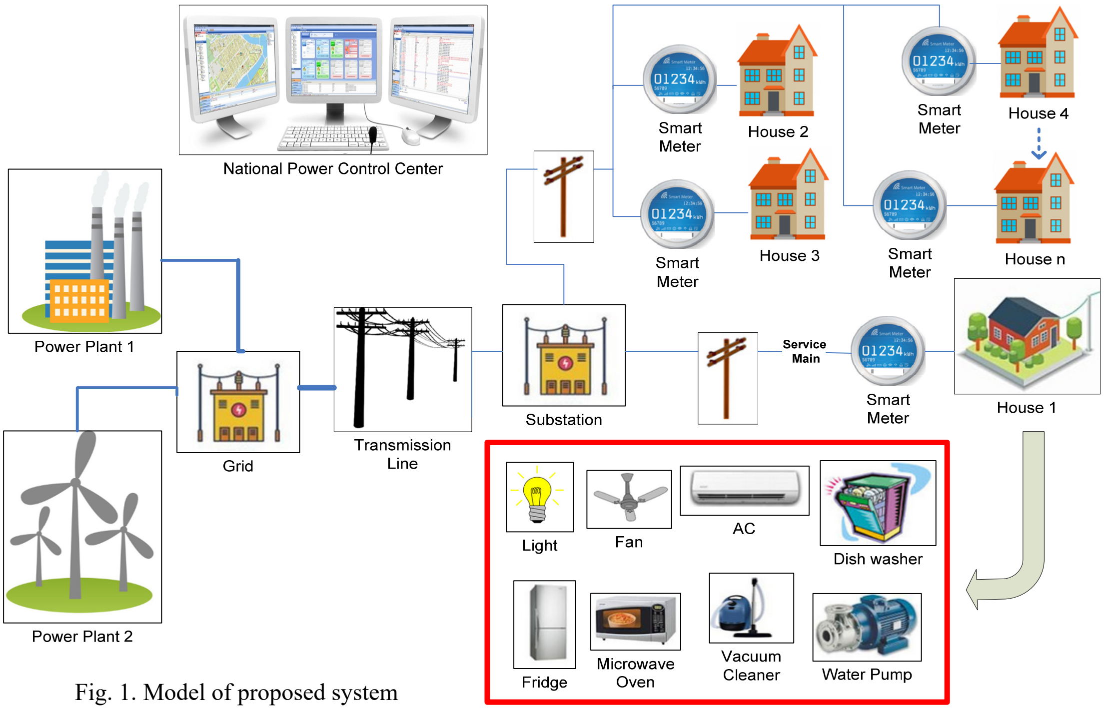

Fig. 1. Model of proposed system

Table 2

Parameters of appliances

Appliances	LOT*, slots	PR*, kW	Category
Washing machine	18	2	Non-controllable
Cloth dryer	10	2	Non-controllable
Dish washer	20	0.5	Non-controllable
Hair dryer	3	1.8	Base
Toaster	2	0.8	Base
Kettle	2	2	Base
Phone	288	0.005	Base
Computer	24	0.15	Base
Hair straighter	2	0.055	Base
Oven	13	2.4	Base
Cooker hood	13	0.225	Base
Iron	6	2.4	Base
Light	90	0.1	Base
Refrigerator	288	1.67	Base
Television	158	0.083	Base

*LOT – length of operation time (time slots); PR – power rating (kW).

Price model. Power prices are determined by the utility and power costs are calculated accordingly. Different dynamic methods are employed to reduce power costs and the PAR levels. These dynamic methods incentivize customers to shift large loads from peak to off-peak hours. Time-of-use, inclining block rate, critical peak pricing, day-ahead pricing and RTP are all included in dynamic pricing plans. In this study, RTP is used to calculate power bills. RTP-based power pricing can fluctuate as frequently as once per hour. Price signals in RTP may vary between time slots, whereas other pricing methods remain consistent for each time slot.

Mathematical formulation of the problem. The HEMS problem is formulated as a multi-objective optimization problem. The goal is to determine the optimal control of household appliances, energy storage units and distributed generation sources to minimize energy cost and PAR, while maintaining acceptable waiting time and maximizing user satisfaction.

