SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 22, No. 1, February 2025, 17-34

UDC: 004.94:[620.92-048.34:64 DOI: https://doi.org/10.2298/SJEE2501017K

Original scientific paper

Scheduling of Home Energy Management Systems for Price-Based Demand Response and End-Users Discomfort Reduction

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Abstract: The home energy management system (HEMS) can effectively participate in price-based demand response programs, significantly reducing electricity costs by optimizing the usage times of shift-able household appliances such as washing machines, dishwashers, and others. However, this optimization may compromise the comfort of the residents. In this paper, a discomfort index is proposed based on the time intervals between the start and end of the operation periods of these shift-able appliances relative to their residents' preferred usage times. The problem of optimal scheduling for these appliances is then modeled as an optimization problem aimed at minimizing the weighted sum of the daily household electricity bill and the discomfort index. A constraint is imposed to restrict the discomfort index to a maximum allowable level. This optimization problem is solved using a simulated annealing algorithm across various scenarios with different maximum allowable values for the discomfort index. The simulation results indicate that, among the optimal schedules across the scenarios, the most cost-effective demand response schedule can be identified based on the marginal reductions in the daily household electricity bill. This approach ensures substantial decreases in electricity expenses while avoiding unnecessary increases in the discomfort index.

Keywords: Home Energy Management System, Demand Response, Discomfort Index, Simulated Annealing Algorithm.

1 Introduction

The increasing demand for electricity and the emergence of smart grids have provided new opportunities for home energy management systems. A Home Energy Management System (HEMS) is an intelligent system that assists users in managing their energy consumption at home and enhancing energy efficiency.

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Additionally, with the deployment of smart meters in homes, the ability to establish communication, enable control, and automate electricity transmission between the grid and households has been enabled, thus facilitating greater participation of households in demand response (DR) initiatives.

The increasing demand for electricity and the emergence of smart grids have provided new opportunities for Home Energy Management Systems (HEMS). A home energy management system is an intelligent system that assists users in managing their energy consumption at home and enhancing energy efficiency. Additionally, with the deployment of smart meters in residential homes, the ability to establish communication, control, and automate electricity transmission between the grid and the home has been enabled, thus facilitating greater participation of residential households in demand response (DR) initiatives.

DR within HEMS entails adjusting energy consumption within a household in response to grid conditions and user needs. The primary function of DR in HEMS is to manage fluctuations in electricity demand. Many electricity providers offer dynamic time-based tariffs, with higher prices during peak periods and lower prices during off-peak hours. DR encourages users to shift their energy consumption during off-peak hours to reducing electricity costs.

The key components of a HEMS generally comprise:

- **Measurement Devices**: These include smart meters, sensors, and other instruments designed to monitor real-time energy consumption.
- **Energy Sources**: These sources comprise the electricity grid, energy storage systems (e.g., batteries), and renewable technologies such as photovoltaic solar panels.
- **Smart Controllers**: These controllers regulate home energy usage by automatically activating or deactivating connected devices based on predefined optimization criteria and operational schedules.
- **Energy Management Software**: This software enables users to monitor and strategize their energy consumption patterns, as well as adjust changes. Moreover, data-driven optimization algorithms can generate actionable recommendations to enhance energy efficiency.
- **Network Connectivity**: These systems are typically integrated with the electricity grid and can interact with utility providers to utilize different dynamic electricity tariffs and time-of-use (TOU) pricing schemes.
- **Smart Technologies**: This refers to smart home devices, IoT-enabled appliances, and internet-connected electrical equipment that can be remotely monitored, controlled, or automated via a centralized system interface.

