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Smart-home electrical energy scheduling system using multi-objective antlion optimizer and evidential reasoning

A. Kaveh* **and Y. Vazirinia**

Centre of Excellence for Fundamental Studies in Structural Engineering, Iran University of Science and Technology, Narmak, Tehran, Postal Code 16846-13114, Iran.

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Abstract. Smart-Home Energy Management Systems (SHEMSs) are widely used for energy management in smart buildings. Energy management in smart homes is an arduous task and necessitates efficient scheduling of appliances in buildings. Scheduling of smart appliances is usually enmeshed by various and sometimes contradictory criteria, which should be considered concurrently in the scheduling process. Multi-Criteria Decision Making (MCDM) techniques are able to select the most suitable alternative among copious ones. This paper tailors a comprehensive framework which merges MCDM techniques with Evolutionary Multi-Objective Optimization (EMOO) techniques for selecting the most proper schedule for appliances by creating a trade-off between optimization criteria. A Multi-Objective Ant Lion Optimizer (MOALO) was tailored and tested on a smart home case study to detect all the Pareto solutions. A benchmark instance of the appliance scheduling was solved employing the proposed methodology. Then, Shannon's entropy technique was employed to find the weights corresponding to the objectives. Finally, the acquired Pareto optimal solutions were ranked utilizing the Evidential Reasoning (ER) method. By inspecting the efficiency of every solution considering multiple criteria such as unsafety, electricity cost, delay, Peak to Average Ratio (PAR), and CO_2 emission, effectiveness of the proposed approach in enhancing the method for smart appliance scheduling was confirmed.

1. Introduction

During the previous decade, the electrical energy consumption of residential sectors has increased rapidly all around the world due to the expansion in appliance ownership [1]. Therefore, improvement in the energy efficiency of electrical facilities is very influential for energy-saving in buildings, reducing the loads on electrical grids, and decreasing the carbon footprint. Consequently, electricity conservation in buildings not only results in saving fossil fuels but also prevents capacity expansion in the power sector [2,3]. Many research results are available for supporting the decisions in the management of networks [4,5]. The emergence of smart homes and the Internet has led to an opportunity for automatic operation, scheduling of the appliances, and energy management in residential buildings.

*. *Corresponding author. Tel.: +98 21 44249493; Fax: +98 21 77240398*
E-mail addresses: alikaveh@iust.ac.ir (A. Kaveh) yasinvazirinia@gmail.com (Y. Vazirinia)

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In recent years, utilization of metaheuristic optimization algorithms to overcome real-life problems has turned out to be a topic of huge interest for related studies. The main objective of such techniques is to sufficiently explore the search space to achieve global or quasi-global solutions. These algorithms have received increasing attention of both academia and industry [6,7]. Many metaheuristics with various philosophies and characteristics are developed and implemented in an immense domain of fields with variations of single-objective optimization, e.g. Genetic Algorithm (GA) [8], Particle Swarm Optimization (PSO) [9], colliding bodies optimization [10], Vibrating Particles System (VPS) [11], Ant Lion Optimizer (ALO) [12], etc., and Multi-Objective Optimization (MOO), e.g. non-dominated sorting GA [13], multi-objective PSO [14,15], multi-objective VPS [16], Multi-Objective Ant Lion Optimizer (MOALO) [17], etc. Some applications of metaheuristics to engineering optimization problems can be found in [18,19]. A newly developed MOALO, which mimics the trapping mechanism of antlions in nature, is selected in this study [17]. Like many metaheuristic algorithms, MOALO has the advantage of simplicity and flexibility.

Electric energy management is involved in various problems in which the decision-maker needs to circumscribe possible scheduling options and select the one with optimal solutions, which have balance among different objectives. The Evolutionary Multi-Objective Optimization (EMOO) methods represent a suitable and practical procedure that supports robust and concurrent optimization of contradictory and frequently incommensurable objectives. In a real system, it is unwise to reach a decision that is founded on meeting only one criterion during the process of decision-making. This proves the exigency of using multiple-criteria assessment techniques to obtain a solution that meets all the decision-making presumptions with an agreeable degree of satisfaction [20].

Diverse EMOO procedures have been utilized to solve Multi-Objective Home Appliance Scheduling Problems (MOHASPs) and their sequent optimal Pareto solutions have been produced, plotted, and widely announced. Nevertheless, no effort has been put into selecting a solution that meets the objectives within a reasonable level. Due to the intimately interwoven multi-criteria nature of scheduling problems, ascertaining which solution is the best alternative can be challenging [21]. These criteria, also called objectives, are frequently incompatible. Multi-Criteria Decision Making (MCDM) approaches offer an efficient mechanism for selecting a suitable Pareto member [22]. In this research, an MCDM approach is combined with an EMOO technique to utilize the capability of the optimization technique for finding the optimal Pareto front (alternatives) and the capability of the MCDM for simultaneously ranking them by various criteria to produce a single-compromise solution with a computational background.