The **objective function** can be expressed as a weighted sum of multiple objectives:

$$F_{\min} = \alpha_1 \cdot C_{tot} + \alpha_2 \cdot PAR + \alpha_3 \cdot W_t - \alpha_4 \cdot U_s, \quad (1)$$

where C_{tot} is the total energy cost; PAR is the peak-to-average ratio of power demand; W_t is the total waiting time, hrs; U_s is the user satisfaction index (0–1); α_1 – α_4 are the weighting coefficients representing the priority of each objectives.

The **cost of energy consumption** is calculated as:

$$C_{tot} = \sum_{t=1}^{T} \gamma(t) \cdot E_{grid}(t), \quad (2)$$

where $\gamma(t)$ is the electricity price at time t (time of use tariff); $E_{grid}(t)$ is the energy purchased from the grid at time t.

The **energy balance constraint** is expressed as:

$$\sum_{h1}^{H} P_h(t) = E_{grid}(t) + E_{DG}(t) + E_{bat}(t), \quad (3)$$

where $P_h(t)$ is the power demand of home appliance h at time t; $E_{grid}(t) + E_{DG}(t) + E_{bat}(t)$ is the combination of grid, local generation and storage.

PAR reduction. The PAR is defined as:

$$PAR = \frac{\max_t \left(\sum_{h1}^{H} P_h(t) \cdot x_h(t) \right)}{\frac{1}{T} \sum_{t=1}^{T} \left(\sum_{h1}^{H} P_h(t) \cdot x_h(t) \right)}, \quad (4)$$

where $x_h(t)$ is the binary control variable (ON/OFF status of appliance h).

Waiting time constraint. If an appliance h is deferred by d_h hours, then:

$$W_t = \sum_{h=1}^{H} d_h . \quad (5)$$

Proposed approaches. HSA. In this work, the heuristic algorithm HSA is applied to achieve the objectives. In 2001, this algorithm was proposed by Prof. Zong Woo Geem. The HSA is motivated by musicians' improvisations to establish harmony in their works [23]. It is based on 3 primary components: harmony memory, harmony memory consideration and pitch correction. Initially, a harmony memory is created with potential solutions. During each cycle, a new solution is generated by either selecting values from the harmony memory or generating new ones using pitch adjustment and a randomization factor. New harmony is tested using a fitness function, and if it outperforms the poorest solution in the harmony memory, it replaces it. This iterative procedure is repeated until an optimal or satisfactory solution is found, making HSA suitable for addressing complex optimization issues [24].

Steps of HSA are next:

```
Initialize all the algorithm parameters
Generate starting harmoniousness memory
Measure the fitness of starting generated memory
for x = 1 : H do
    for itr = 1 : Maximum.iterations do
        Improvise new harmony vector newh
        for y = 1 : 12 do
            if rand() < HMCR then
                Choose value from
                harmoniousness memory
                if rand() < PAR then
                    Tune the value
                end if
            else
                Select a random value
            end if
        end for
    end for
    Perform selection process
    Compare newh with worst harmony Xworst
    if f(xnew) < f(xworst) then
        xworst = xnew
    else
        Keep the existing value
    end if
end for
```

FPA is inspired by the pollination process in flowering plants [25]. It uses 2 modes of pollination: global and local. In global pollination, solutions are updated by considering the best solution and a Lévy flight-based random walk. In local pollination, neighboring solutions are combined to create new candidate solutions. The transition between global and local pollination is controlled by a switch probability parameter. FPA mimics the natural foraging and pollination behaviors of insects to effectively explore and exploit the solution space, making it a robust approach for optimization tasks. The most recent nature-inspired algorithm is FPA, which is based on the pollination process of plants. Flowering plants' flower pollination technique led Xin-She Yang to develop FPA in 2012. FPA is primarily used to address both constrained and unconstrained optimization issues. The primary advantages of FPA that interest researchers are its processing speed, resilience and simplicity of modification based on requirements [26]. The 4 rules listed below are used for simplicity of reference.

1) Biotic and cross-pollination are considered global pollination processes; pollen is carried by pollinators in a manner consistent with Lévy flights.