HEMS are pivotal in optimizing energy consumption and managing DR in smart homes. Research in this area has focused on advanced algorithms and adaptive control strategies to enhance energy efficiency, reduce costs, and improve user satisfaction while addressing real-world constraints such as grid stability and dynamic pricing models. One study [1] proposes a HEMS framework incorporating three key DR strategies: peak clipping, load allocation, and load demand flattening. This system enhances flexibility in energy consumption while mitigating peak demand. Another approach [2] proposes a supervised learning-based strategy for optimally scheduling energy, integrating energy storage systems and electric vehicles, demonstrating the efficacy of machine learning in HEMS. Research in investigates flexibility during peak demand periods through a HEMS to reduce electricity bills under Time-of-Use (TOU) tariffs, achieving significant user cost savings. In a similar vein, [3] introduces a short-term (one-hour) DR algorithm to minimize user energy bills and dissatisfaction costs, achieving significant reductions in electricity expenses. A self-scheduling model [4] for HEMS incorporates user preferences into daily operations, employing a linear discomfort index to optimize the trade-off between comfort and efficiency. Another study [5] optimizes the coordination of residential load demand and distributed energy resources, accounting for utility price signals and customer satisfaction. Fuzzy decision-making algorithms are employed in [6] to adjust energy-consuming devices based on user preferences and real-time pricing signals, optimizing energy use and reducing peak demand. A unified home energy management controller proposed in [7] manages diverse household loads in response to dynamic price signals, effectively reducing consumer electricity bills. The application of the Non-Dominated Sorting Genetic Algorithm (NSGA-II) for multi-objective optimal scheduling in residential HEMS is demonstrated in [8], targeting minimizing energy costs and maintaining consumer comfort. Research in [9] explores smart grid technologies and demand-side management, proposing an innovative architecture for automated DR and a metaheuristic genetic algorithm-based approach for user-centric appliance scheduling. A standardized architecture for HEMS within a smart grid environments is proposed in [10], targeting advanced scheduling methods and reducing peak-to-average power ratios (PAPR) to enhance grid stability. A reinforcement learning (RL) and fuzzy logic integration is explored in [11], where a HEMS incorporates user-defined preferences for energy management. In [12], an enhanced leader particle swarm optimization (ELPSO) algorithm is developed for optimal appliance scheduling, balancing user comfort and electricity cost minimization. Research in [14] investigates the integration of energy-efficient devices in smart homes, focusing on energy conservation without compromising user comfort. A three-objective optimization framework for residential energy consumption scheduling is introduced in [13], targeting energy cost reduction and PAPR minimization. The role of domestic DR programs in improving energy efficiency is examined in [14], underscoring the critical importance of consumer engagement. A smart home energy management is proposed in [15], which prioritizes and schedules household loads to maintain electricity consumption within predefined thresholds. The study [16] proposes an integrated framework for electricity demand forecasting and re-engineering, targeting peak load reduction and demand shifting. A hybrid approach integrating machine learning, optimization techniques, and data structure design is employed in [17] to develop a DR and HEMS. The influence of convenience factors on DR programs is investigated in [18], demonstrating how user behavior can affects load shifting strategies. A fuzzy logic-based smart thermostat integrated with HEMS is discussed in [19], targeting energy efficiency improvements and cost reduction. A DR program employing a gradient-enhanced particle swarm optimization (PSO) algorithm is developed in [20], tackling hybrid discrete-continuous optimization challenges in energy scheduling. An optimal sizing model for photovoltaic (PV) and battery energy storage systems (BESS) in HEMS is investigated in [21], highlighting the economic benefits of integrated renewable energy systems. Finally, [22] presents a hybrid lightning search algorithm and artificial neural network-based controller for optimized appliance scheduling, achieving significant reduction in peak-hour energy consumption. Additionally, [23] investigates a convex programming framework for DR optimization in smart homes. This approach tackles the challenges of binary decision variables in appliance scheduling, utilizing L1 regularization techniques to efficiently solve the mixed integer problem, thereby facilitating automatic load management.

This comprehensive review underscores the diverse methodologies and technologies into HEMS to optimize energy management, reduce costs, and enhance user satisfaction in smart homes.

The HEMS can participate in DR based on pricing by adjusting the timing of the use of home appliances such as washing machines, dishwashers, and other equipment, thereby reducing the household electricity costs. However, this may affect resident comfort. Given the critical role of comfort in DR adoption, this study aims to implement price-based DR by scheduling the use of shift-able household appliances to reduce daily electricity costs while minimizing resident discomfort. Thus, the optimal scheduling of shift-able electric appliances is formulated as a weighted optimization problem minimizing the daily electricity bill and discomfort index, subject to operational constraints. This problem is then solved using the Simulated Annealing algorithm to identify the most cost-effective solution.

The main contributions of this paper are as follows:

- A user-centric flexibility window for shift-able appliances is introduced, allowing users to define preferred operating intervals that may equal or exceed the appliance’s operational duration.

– A novel discomfort index is formulated, quantifying user inconvenience based on deviations between an appliance's operational duration and its user-defined flexibility window. The index satisfies two key properties: (1) Unique valuation: Distinct discomfort values are assigned to different scheduling scenarios to reflect varying comfort levels. (2) Comfort preservation: The index remains zero if the appliance operates within the flexibility window, even when the flexibility window exceeds the appliance's required runtime.
– The optimal scheduling of shift-able appliances is formulated as a multi-objective optimization problem, minimizing a weighted combination of daily energy costs and the user discomfort index.
– A constraint is imposed to bound the user discomfort index below a user-defined threshold, ensuring comfort remains within acceptable limits while pursuing cost.
– This optimization problem is solved using the Simulated Annealing algorithm for varying maximum allowable discomfort indices.
– The study introduces the concept of marginal cost reduction, quantifying the incremental savings in daily energy costs relative to increases in the discomfort index. This analysis is conducted across multiple scenarios to evaluate the trade-off between energy savings and user comfort.
– Among the optimal solutions for the various scenarios, the most effective and cost-effective DR scheduling is selected by leveraging marginal reductions in the daily electricity bill, ensuring that the household electricity bill is substantially reduced while the discomfort index remains within acceptable limits.

The remainder of this paper is organized as follows: Section 2 formulates and analyzes the optimization problem. Section 3 elaborates on the key features of the proposed discomfort index. Section 4 details the solution method, specifically focusing on the use of the simulated annealing algorithm employed in this study. Section 5 presents the results of implementing price-based DR scheduling in a typical residential home across multiple operational scenarios, along with methodology employed for identifying the optimal solution. Finally, the principal conclusions of the paper are summarized in the final section.

2 Problem Formulation

Suppose we want to schedule the energy management system of a residential house equipped with N_A non-interruptible shift-able devices operating over a day divided into N_t time slots (48 slots in this study). In this work, we define the following two key intervals for each shift-able appliance:

(a) Allowable Interval ($[LA_i, UA_i]$:): From the point of view of the residents, appliance *i* is permitted to operate exclusively within this interval. Here, LA_i and UA_i denote the earliest and latest allowable time slots, respectively.