Since the end of the 1970s, several MCDM methods have been proposed to assist decision-makers in finding values of the criteria and the alternatives based on their preferences [23]. The goal of using MCDM techniques in decision making is to ease the process of organizing and harmonizing the requisite data in evaluation so that users feel comfortable with and sure in making decisions [24]. However, MCDM techniques are dissimilar in terms of theoretical background, formulation, questions, and types of input and/or output [25]. They can be divided into three main categories [26]: (a) value measurement techniques; (b) goal, aspiration, and reference level techniques; and (c) outranking techniques.

In the value measuring technique, a numerical value is assigned to every alternative, which intimates the rank of a solution versus others. Then, for making a trade-off between multiple criteria, each criterion is weighted based on decision-maker-accepted criteria [21]. The Analytical Hierarchy Process (AHP) [27] and multi-attribute utility theory fall into this category. The second category involves iterative methods that indicate closeness of the solutions to a predefined goal or reference level. The examples of this category are Evidential Reasoning (ER) [28] and the Technique for Order of Performance by Similarity to Ideal Solution (TOPSIS) [29]. Generally, these techniques are focused on purifying the most inappropriate alternatives at the initial stage of the multi-criteria assessment process [24]. In the outranking techniques, the alternatives are sorted by a pairwise matching and if enough proof exists to show that alternative (a) is preferable to alternative (b), it is assumed that alternative (b) is outranked by (a). PROMETHEE [30] and ELECTRE [31] are examples of the outranking techniques.

Regarding the number of MCDM techniques available, the decision on selecting a suitable decision support tool can be challenging to justify. None of the techniques are perfect nor can they be applied to all problems. Every technique has its limitations, particularities, hypotheses, premises, and perspectives. There are different ways of selecting a suitable MCDM technique to solve particular problems. One way is to consider the requisite input information, that is, the data and parameters of the method and, consequently, the modeling effort, as well as to take into account the outcomes and their granularity [32].

In this research, the ER technique is accommodated to produce an efficient Pareto solutions ranking system and discover the most appropriate solution. ER technique considers incomplete assessments or ignorance as a kind of probabilistic uncertainty, fuzziness, and vagueness and incorporates qualitative/quantitative attributes in an integrated framework using belief structures, belief matrices, and a rule/utility-based grading strategy for aggregating the information. The influential feature of this method is that varieties of data can consistently be modelled in an integrated system [33].

There are two general approaches to adopting MCDM in EMOO methods [34]: (a) employing MCDM for Pareto optimal solutions set obtained by EMOO; or (b) integrating MCDM with EMOO as a robust parallel searching means.

Decision-making is widely gone through in several aspects of engineering and some studies have employed MCDM techniques to determine the most appropriate Pareto solutions in project scheduling problems [21], building design [22], water distribution systems [28], etc. However, in most of the appliance scheduling problems, only Pareto solutions are acquired, plotted, and informed. This was one of the reasons that the authors of the present paper were persuaded to employ MCDM techniques in solving MOHASP to determine the best appliance operation schedule of a given smart home. Except for the paper of Du et al. [35], in which a user-oriented weighting approach decided the best schedule, there is no research proposing an exhaustive framework for synthesizing the MCDM techniques with MOO methods to more efficiently schedule the appliances.

Previous studies have investigated the influence of smart home appliances scheduling on their operational unsafety [35], electricity cost of household [35], operational delay of appliances [36], peak-to-average power ratio, and CO_2 emission [37]. However, joint optimization of these objectives has been considered in none of the studies. This study tries to optimize all the objectives mentioned above concurrently by assuming that households are equipped with smart appliances. Other new contributions of this paper include a proposed MOHASP modeling framework incorporating an MOALO algorithm, tailored for methodical multi-criteria assessment handling, alongside an ER approach for ranking the Pareto solutions. In order to illustrate efficiency and compatibility of the proposed system, an example of home appliance scheduling is solved for identifying the best Pareto solution. The MOALO algorithm is presented in the following sections. First, the Shannon entropy procedure for acquiring the associated relative normalized weights of each objective is explained. Furthermore, the ER approach is elaborated on and the integration framework for the MCDM approaches and for MOO methods is discussed. Then, the formulations and modeling of the MOHASP are given. A benchmark instance from the literature will be solved and the optimal Pareto solutions are identified in order to show the efficiency of the suggested procedure. Given the expectations of the decision makers, the most suitable solution is determined by the ER approach. Efficiency of the results of the suggested methodology is discussed using an identical method and the optimal solution is presented. Finally, concluding remarks and suggestions for future research are provided.