2) Local pollination involves abiotic pollination and self-pollination.

3) Pollinators, like insects, contribute to the likelihood of reproduction based on the matching of two flowers.

4) The interplay of local and global pollination may be regulated by a switch probability p [0, 1], which is somewhat biased in favor of local pollination. The algorithm 2 depicts the entire FPA process.

Steps of FPA are next:

```
for x = 1 − population.size do
    for y = 1 − loads do
        Generate a random population
        Calculate F = fitness function
        if F()F(i−1)||load(t) < unscheduledload(t) then
            F(i) = F(i)
            if (va using (4) – (ha < ta) then
                Load is ON
            else
                wait until Low demand period (off-peak hours)
            end if
        else
            F(i) = F(i − 1)
        end if
    end for
end for
for z = 1 − MaxItr do
    Generate random flowers (population)
    for m = 1 : appliances do
        if rand > ProbabilitySwitch then
            use levy flight to update solution
        else
            select random population
            check simple bounds
        end if
    end for
    Evaluate new solution
    if Fnew < Fold then
        update the solution using new fitness values
    end update the global best
end Return best solution
```

HFPA is a hybrid optimization technique combining the strengths of HSA and FPA [27]. It utilizes the harmony memory concept of HSA to generate and refine solutions in the early phases and uses the global and local pollination concepts of FPA to make better use of the solution exploration and exploitation. Such hybridization will be used to strike a balance between convergence speed and solution space diversity. The incorporation of these 2 methodologies has resulted in better performance of HFPA in terms of computational efficiency and solution quality, and makes HFPA effective in dealing with complex optimization problems [28].

Steps of HFPA are next:

```
Initialize all the parameters
Generate initial harmoniousness memory
for x = 1 − MaxItr do
    Generate random flowers (population)
    for m = 1: appliances do
        if rand > P robabilitySwitch then
            use levy flight to update solution
        else
            select random population
            check simple bounds
        end if
    end for
    Evaluate new solution
    Perform selection
    Compare new solution with worst harmony
    if (xnew) < f(xworst) then
        xworst = xnew
    else
        Keep existing
    end if update the global best
end for Return best solution
```

The suggested hybrid algorithm HFPA employs FPA in initializing the population of n flowers or pollen gametes with random solutions. A d-dimensional step vector L is drawn from a Lévy distribution, then the new solutions are compared to the worst harmony vectors.

MVO algorithm is inspired by such concepts as the multiverse theory [29]. It applies the theory of white holes, black holes and wormholes to explore and exploit the processes of optimization. White holes represent solutions that are being found and carry positive characteristics with the previous but black holes represent the substitution of unwanted solutions with better solutions. Wormholes lead to random modifications in solutions and this keeps the space of search diverse. It uses dynamic exploration and exploitation to dynamically balance between them to optimally converge upon the best solution and, therefore, it can be applied to a broad class of optimization problems [30].

Steps of MVO algorithm are next:

Initialize all parameters
Generate initial population of universes
Evaluate fitness of each universe
for i = 1 : T **do**
    for itr = 1 : Max.iterations do
    Sort universes based on fitness
    Normalize inflation rates
        for j = 1 : N do
            if rand() < WEP then
            Perform white hole tunneling
        else
            Perform wormhole existence probability adjustment
        end if
    end for
    end for
    Perform selection
    Compare new universe with worst universe $Xworst$
    if $f(Xnew) < f(Xworst)$ **then**
        $Xworst = Xnew$
    else
        Keep existing
    end if
end for

CSA is a bio inspired optimization algorithm that emulates the collaborative foraging process of cuckoo birds [31]. The techniques employed by the algorithm include selection of nest, egg-laying area and finding of prey. Cuckoo eggs are solutions that might be good, and the algorithm repeats the process of replacing the old with a better one as it searches through the cuckoo eggs. It utilizes search mechanisms such as global and local search in maintaining diversity combined with speed in approaching convergence. The flexible characteristic of the method defines its applicability in addressing non-linear as well as multidimensional optimization [32].