(b) Preferred Interval ($[LP_i, UP_i]$): From the residents' perspective, it is preferred that electrical appliance i ideally operates within this interval. Here, LP_i and UP_i denote the earliest and latest preferred time slots, respectively. In this work, we assume that the duration of the preferred interval can be equal to or longer than the daily operational period of the appliance. The discomfort index is defined to quantify resident dissatisfaction based on deviations from the preferred interval: the further the appliance's operation deviates from the preferred interval, the higher the discomfort index.

If the preferred interval for one or more shift-able appliances exceeds their operational duration, each of these appliances may operate in multiple distinct states within their preferred time interval. Consequently, various combinations of operational states for the shift-able appliances may exist, all satisfying operation within their respective preferred time intervals. We define the baseline operational state as the combination of states that satisfies two criteria: 1) all appliances operate within their preferred intervals, and 2) it minimizes total electricity cost compared to other combinations. The baseline starting and ending slots for appliance *i* are denoted as SB_i and EB_i respectively. The duration of the baseline interval $[SB_i, EB_i]$ precisely matches the daily operational duration.

In this work, the scheduling problem for the residential energy management system is formulated as a mathematical optimization problem under (1) to (8):

$$\text{Minimize } f(\mathrm{S}) = K_{bill} f_{bill}(\mathrm{S}) + K_{disc} f_{disc}(\mathrm{S}) , \tag{1}$$

$$f_{bill}(\mathrm{S}) = \sum_{i=1}^{N_A} \sum_{t=s_i}^{e_i} \rho_t P_i \Delta t , \tag{2}$$

$$f_{disc}(\mathrm{S}) = \sum_{i=1}^{N_A} (LP_i - s_i)\mathrm{Pos}(LP_i - s_i) + (e_i - UP_i)\mathrm{Pos}(e_i - UP_i) , \tag{3}$$

$$e_i = s_i + n_i - 1 , \tag{4}$$

$$LA_i \le s_i < UA_i - n_i , \quad \text{for } i = 1, 2, \ldots, N_A , \tag{5}$$

$$P_t \le P_{max} , \quad \text{for } t = 1, 2, \ldots, N_t , \tag{6}$$

$$P_t = \sum_{i \in A} P_i , \quad A = \{ i \mid s_i \le t \le e_i \} , \tag{7}$$

$$f_{disc} \le Uf_{disc} . \tag{8}$$

In the formulation above, s_i represents the starting time slot of the operational period for shift-able appliance *i*. These s_i values are the primary decision variables and must be determined via the optimization process. n_i denotes the number of consecutive time slots required to fulfil appliance *i*'s task. e_i indicates the ending time slot of the operational period for appliance *i*, calculated using (4). $f(\boldsymbol{S})$ is the objective function to be minimized. The terms $f_{bill}(\boldsymbol{S})$ and $f_{disc}(\boldsymbol{S})$ represent the household's total daily electricity cost and the discomfort index, respectively, for the decision set $\boldsymbol{S} = \{s_1, s_2, \ldots, s_{NA}\}$. $\mathrm{K}_{\mathrm{bill}}$ and $\mathrm{K}_{\mathrm{disc}}$ are weighting coefficients for balancing the total bill and discomfort index in the overall objective function. Uf_{disc} defines the maximum allowable discomfort index. ρ_t denotes the electricity price ($/kWh) in time slot *t*, P_i is the rated power of shift-able appliance *i*, and Δt is the duration of each time slot (0.5 hours in this study). P_t represents the total power demand of shift-able appliances during time slot *t*, while $P_{\max}$ is the maximum allowable demand for shift-able appliances in any time slot. A_t is the set of active shift-able appliances during time slot *t*. The positivity function $\mathrm{Pos}(.)$ returns 1 if its argument is positive and 0 otherwise.

In (1), the overall objective function minimizes a weighted sum of two objectives. The first term is the total daily electricity cost of the household, denoted by $f_{bill}(\boldsymbol{S})$, defined in (2), and the second term is the discomfort index, given by $f_{disc}(\boldsymbol{S})$.

The discomfort index is defined in (3). In this definition, the sigma symbol indicates the aggregation of the discomfort index for all appliances in the household. The discomfort index of each appliance is defined as the sum of two expressions. The first expression, $(\mathrm{LP}_i - s_i)$, represents the difference between the lower limit slot of the preferred interval and the starting slot of that appliance. The second expression, $(e_i - \mathrm{UP}_i)$, refers to the difference between the ending slot of appliance *i* and the upper limit slot of its preferred interval. It is noteworthy that, according to the positivity function $\mathrm{Pos}(.)$, which is used as a multiplier in both expressions, the first expression yields a non-zero value only when the starting slot of appliance *i* is less than the lower limit of its preferred interval $(s_i < \mathrm{LP}_i)$. Similarly, the second expression yields a non-zero value only when the ending slot of appliance *i* is greater than the upper limit of its preferred interval $(e_i > \mathrm{UP}_i)$. Clearly, when both the starting and ending slots of appliance *i* fall within the preferred interval (i.e., $s_i \geq \mathrm{LP}_i$ and $e_i \leq \mathrm{UP}_i$), the discomfort index for that appliance will be zero since the positivity function results in zero for both expressions.

Considering the constraint stated in (8), this research optimizes the usage timing of household appliances such that the discomfort index $f_{disc}(\boldsymbol{S})$ remains less than or equal to a specified maximum allowable value (Uf_{disc}).