2. Methodology

Figure 1 shows the process of the suggested system for energy management beginning by initial adjustment and collection of the necessary data for the real-time day-ahead electricity price, real-time day-ahead CO_2 footprint, requirements of the users for the operations of the appliances, at-home and awake statuses of the users, and energy consumption of the appliances. Then, the MOALO algorithm for meeting the global Pareto optimal front is served up. Each objective, consisting of safety, electricity cost, delay, PAR, and CO_2 emission, holds a particular corresponding normalized weight. These objectives make employing Shannon's entropy method possible. For the purpose of relating the objectives mentioned above with the overall performance indicator, a hierarchical structure can be formed with the computed corresponding weights to indicate the modality of assessing the overall performance. In the following procedure, the ER technique assists the users in evaluating Pareto solutions (alternatives), specifies overall utility scores, and indicates their level of comfort by each solution while simultaneously considering all the criteria. Finally, the Pareto solutions are sorted according to their utility scores in descending order and the first one is picked as the best solution. The flowchart of the proposed Smart-Home Energy Management System (SHEMS) methodology is presented in Figure 1.

2.1. Preparing the required information for appliances scheduling operation

The day-ahead real-time electricity price for tomorrow is passed on from the utility company to the SHEMS. Since users have various demands for the operations of appliances and their at-home statuses and awake statuses are dissimilar, the awake and at-home statuses of the users and their demands for the operations of appliances are put in the SHEMS by the users. The SHEMS provides the schedules for the home appliances by the proposed approach according to the electricity price as well as status and demands of the users. Then, it will automatically control the appliances based on the energy consumption schedules by the home area network [35,36]. The smart home appliances are categorized into schedulable, such as washing machines and water heaters, and non-schedulable, such as TV and lights. Energy consumption of schedulable appliances is adjustable and they are schedulable in progress. They are supposed not to be interrupted [35]. The