Steps of CSA are next:

Initialize all parameters
Generate initial population
Evaluate fitness of each individual
for i = 1 : T **do**
    for itr = 1 : $Max.iterations$ do
    Sort universes based on fitness
    Select the best individuals
        for j = 1 : N do
            if rand() < Pm then
            Perform mutation
        else
            Perform local search
        end if
    end for
    end for
    Perform selection
    Compare new universe with worst universe $Xworst$
    if f($Xnew$) < f($Xworst$) **then**
        $Xworst = Xnew$
    else
        Keep existing
    end if
end for

Simulation and results. This section evaluates the performance of the suggested approach using MATLAB simulations with the RTP scheme. The algorithm's efficacy is evaluated using measures such as power cost, energy usage, PAR reduction and user satisfaction. The simulation scenario includes single and multiple households, each with 15 appliances divided into 2 categories: non-controllable and base appliances.

Figure 2 depicts the power cost of the simulated algorithm for single and multiple homes, as determined during the scheduling process. It also shows the electricity cost of HAS, FPA, HFPA, MVO and CSA, which is less than the unplanned cost. The comparative data is provided in Table 3. The results demonstrate that the hybrid approach of HFPA and MVO outperforms than the other strategies in terms of cost in all scenarios.

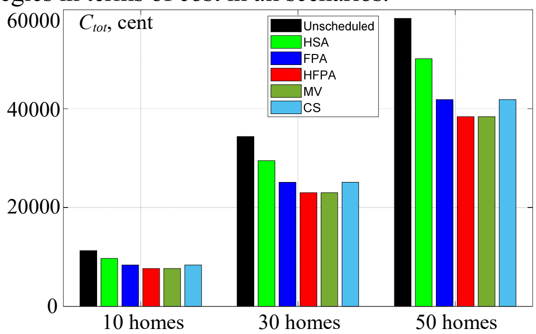

Fig. 2. Total cost against different OTIs

Table 3

Cost comparison of single home for different OTIs

OTI	Parameters	Unscheduled	HSA	FPA	HFPA	MVO	CSA
5-min	Cost, cent	71.09	66.577	65.14	61.647	63.134	64.98
	Difference	–	4.513	5.95	9.443	7.956	6.11
	Efficiency, %	–	6.34	8.36	13.28	11.19	8.59
30-min	Cost, cent	480.822	420.614	408.977	386.912	390.883	407.214
	Difference	–	60.207	71.844	93.909	89.939	73.608
	Efficiency, %	–	12.53	14.94	19.54	18.70	15.31
1-hour	Cost, cent	963.304	847.751	836.283	771.988	793.218	835.012
	Difference	–	115.552	127.021	191.313	170.086	128.292
	Efficiency, %	–	11.99	13.59	19.86	17.65	13.31

The reduction of PAR is beneficial to both utilities and consumers. During the scheduling process, if PAR increases, then the cost also increases, and if PAR is reduced, then the electricity cost decreases. The PAR performance of HSA, FPA, HFPA, MVO and CSA is listed in Table 4 for all OTIs. It is shown that PAR is reduced compared to the unscheduled case. Result shows (Fig. 3) that HFPA and MVO perform better in all OTIs compared to CSA, HSA and FPA.

Table 4 compares the PAR for different optimization techniques. HFPA stands out by significantly reducing PAR, particularly in the 30-min interval, where it achieves an efficiency improvement of 81.03 %. This demonstrates how HFPA reduces power consumption while maintaining system performance. The results complement this by showing the efficiency levels of the optimization techniques over time. It highlights that HFPA and MVO maintain higher efficiency across all time intervals, with particularly strong performance in the 1-hour interval. These results underscore the effectiveness of HFPA and MVO in reducing power consumption and ensuring high efficiency over extended periods.