Inequality (4) expresses the constraints on the allowable operational interval of all shift-able appliances. The constraints delineated in Inequality (5) ensure that the total demand of shift-able appliances in each time slot *t* does not exceed the maximum allowable demand for shift-able appliances within a single time slot $(P_{\max})$.

3 Features of the Suggested Discomfort Index

In this study, the discomfort index defined in (3) is based on the distance between the start and end times of each appliance's operation and its preferred interval bounds. This definition offers the following two advantages:

– The proposed discomfort index for each appliance assigns distinct values for the various operating schedules of that appliance, reflecting varying comfort levels. In contrast, prior work [4] identifies a critical flaw in the discomfort index defined in [12]: the index fails to reflect variations in the distance between the appliance's operational interval and the baseline interval. This limitation also extends to the discomfort index defined in [8].

– The proposed discomfort index for each appliance remains valid even when the preferred interval's duration exceeds the operational duration of that appliance. In contrast, the discomfort indices defined in [4, 8], and [12] rely on a baseline interval, assuming the baseline interval's duration matches the appliance's operational duration. If the baseline interval is extended beyond the required operational duration, their indices fail to reach zero when the appliance operates within this interval, even though discomfort is expected to vanish. Conversely, the proposed index vanishes, regardless of its duration relative to the appliance's needs.

4 The Proposed Optimization Problem-Solving Approach

The optimization problem for the scheduling of the HEMS, introduced in the previous section, is a combinatorial nonlinear optimization problem with integer decision variables. In this research, the Simulated Annealing (SA) algorithm is employed to identify the optimal solution to this problem. The SA algorithm begins with an initial solution and iteratively generates other solutions that progressively improve the optimization objective. The number of solutions evaluated by SA to converge is relatively low compared to other heuristics, as only one candidate solution is assessed in each iteration, instead of a population. From a theoretical perspective, the SA algorithm is guaranteed to converge to the global optimal solution of any problem under sufficient iterations. Numerical studies validate that SA achieves the desired optimal solution within 10,000.

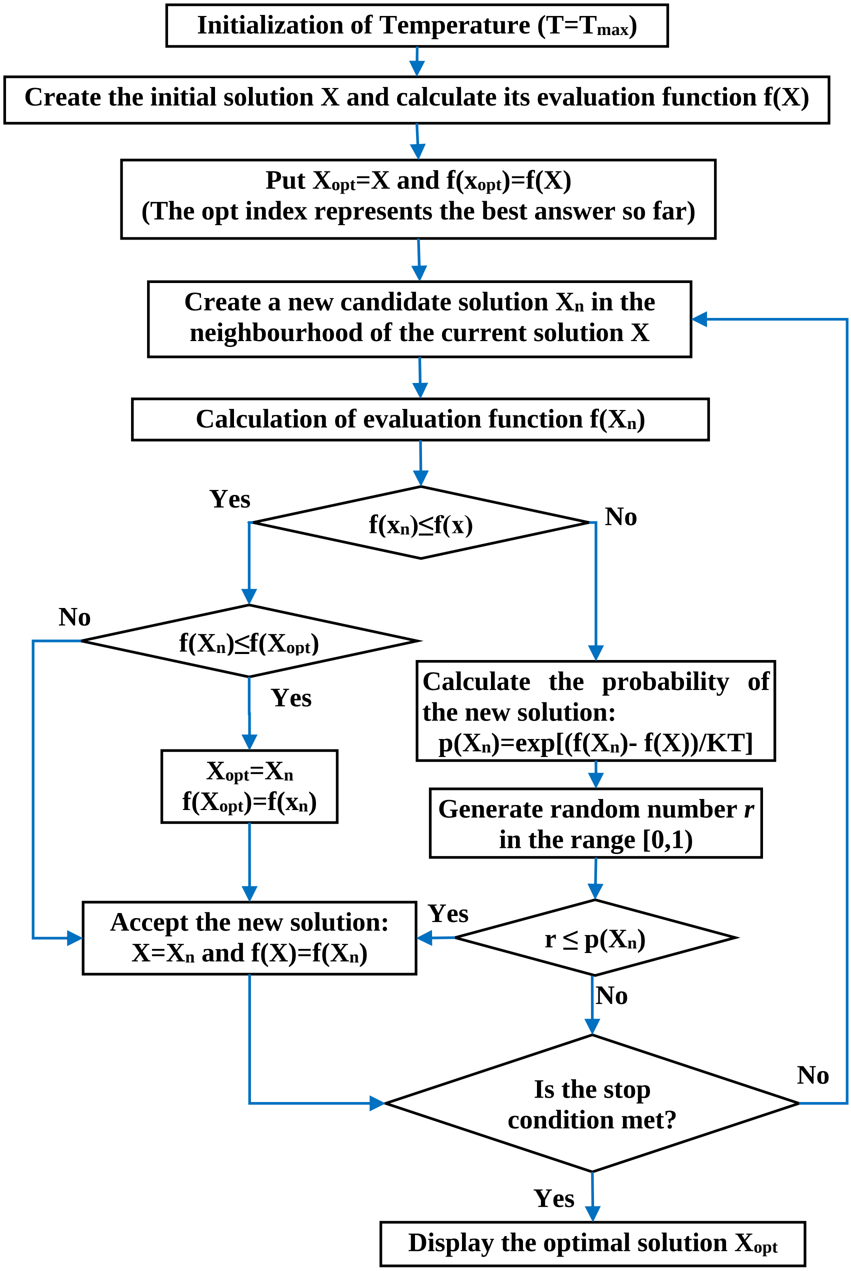

Fig. 1 – *Flowchart of simulated annealing algorithm.*

Since the decision variables in this problem represent the starting slots of shift-able household appliances, the SA solution vector is structured as $[s_1 \quad s_2 \quad \cdots \quad s_{N_A}]^{\mathrm{T}}$, where s_i is an integer within the allowable interval defined by Inequality (5).