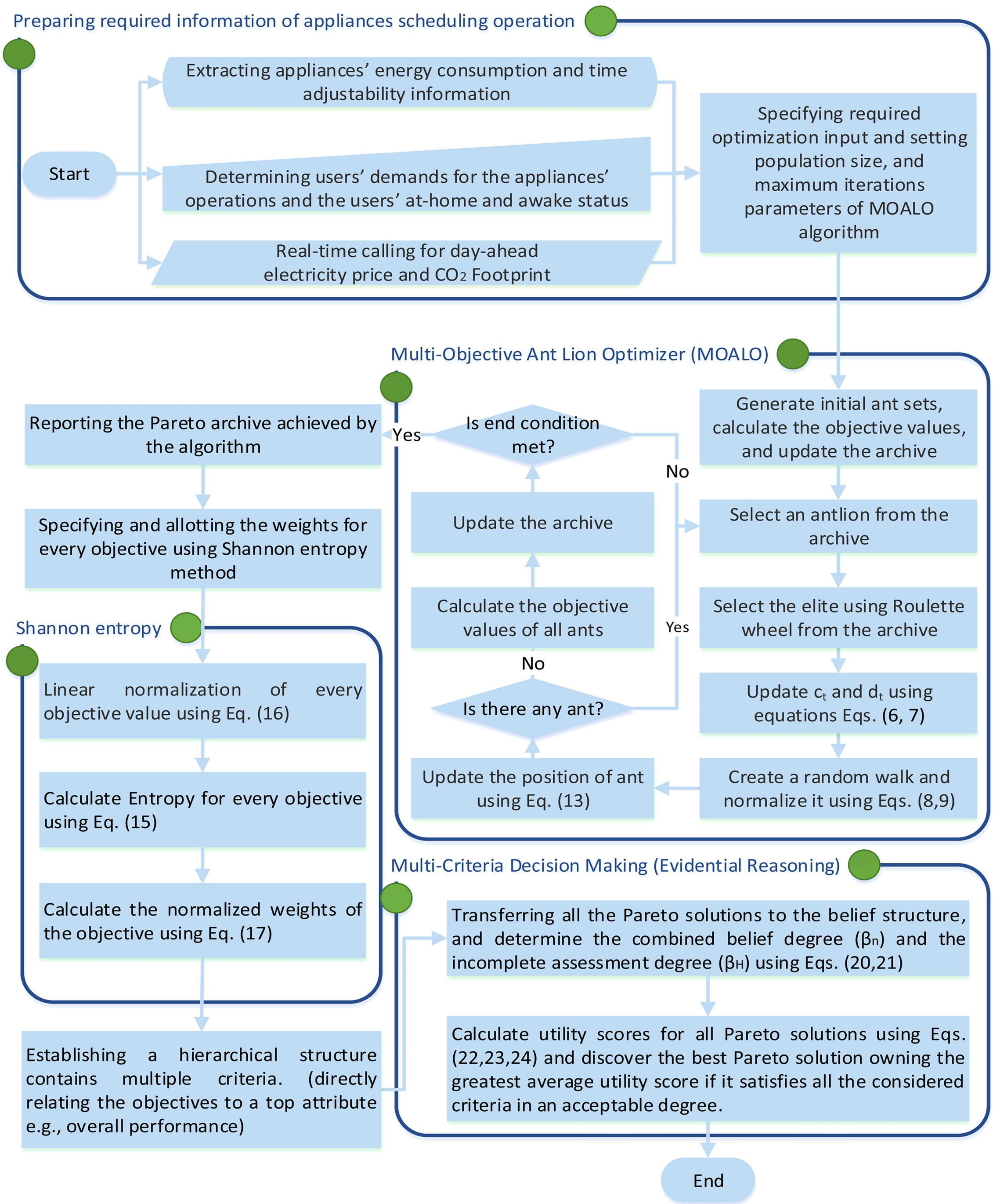


Figure 1. Flowchart of the proposed Smart-Home Energy Management System (SHEMS) methodology.

energy management system will not include the non-schedulable appliances for which the real-time demands of users will be in control of their operation [35]. The information concerning operations of appliances includes the Length of Operation Time (LOT) and the Operation Time Interval (OTI), which are denoted by γ_a and $[\alpha_a, \beta_a]$ for appliance a, respectively. Here, α_a is the earliest start time and β_a is the latest finish time of the operation. Regarding the general operation time of appliances, each time slot has 12 minutes and the LOT is assigned to the time slots. The LOT is planned to the least integer greater than or equal to the number when the length of the operation is not an integer multiple of 12. Therefore, one day is planned in 120 time slots and the OTI is assigned to the related time slot. For example, the LOT is 3, i.e., $\gamma = 2$, for an appliance whose LOT is 36 minutes and the OTI is from 1 to 60, i.e., $\alpha = 1$; $\beta = 60$ for an appliance whose operation is considered in the range of 12 midnight and 12 noon [36].

2.2. Multi-Objective Optimization (MOO)

2.2.1. Basic definitions for MOO

Without loss of generality, the brief fundamentals of MOO (minimization) are defined as follows.

Definition 1 (Pareto dominance). Considering two vectors like $\vec{x} = (z_1, x_2, ..., x_k)$ and $\vec{y} = (y_1, y_2, ..., y_k)$ vector $\vec{x}$ is called to dominate $\vec{y}$ (denoted by $\vec{x} \prec \vec{y}$) if and only if [17]:

$$\forall i \in \{1, 2, ..., k\} : f_i(\vec{x}) \leq f_i(\vec{y}) \wedge$$
$$\exists i \in \{1, 2, ..., k\} : f_i(\vec{x}) < f_i(\vec{y}). \tag{1}$$

The definition of Pareto optimality is presented as follows [38,39]:

Definition 2 (Pareto optimality). A solution $\vec{x} \in X$ is assumed Pareto optimal if and only if:

$$\{\nexists \vec{y} \in X | \vec{x} \prec \vec{y}\}. \tag{2}$$

Definition 3 (Pareto optimal set). The set of all Pareto optimal solutions is defined as follows:

$$P_s := \{\vec{x}, \vec{y} \in X | \nexists \vec{x} \prec \vec{y}\}. \tag{3}$$

Definition 4 (Pareto optimal front). A set including the values of objective functions for Pareto solutions set is:

$$P_f := \{\overrightarrow{f(x)} | \vec{x} \in P_s\}. \tag{4}$$

2.2.2. Multi-Objective Ant Lion Optimizer (MOALO)

MOALO is one of the newest nature-inspired optimization algorithms introduced by Mirjalili et al. [17], which mimics hunting behavior of antlions and their interactions with the favorite corresponding prey-ants. The antlion algorithm has two types of populations, namely the antlions and the ants. The general hunting process of MOALO represents the interaction among antlions and ants in the trap as follows: random walk of ants, building traps, entrapment of ants in traps, catching preys, re-building the traps, and elitism. An antlion larva walks on a circular path and throws out sand by its massive jaw to dig a cone-shape trap by a very sharp edge in the sand so that the insects easily fall to its bottom. Then, the larva hides underneath the bottom of the trap and waits for preys to fall in. If the antlion realizes that a prey has fallen in the trap, it tries to catch the prey and then, pulls it under the soil. After consuming the prey, it throws the leftovers outside the pit, amending the pit for the next catch [12]. In the algorithm, the archive is first used to save non-dominated Pareto optimal solutions obtained so far. Then, solutions are chosen from this archive using a roulette wheel mechanism based on coverage of the solutions (as antlions) to guide ants to promising areas of multi-objective search spaces. Reviewing the literature shows its efficiency in solving challenging real-world problems and it is selected not only due to its solution quality but also for its convergence speed and very small number of parameters. The optimization process of the MOALO algorithm is described below [17]:

Step 1. Initialize the set of ants and antlions with random values.