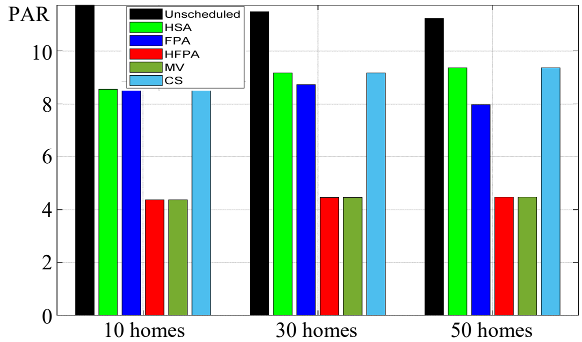

Fig. 3. PAR against different OTIs

Table 4

PAR comparison of single home for different OTIs

OTI	Parameters	Unscheduled	HSA	FPA	HFPA	MVO	CSA
5-min	PAR	16.204	7.8312	7.9717	3.4293	5.4567	7.6243
	Difference	–	8.3728	8.2323	12.7747	10.7473	8.5797
	Efficiency, %	–	51.67	50.8	78.83	66.32	52.94
30-min	PAR	14.421	6.2447	5.3035	2.7345	4.4155	5.0005
	Difference	–	8.1763	9.1175	11.6865	10.0055	9.4205
	Efficiency, %	–	56.69	63.22	81.03	69.38	65.32
1-hour	PAR	8.0991	5.2407	5.3035	2.7345	3.5535	5.1545
	Difference	–	2.8584	2.7956	5.3646	4.5456	2.9446
	Efficiency, %	–	35.29	34.51	66.23	56.12	36.36

The waiting time and electricity cost both affect user comfort. In this case, waiting time is used to gauge consumer comfort. Customers must use the most energy-efficient appliance schedule in order to reduce their power costs. Power costs and user comfort are a trade-off; if customers value comfort more than power costs, they will have to pay more for electricity. Power costs and user comfort are inversely related.

Figure 4 shows the average waiting time for HSA, FPA, HFPA, MVO and CSA. These results show that waiting time is reduced compared to unplanned cases. The results show that HFPA and MVO perform better in all OTIs than CSA, HSA, and FPA.

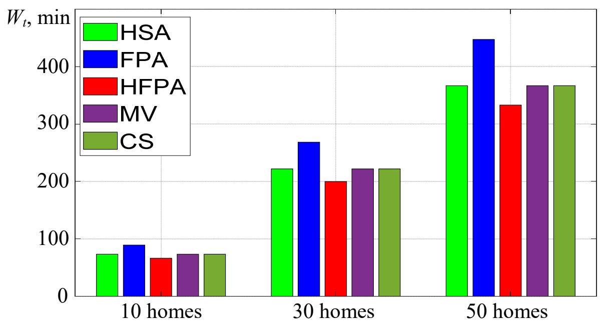

Fig. 4. The average waiting time for different OTIs

Table 5 compares the waiting times for each optimization technique across the 3 OTIs. HFPA achieves the lowest waiting times, particularly in the 1-hour interval, where the waiting time is reduced to just 7 min. This demonstrates HFPA's ability to enhance system responsiveness.

Table 5

Waiting time comparison of single home for different OTIs

Parameter	OTI	HSA	FPA	HFPA	MVO	CSA
Waiting time	5-min	115	110	102	105	108
	30-min	23	20	18	19	21
	1-hour	9	7.5	7	7.5	8.2

Comparison of techniques. HFPA emerges as the best choice because it offers excellent performance across all 3 criteria (cost, waiting time and PAR). It effectively handles the interdependencies between multiple homes, optimizing energy sharing and scheduling. Its hybrid nature makes it adaptable to multi-objective problems common in multi-home systems. The MVO is a close second because it performs well in dynamic, highly interconnected environments where energy demands fluctuate significantly. However, its computational complexity may be a limitation for very large-scale systems.

Figure 5 shows a comparison of the proposed algorithms for all constraints. Table 6 shows a comparison of algorithms for HEMS for multiple homes.