5 Numerical Studies

In this section, the results of implementing price-based DR scheduling for a sample residential household [4] using the proposed method are presented. The specifications of the shift-able appliances in this household are summarized in **Table 1**. Here, all time slots are 30 minutes long, resulting in 48 daily time slots.

Table 1 lists the starting and ending time slots of the preferred and allowable operational intervals for each appliance. Notably the preferred interval duration for the dishwasher and washing machine exceeds the required operational slots. As shown in the table, the household consists of 10 shift-able appliances with a total energy consumption of 58.1 kWh. The DR program follows a Time-of-Use (TOU) tariff structure. Under this scheme the base rate is \$0.02/kWh, while peak rates apply during peak day hours (from 9 to 11) and peak night hours (from 18 to 20), charged at \$0.08/kWh, as depicted in Fig. 7.

Table 1
Specifications of Household Appliances for the Studied Home Energy Management System.

Appliance	Rated Power (P_i) [kilowatts]	Number of Required Operational Slots (T_i)	The Start Slot of the Preferred Interval (LP_i)	The End Slot of the Preferred Interval (UP_i)	Permissible Start Slot for Scheduling Interval (LA_i)	Permissible End Slot for Scheduling Interval (UA_i)
Dishwasher	2.5	4	18	23	15	33
Washing Machine	3.0	3	18	22	16	23
Spine Dryer	2.5	2	27	28	25	35
Cooker Hub	3.0	1	17	17	16	17
Cooker Oven	5.0	1	37	37	36	37
Microwave	1.7	1	17	17	16	17
Laptop	0.1	4	37	40	33	47
Desktop Computer	0.3	6	37	42	31	47
Vacuum Cleaner	1.2	1	19	19	18	33
Electric Vehicle	3.5	6	37	42	31	47

Given that the primary objective in this study is to minimize the daily electricity bill, with the secondary objective being the minimization of the discomfort index, the weighting factor for the cost minimization goal is set at a significantly higher value ($\mathrm{K_{bill}} = 1000$), while the weighting factor for the discomfort minimization goal is set at a relatively lower value ($\mathrm{K_{bill}} = 1$).

The scheduling of the appliances in this household is performed using the proposed method ((1) – (8)) by implementing the SA algorithm, evaluated for different maximum allowable discomfort index values (Uf_{disc}), as summarized in **Table 2**. The first column of **Table 2** lists the maximum allowable discomfort index values (Uf_{disc}). The second and third columns report the discomfort index values and the corresponding daily electricity bills obtained through the proposed optimization, as defined in equations (1) – (8).The fourth column shows the percentage reduction in the electricity bill relative to the baseline bill (i.e., the result for $Uf_{disc} = 0$, indicated in the second row of the table). For example, for the third row in the table ($Uf_{disc} = 1$), the percentage reduction in the daily bill is calculated as

$$\frac{f_{bill}\left(\boldsymbol{SB}\right) - f_{bill}\left(\boldsymbol{S}\right)}{f_{bill}\left(\boldsymbol{SB}\right)} = \frac{1640 - 1490}{1640} = 0.0915 .$$

The fifth column provides the marginal bill reduction $(\Delta f_{bill} / \Delta f_{disc})$. The marginal bill reduction for each scenario (i.e., each row in the table) is defined as the difference in the bill between that scenario and the previous one (the row above in the table), divided by the difference in the discomfort index between the two scenarios. For instance, for the third row ($Uf_{disc} = 1$), the marginal bill reduction is given by

$$\frac{\Delta f_{bill}}{\Delta f_{disc}} = \frac{1490 - 1640}{1 - 0} = -150 .$$

The last column of **Table 2** specifies the starting time slots for the ten shift-able appliances, which are the decision variables (S).

Based on the results presented in **Table 2**, the following points are noteworthy:

– The solution obtained in the scenario where $Uf_{disc} = 0$ (second row of **Table 2**) defines the starting slots for the baseline case. By definition, the baseline case is an operational state that lies within the preferred interval and achieves the lowest daily electricity bill. The solution for $Uf_{disc} = 0$ satisfies both criteria. First, only the operational states within the preferred interval have a discomfort index of zero, thus satisfying $Uf_{disc} = 0$. Second, the solution for all scenarios, including $Uf_{disc} = 0$, minimizes daily electricity bill. Therefore, the solution for $Uf_{disc} = 0$

represents the baseline case, and its starting slots are the baseline time slots (i.e., $\boldsymbol{S} = \boldsymbol{SB}$). Thus, $f_{bill}\left(\boldsymbol{SB}\right) = 1640$.

– The scenario with $Uf_{disc} = \infty$ (the last row of **Table 2**) corresponds to minimizing the household's electricity bill without discomfort index constraints. For this scenario, the electricity cost reaches its minimum value (581); but the discomfort index is significantly high (19). Thus, to determine the optimal trade-off, we analyse scenarios with $Uf_{disc} = 1$ to $Uf_{disc} = 18$.

Table 2
Simulation results for multiple scenarios with varying maximum allowable discomfort indices (Uf_{disc}).