Step 2. Choose a random antlion from the archive.

Step 3. Choose the elite by Roulette wheel and Eq. (5) from the archive:

$$P_i = \frac{c}{N_i}. \tag{5}$$

Step 4. Update c and d by Eqs. (6) and (7):

$$c_t = \frac{c_t}{I}, \tag{6}$$

$$d_t = \frac{d_t}{I}, \tag{7}$$

where c_t is the minimum of all variables at the tth iteration, d_t presents the vector including the maximum of all variables at the tth iteration, and $= 1 + 10^{\omega} \frac{t}{T}$; in this formula, t is the current iteration, T is the maximum number of iterations, and ω is defined based on the current iteration to adjust the accuracy level of exploration:

$$\omega = \begin{cases} 2 & \text{when } 0.1T < t \\ 3 & \text{when } 0.5T < t \\ 4 & \text{when } 0.75T < t \\ 5 & \text{when } 0.9T < t \\ 6 & \text{when } 0.95T < t \end{cases} \tag{8}$$

Step 5. Create a random walk and its normalization. The ALO algorithm uses the following formulation to simulate the random walk of ants:

$$X(t) = [0, cumsum(2r(t_1) - 1),$$
$$cumsum(2r(t_2) - 1), ...,$$
$$cumsum(2r(t_3) - 1)]. \tag{9}$$

In this formulation, cumsum computes the cumulative sum, n shows the maximum iteration number, t is the iteration (random walk step in this study), and:

$$r(t) = \begin{cases} 1 & \text{if } rand > 0.5 \\ 0 & \text{if } rand \leq 0.5 \end{cases}$$

is a stochastic function in which rand is a random number produced with uniform distribution in the range of [0,1]. The random walks should be normalized by Eq. (10) to prevent ants from overshooting and to keep random walks in the boundaries of the search space:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t, \tag{10}$$

$$c_i^t = Antlion_j^t + c^t, \tag{11}$$

$$d_i^t = Antlion_j^t + d^t, \tag{12}$$

where c_i^t presents the minimum of all variables for the ith ant, d_i^t is the maximum of all variables for the ith ant, and $Antlion_j^t$ shows the position of the selected jth antlion at the tth iteration.

Step 6. Update position of the ant using Eq. (13):

$$Ant_i^t = \frac{R_A^t \times R_E^t}{2}, \tag{13}$$

where Ant_i^t shows the position of the ith ant at the tth iteration, R_A^t represents random walk around the antlion chosen using the roulette wheel at the tth iteration, and R_E^t is the random walk around the elite at the tth iteration.

Step 7. If every ant has been traversed, then go to Step 8; otherwise, go to Step 2.

Step 8. Calculate the objective values of all the ants.

Step 9. Update the archive.

Step 10. If the archive is full, eliminate some solutions by roulette wheel and Eq. (14) from the archive to accommodate the new solutions.

$$P_i = \frac{N_i}{c}. \tag{14}$$

Step 11. Check whether the termination condition is met or not. If the condition is met, then go to Step 12; otherwise, go to Step 2.

Step 12. Output the Pareto optimal solutions.

Pareto optimal solutions can be obtained and ranked in various ways using metaheuristic algorithms. MOALO uses an archive to store Pareto optimal solutions and its convergence is inherited from ALO algorithm. Once a solution has been selected from the archive, the ALO algorithm is used in order to improve its quality. Nonetheless, finding the Pareto optimal solutions set with a great variety is a challenging task. To overcome this challenge, the MOPSO based leader selection and archive maintenance strategies are employed. Of particular importance is providing a limit for the archive and to increase the distribution, solutions should be selected from the archive. Distribution of the solutions in the archive is measured by the niching technique in which the proximity of every solution is checked upon a prearranged radius. Then, the number of solutions in the proximity is counted and considered as the distribution measure. To improve the distribution of solutions in the archive, two mechanisms identical with those in MOPSO are considered. First, the solutions with the minimum inhabited vicinity are picked as antlions. Eq. (1) is then used to define the probability of picking a solution from the archive. The flowchart of the MOALO algorithm is shown in Figure 1.