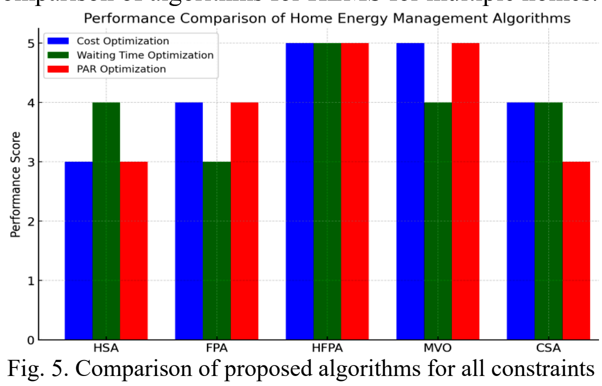

Fig. 5. Comparison of proposed algorithms for all constraints

Table 6

Comparison of algorithms for HEMS for multiple homes

Algorithm	Cost optimization	Waiting time optimization	PAR optimization	Strengths	Weaknesses	Suitability
HSA	Moderate	Good	Moderate	Simple algorithm, computationally efficient for small-scale systems	Limited global optimization capabilities, struggles with interdependencies between homes	Better for simpler, independent multi-home systems with less complex constraints
FPA	Good	Moderate	Good	Balances local and global optimization, effective for multiple objectives	May struggle with dynamic changes in load-sharing and inter-home dependencies	Suitable for moderately interconnected multi-home systems with predictable energy patterns
HFPA	Excellent	Excellent	Excellent	Combines the strengths of HSA and FPA, handles interdependencies effectively	Computationally demanding, requires more resources	Ideal for highly interconnected systems requiring robust optimization for cost, waiting time and PAR
MVO	Excellent	Good	Excellent	Excels in handling dynamic and interdependent systems, adaptable to changes in energy demand	High computational complexity, slower convergence for very large-scale systems	Suitable for complex and highly dynamic multi-home systems, especially with fluctuating demands
CSA	Good	Good	Moderate	Fast convergence, effective for systems with straightforward optimization needs	Less capable of handling complex interdependencies and dynamic energy management	Best for smaller-scale multi-home systems with limited interaction between homes

Conclusions. The introduction of smart grids has enabled considerable advances in energy system optimization, notably through the use of HEMS in smart homes. Effective energy management in these contexts requires accurate scheduling of smart appliances, a challenge addressed by ground breaking discoveries in DSM. DSM approaches have been effectively deployed in the residential, commercial and industrial sectors, proving their ability to balance consumer load profiles within grid networks.

This study investigates metaheuristic optimization methodologies for increasing energy efficiency in smart homes. The strategies studied include the HSA, FPA, HFPA, MVO and CSA. These solutions optimize energy use across multiple loads while using the RTP model to determine power bills. Simulations in MATLAB show that these strategies effectively reduce electricity bills and PAR. Compared to the unscheduled case, energy costs decreased by up to 19.86 % (HFPA), 19.54 % (HFPA, 30-min OTI), and 13.28 % (HFPA, 5-min OTI). The highest savings were achieved by the HFPA algorithm, consistently outperforming others. The PAR was reduced by up to 81.03 % (HFPA, 30-min OTI), 78.83 % (HFPA, 5-min OTI), and 66.23 % (HFPA, 1-hour OTI). This confirms effective load shifting and peak shaving. All algorithms maintained waiting times within acceptable limits. HFPA achieved the best results with only 102 min (5-min OTI), 18 min (30-min OTI), and 7 min (1-hour OTI), ensuring high user comfort.

The HFPA is the most successful of the proposed approaches, outperforming others in key criteria such as cost reduction, reduced waiting time, and enhanced PAR. Its hybrid formulation enables it to deal with the multi-objective attribute of energy management in multi-home systems by optimizing energy sharing as well as appliance schedules. The MVO is in second place and has an exceptional performance in the context of various dynamic and interconnected environments where energy requirements are highly volatile. But it can be considered computationally intensive to scale to the larger size.

The research shows that metaheuristic optimization methods can be used to enhance smart home energy management that would allow developing a more sustainable and efficient practice of energy consumption.

It is recommended that future research would concentrate on improvement and optimization of HFPA so it can be introduced at an even greater scale. It must also be combined with the machine learning and deep learning models to improve predictability and accuracy. The MVO is associated with greater complexity and hence, there is need to lower the degree of complexity of this algorithm in any follow up research. The proposed model should be combined with renewable energy resources in order to enhance sustainability.

Conflict of interest. The authors declare that they have no conflicts of interest.

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