Uf_{disc}	f_{disc}	f_{bill}	Percentage reduction of the bill compared to the base response bill	Marginal reduction of the daily bill $(\Delta f_{bill} / \Delta f_{disc})$	Start slots of shift-able appliances (values of decision variables *S*)
0	0	1640	0	-	[18 18 27 17 37 17 37 37 19 37]
1	1	1490	0.0915	-150	[18 18 27 17 36 17 37 37 19 37]
2	2	1385	0.1555	-105	[18 18 27 17 36 17 37 37 19 38]
3	3	1295	0.2104	-90	[18 17 27 17 36 17 37 37 19 38]
4	4	1205	0.2652	-90	[20 16 27 17 36 17 37 37 19 38]
5	5	1070	0.3476	-135	[20 18 27 17 36 17 37 37 19 41]
6	6	980	0.4024	-90	[18 17 27 17 36 17 37 37 19 41]
7	7	890	0.4573	-90	[18 16 27 17 36 17 37 37 19 41]
8	8	830	0.4939	-60	[22 17 27 17 36 17 37 37 19 41]
9	9	806	0.5085	-24	[21 16 27 17 36 17 37 38 19 41]
10	10	665	0.5945	-141	[23 16 27 17 36 17 37 37 19 41]
11	11	629	0.6165	-36	[23 16 27 17 36 17 37 37 18 41]
12	12	626	0.6183	-3	[15 16 27 17 36 17 38 37 18 41]
13	13	611	0.6274	-15	[23 16 27 17 36 17 37 39 18 41]
14	14	608	0.6293	-3	[23 16 27 17 36 17 38 39 18 41]
15	15	599	0.6348	-9	[15 16 27 17 36 17 36 40 18 41]
16	16	596	0.6366	-3	[23 16 27 17 36 17 39 40 18 41]
17	17	587	0.6421	-9	[15 16 27 17 36 17 35 41 18 41]
18	18	584	0.6439	-3	[23 16 27 17 36 17 34 41 18 41]
Infinite	19	581	0.6457	-3	[23 16 27 17 36 17 41 41 18 41]

– In Fig. 2, the daily electricity costs for the scenarios listed in **Table 2** are plotted. The results show that as the discomfort index increases, the electricity cost decreases nonlinearly.

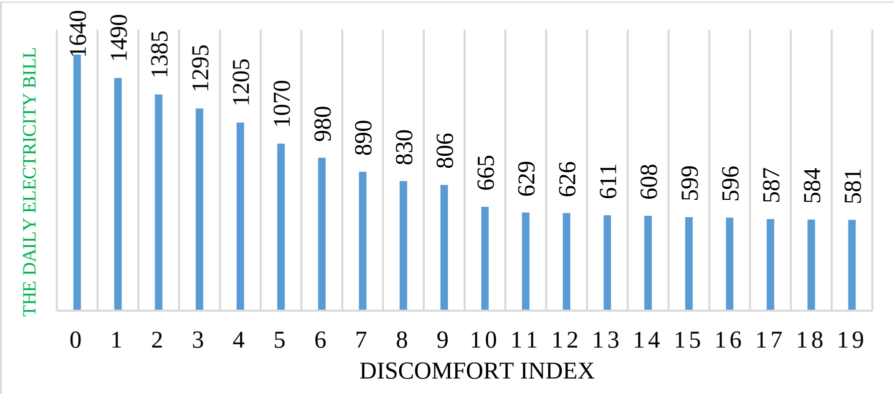

Fig. 2 – *Daily household electricity bill for all scenarios.*

– Fig. 3 shows the marginal reduction in the daily electricity cost for different discomfort index levels from **Table 2**. It is observed that with an increase in the discomfort index, the marginal reduction tends to decrease. However, when the discomfort index exceeds 11, the marginal reduction drops sharply. Thus, the most cost-efficient solution where increasing the discomfort index significantly reduces the bill occurs at $Uf_{disc} = 11$. This solution is therefore recommended as the optimal solution for energy management in this household. For the row corresponding to $Uf_{disc} = 11$ in **Table 2**, the proposed optimal solution yields a discomfort index of 11, a daily electricity cost of 629, and a bill reduction of 61.65% relative to the baseline. In practical terms, this solution achieves a 62% reduction in the daily bill with only 11 units of discomfort.

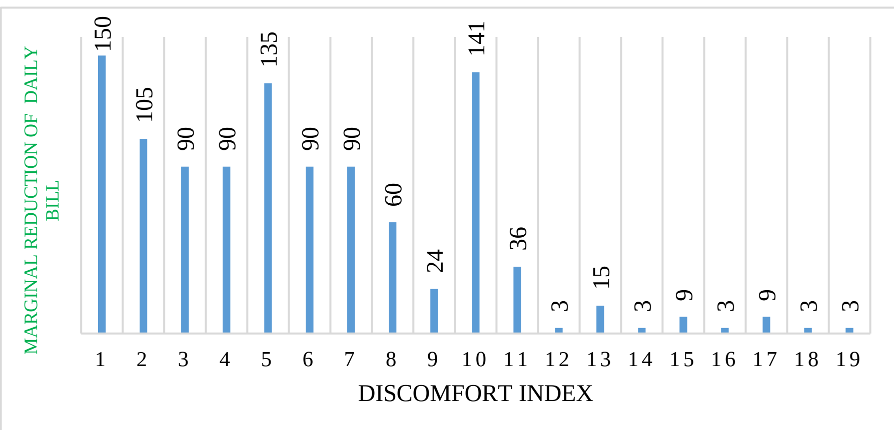

Fig. 3 – *Marginal reduction values of the daily household electricity bill across the discomfort index levels.*

– In Fig. 4, the contribution of each shift-able appliance in generating the daily household electricity bill is compared for the baseline scenario and the proposed optimal solution ($Uf_{disc} = 11$). The results show that optimal scheduling reduces the electricity costs of the dishwasher, washing machine, cooker oven, vacuum cleaner, and electric vehicle relative to the baseline scenario.