2.3. Multi-Criteria Decision Making (MCDM)

2.3.1. Shannon's entropy

Several methods can be utilized to discover the normalized weights of objectives, e.g., Shannon's entropy technique [40], AHP [27], ordered weighted averaging [41], and simple additive weighted approach [42]. In this research, weighting of the attributes is based on crude values of optimal Pareto solutions, because, according to the above-mentioned methods, decisions of the users might be insufficient and result in a partial judgment on weights. To evaluate the relative weights, Shannon's entropy method declares the corresponding importance weights of the attributes based on the differentiation amongst data. Thus, Shannon's entropy can present a more reliable measure for the corresponding weights of the objectives in the loss of preferences of the users [21]. Shannon's entropy acts as a measure for the degree of uncertainty in information formulated in terms of probability theory. It is associated with the information source as a measure of uncertainty. The information can be easily defined as objective values. The uncertainty in information is addressed by Shannon's entropy utilizing the theory of probability. The inherent hypothesis is that lower probability of an event shows its higher chance to provide more information by its occurrence, i.e., an objective with a biased distribution offers more relative importance than a sharply peaked one does [21,43]. The Shannon's entropy parameter (E_j) of the jth objective is formulated as follows:

$$E_j = -\frac{\sum_{i=1}^{n} P_{ij} \ln P_{ij}}{\ln n}, \quad \text{where} \quad i \in \{1, 2, ..., n\} \quad \text{and}$$
$$j \in \{1, 2, ..., m\}, \tag{15}$$

$$P_{ij} = \frac{f_{ij}}{\sum_{i=1}^{n} f_{ij}}, \quad \text{where} \quad i \in \{1, 2, ..., n\} \quad \text{and}$$
$$j \in \{1, 2, ..., m\}, \tag{16}$$

$$\omega_j = \frac{(1 - E_j)}{\sum_{j=1}^{m} (1 - E_j)}, \quad \text{where} \quad \sum_{j=1}^{m} \omega_j = 1, \tag{17}$$

where f_{ij} indicates the jth objective function of the ith solution and P_{ij} is the jth linear normalized objective of the ith solution, which is utilized to calculate the value of E_j for the jth objective. n and m are the number of solutions and number of objectives, respectively. Finally, ω_j shows the corresponding relative normalized weight of the jth solution, which is determined by Eqs. (15) and (16).

2.4. Evidential Reasoning (ER)

Decision making is widely used in different fields of engineering and several approaches have been presented and employed in dealing with MCDM problems, e.g., additive utility function approaches [44], outranking approaches [45], and ER [28]. Using MCDM approaches makes user preference criteria controllable and more efficient. Moreover, the data may be easily transferred to the controller. Hence, the daily repetitive and time-consuming procedure of review and action of the schedule can be adjusted.

The ER is a comprehensive approach to integrated investigation of the MCDM problems under various uncertainty types like ignorance and fuzziness jointly [28]. The ER approach comprises all parts of the MCDM framework, employing the belief matrices and the belief structures. The ER information aggregation methodology contains a rule-or-utility-based information transformation procedure concerning different quantitative and qualitative information types under the required circumstances of utility and value equality [21,33].

In MOO, where objectives are frequently conflicting, the Pareto solutions might be so copious and it could be time-consuming to ultimately select an individual compromising solution. The output of MOO algorithms is a set of non-dominated solutions. Every non-dominated solution meets the scheduling objectives to some extent, which requires the utilization of the MCDM methods to pick the most suitable non-dominated solution. The MCDM problems handle the procedure of ordering solutions by considering various criteria. Therefore, taking multiple attributes into consideration, non-dominated solutions can be ordered by using the ER approach, which is able to present more efficient and practical appliance scheduling alternatives. The ER approach includes the following steps [28,46]:

1. Identification and analysis of multiple assessment criteria using a comprehensive study of engineering judgments or expert interviews with regard to the weight assigned to each criterion. This step collects and models various kinds of supporting attributes such as qualitative, quantitative, precise numbers, fuzziness, uncertainties, comparison numbers, and belief structures concerning criteria weights and utility by a belief decision matrix. Precise numbers show single or exact values without any uncertainty, whereas interval numbers denote estimates in ranges and belief structures indicate an evaluation as a distribution (for instance, unsafety of a specific alternative is "Good" to a belief degree of 71% and, at the same time, it can be evaluated to be "Moderate" to a degree of belief of 29%; such an evaluation can be represented as $\{(\text{Good}, 0.71), (\text{Moderate}, 0.29)\}$ and is referred to as a belief structure). When the assessor is not sufficiently sure on the assessment because of the lack of knowledge or evidence, the sum of probabilities is unequal to one (incomplete assessment). Furthermore, when no data is available to assess the performance of an alternative for a criterion, the total belief degree is assumed to be zero in the belief structure;
2. Transformation of different types of assessment degrees into a general framework of judgment by unifying the belief structures employing rule-and-utility-based information transformation procedures so that they can be consistently compared and aggregated. Belief structures should be translated during this step. For instance, 'Very Bad' and 'Very Good' respectively indicate zero and one, and the remaining grades may/may not be uniformly distributed;
3. Employment of the ER formulation and algorithm to agglomerate the assessing information on multiple criteria types to attain the overall assessment of each alternative;
4. Generation of utility scores or utility intervals in the state of the lack of information. Utility-based ranking is able to assess the overall performance of every alternative with respect to all aspects (criteria) jointly using a systematic-rational prioritizing framework, which presents the best schedule for smart home appliances and a schedule that satisfies all preferences of the users. The ultimately selected solution is a trade-off among preferences of the users.