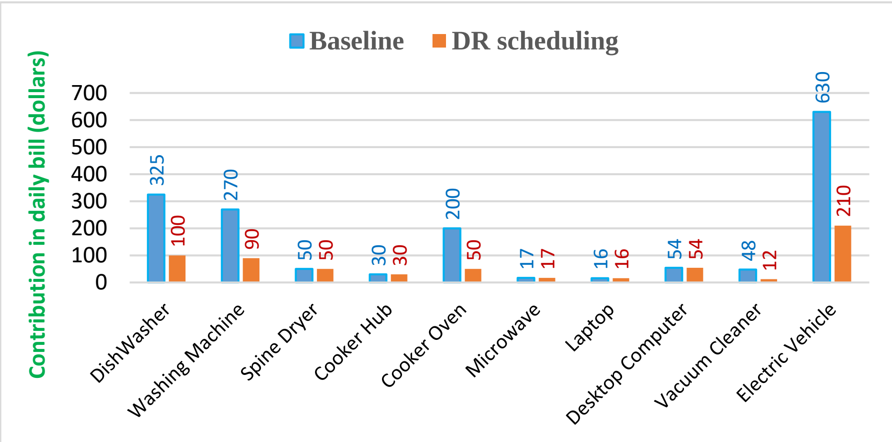

Fig. 4 – *Contribution of each appliance to the daily electricity bill for both the baseline case and the optimal scheduling achieved in the scenario* $Uf_{disc} = 11$.

– Fig. 5 shows the contribution of each shift-able appliance to the discomfort index under the proposed optimal solution ($Uf_{disc} = 11$). The results indicate the electric vehicle contributes most significantly to discomfort, as it shifts its operation by four slots from its preferred interval.

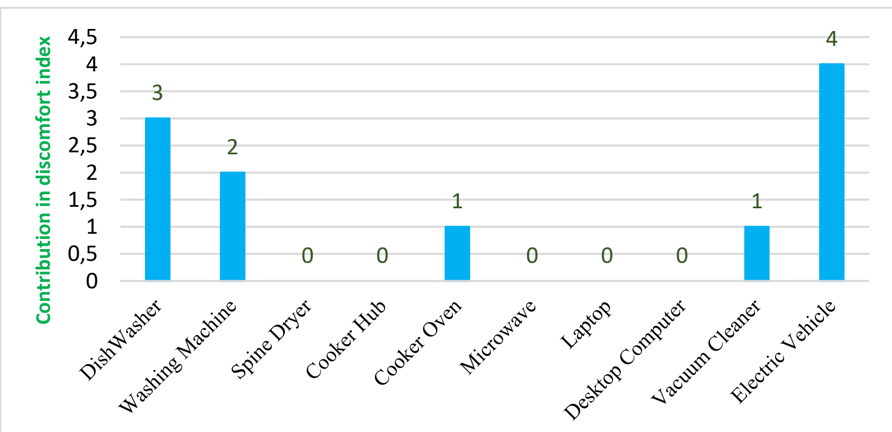

Fig. 5 – *Contribution of each appliance to the discomfort index for the optimized scheduling in Scenario* $Uf_{disc} = 11$.

– Fig. 6 presents the total daily load demand under the optimal scheduling for $Uf_{disc} = 11$. The results indicate during the nighttime peak period (time slots 37–40), only low-power devices (e.g., laptops and computers) operate. Conversely, during the daytime peak period (time slots 19–22), no appliances are activated.

– In Fig. 7, the TOU tariff rates, the total daily load in the baseline scenario, and the load under the optimal scheduling solution ($Uf_{disc} = 11$) are compared.

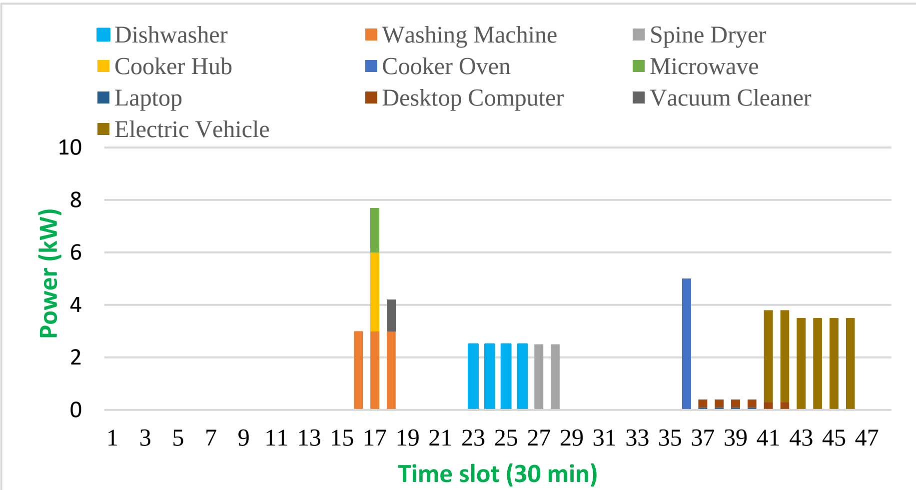

Fig. 6 – *Total daily load demand according to the optimal scheduling obtained in Scenario* $Uf_{disc} = 11$.

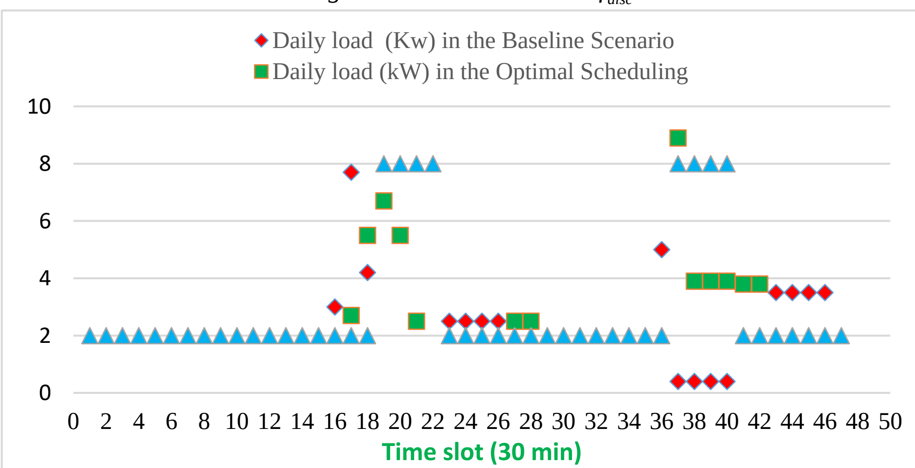

Fig. 7 – *TOU Tariffs and Total Daily Load Demand for the baseline and optimal scheduling scenarios.*

– The results show that loads previously concentrated during peak periods in the baseline scenario shift to off-peak periods in the optimal scenario. Specifically, during the nighttime peak (time slots 37–40), a minimal load of 0.4 kW (laptops and computers) is scheduled, while no load is scheduled during the daytime peak (time slots 19–22).

– To demonstrate the convergence of the Simulated Annealing (SA) algorithm, Fig. 8 plots the evaluation function values across SA iterations for the scheduling scenario $Uf_{disc} = 11$. This figure demonstrates that in the early iterations, controlled uphill moves) were accepted to escape local optima; as iterations progressed, such acceptance decreased. By the 3,605[th] iteration of 5,000, the algorithm converged to the final optimal solution.

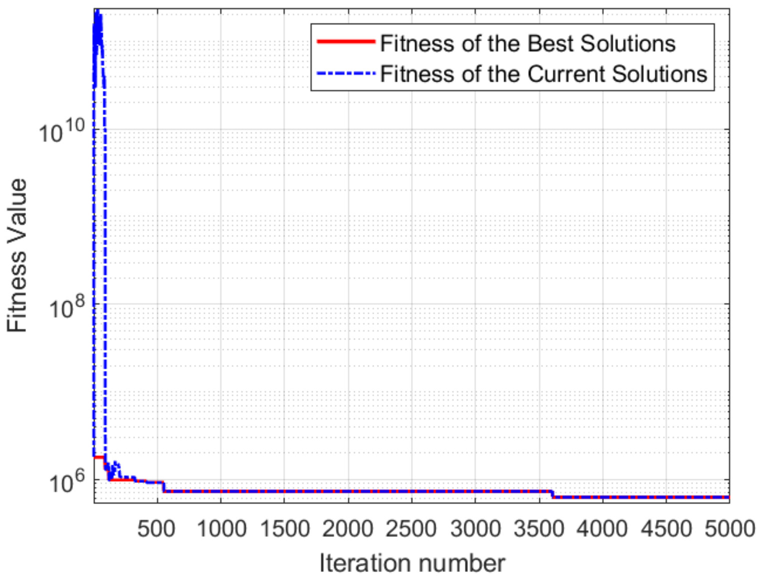

Fig. 8 – *Plot of the evaluation function values in the implementation of the SA algorithm for the optimal scheduling of Scenario* $Uf_{disc} = 11$.

– The findings demonstrate that the proposed method enables selecting a cost-effective DR schedule, substantially reducing the electricity bill while maintaining the discomfort index within acceptable limits.

6 Conclusion

The present study demonstrated that a home energy management system, through optimal scheduling of shift-able household appliances, can effectively implement price-based DR. This approach reduces electricity costs without unduly compromising resident comfort. The proposed discomfort index, defined by deviations between the operational start/end times and the preferred interval bounds, offers two key advantages: (1) It uniquely quantifies discomfort for each appliance across operational states, reflecting varying comfort levels, and (2) It vanishes when appliances operate within their preferred interval, even if the interval exceeds their operational duration. The scheduling problem was formulated as a weighted multi-objective optimization: minimizing the electricity cost and discomfort index, subject to a discomfort index constraint. This problem was solved using the Simulated Annealing algorithm for varying maximum discomfort indices. Results show that leveraging the marginal bill reduction, enables identifying an optimal trade-off achieving substantial cost savings with minimal discomfort. These findings provide a foundation for developing smart HEMS technologies, enhancing both cost efficiency and user satisfaction.

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