There are various techniques for calculating the weights of every criterion, such as pairwise matching defined by users, Shannon's entropy, and so on. Since the weights denote the relative importance, normalizing the values is more helpful than using absolute values. The normalized values can be calculated by the following equations:

$$\omega_i = \frac{W_j}{\sum_{i=1}^{L} W_j}, \quad \text{where} \quad i = \{1, 2, ..., L\}, \tag{18}$$

subject to:

$$0 \leq \omega_i \leq 1, \quad \text{where} \quad \sum_{i=1}^{L} \omega_i = 1. \tag{19}$$

The linguistic phrases like 'worst,' 'good,' etc. are

$$\beta_n = \frac{\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1,j\neq n}^{N}\beta_{i,j}\right)-\Pi_{i=1}^{L}(1-\omega_i\sum_{j=1}^{N}\beta_{i,j})}{\sum_{n=1}^{N}\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1,j\neq n}^{N}\beta_{ij}\right)-(N-1)\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1}^{N}\beta_{i,j}\right)-\Pi_{i=1}^{L}(1-\omega_i)}, \tag{20}$$

$$\beta_H = \frac{\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1}^{N}\beta_{i,j}\right)-\Pi_{i=1}^{L}(1-\omega_i)}{\sum_{n=1}^{N}\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1,j\neq n}^{N}\beta_{ij}\right)-(N-1)\Pi_{i=1}^{L}\left(1-\omega_i\sum_{j=1}^{N}\beta_{i,j}\right)-\Pi_{i=1}^{L}(1-\omega_i)}. \tag{21}$$

Box I

known as grades and their entire set is denoted by $H = \{H_n, n = 1, 2, ..., N\}$ [21]. The analytical format of the ER procedure is able to determine the combined beliefs degree β_n of the nth grade, where $n \in \{1, 2, ..., N\}$ and β_H denotes the assessment of incompleteness for the entire set H. Contrarily to the recursive ER, the analytical format necessitates no iteration to assess several attributes, hence presenting more flexibility for optimization and assessment [33]. Eqs. (20) and (21) are presented in Box I to calculate β_n and β_H, where $\beta_{i,j}$ is degree of belief of the ith primary criterion for the jth grade and N is the number of grades in set H. Combined belief degrees and incomplete assessment (β_n and β_H) need to be translated into a single utility score for ranking the alternatives. Therefore, it is essential to produce numerical values corresponding to the belief structures:

$$u_{\max} = \sum_{n=1}^{N-1}\beta_n u(H_n) + (\beta_n + \beta_H)u(H_n), \tag{22}$$

$$u_{\min} = (\beta_1 + \beta_H)u(H_1) + \sum_{n=2}^{N}\beta_n u(H_n), \tag{23}$$

$$u_{ave} = \frac{u_{\max} + u_{\min}}{2}. \tag{24}$$

The minimum, maximum, and average values of utility scores are denoted by $u_{\max}$, $u_{\min}$, and u_{ave}, respectively, and $u(H_n)$ is a function showing utility score of the the nth grade. For instance, if $n = 6$ and all of the grades are equally ranged in $[0, 1]$, then $u(H_n) = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$. According to Eqs. (7) and (8), if there is no incomplete assessment ($bH = 0$), all the three states of minimum, maximum, and average values of utility scores are equal and can be calculated by the following formulation:

$$u_{\max} = u_{\min} = u_{\text{ave}} = \sum_{n=1}^{N}\beta_n.u(H_n). \tag{25}$$

3. Multi-objective home appliance scheduling problem

The main model in this paper is derived from the multi-objective demand-side scheduling problem, which was presented by Du et al. [35], and smart-home appliance scheduling problem, which was presented by Sou et al. [37]. Du et al. [35] considered the objectives of operational unsafety of appliances, electricity cost of household, and operational delay of appliances. Peak to Average Ratio (PAR) has a common formula and CO_2 emission is taken from Sou et al. Objective functions and formulations of the model are presented in the following:

3.1. Objective functions

3.1.1. Operational unsafety of appliances

The awake and at-home statuses of the users for controlling the operations of the appliances are considered as operational unsafety of the appliances. This objective function decreases the appliance operation in out-of-home or sleeping condition of users and Unsafety Time Rate (UTR) quantifies this situation. The minimization formulation for operational unsafety ($f_1(x)$) of appliances in a home with n time-adjustable appliances has been presented by Du et al. [35] as follows:

$$\min_x f_1(x), \tag{26}$$

$$f_1(x) = \sum_{a=1}^{n}\rho_a^{UTR_a(X_a)}, \tag{27}$$

$$UTR_a(X_a) = \frac{\gamma_a - S_a(X_a)}{\gamma_a}, \tag{28}$$

$$S_a(X_a) = \sum_{t=1}^{T} S_a(X_a, t).M(t).N(t), \tag{29}$$

$$S_a(X_a, t) = \begin{cases} 1, & t \in [X_a, X_a + \gamma_a - 1] \\ 0, & t \in H[X_a, X_a + \gamma_a - 1] \end{cases} \tag{30}$$

$$M(t) = \begin{cases} 1, & \text{if users are at home} \\ 0, & \text{if users are away} \end{cases} \tag{31}$$

$$N(t) = \begin{cases} 1, & \text{if users are awake} \\ 0, & \text{if users are asleep} \end{cases} \tag{32}$$

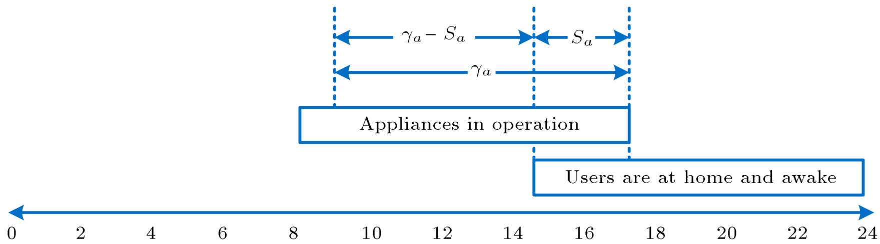


Figure 2. Representation of the Unsafety Time Rate (UTR) concept.

$$H = \{1, 2, ..., T\}, X_a \in [\alpha_a, \beta_a \gamma_a + 1], \tag{33}$$

$$X = \{X_1, X_2, ..., X_a, ..., X_n\}, \tag{34}$$

subject to:

$$X_a \in [\alpha_a, \beta_a - \gamma_a + 1], \text{ where } a = \{1, 2, ..., n\}. \tag{35}$$

Within these formulations, UTR of appliance a is denoted by UTR_a and X_a is the starting time slot of the operation of the appliance. ρ_a is the unsafety parameter; with higher values of ρ_a, the cost of operational unsafety will be higher. The set $X = \{X_1, X_2, ..., X_a, ..., X_n\}$ indicates the starting time slots of appliances. S_a is the number of time slots that users are awake and at home during the time appliance a is in operation and it is determined by the operation status of the appliance S_a (X_a, t) with the information of at-home status $M(t)$ and awake status $N(t)$ of the users in a day. The phrase $t \in H[X_a, X_a + \gamma_a - 1]$ demonstrates that t pertains to $H = \{1, 2, ..., T\}$ excluding the range within this formulation. UTR of appliance a is denoted by UTR_a and X_a is the starting time slot of its operation. Also, ρ_a is the unsafety parameter. The higher the value of ρ_a, the higher the cost of operational unsafety will be. The set $X = \{X_1, X_2, ..., X_a, ..., X_n\}$ indicates starting time slots of the appliances. S_a represents the number of time slots that users are awake and at home, while the appliance a is in operation and determined using its operation status $S_a(X_a, t)$ with the information of the at-home status $M(t)$ and awake status $N(t)$ of the users in a day. The phrase $t \in H \backslash [X_a, X_a + \gamma_a - 1]$ demonstrates that t pertains to $H = \{1, 2, ..., T\}$ excluding the range $[X_a, X_a + \gamma_a - 1]$ and $T = 120$ is the boundary of scheduling, which intimates the number of time slots forward that the schedule of energy consumption is made for time-adjustable appliances. $X_a \in [\alpha_a, \beta_a \gamma_a + 1]$, because the operation should start ahead of the deadline with at least the length of the operation time. After determining the start time slots of appliances, the UTRs of appliances are calculated by Eqs. (28)–(33) and the operational unsafety is calculated by UTR. UTR is the ratio of the unsafe operation time slots (the time slots that users are asleep or away, but the appliance is in operation) to the operation length. Consider that various appliances may have identical UTRs and ρ_a is presented for distinguishing the operational unsafety of appliances. Also, suppose that both the UTR and ρ_a jointly define operational unsafety of the appliance by $\rho_a^{UTR_a}$. The concept of UTR is depicted in Figure 2.

The at-home status $M(t)$ and awake status $N(t)$ of the users are separately determined by users as various users have various at-home statuses and awake statuses. Based on the predefined at-home and awake statuses of the users, the operational unsafety of appliances is calculated by Eqs. (26)–(35). The operational unsafety of the same energy consumption schedule differs under various statuses of users.

3.1.2. Electricity cost of household

P_a shows the power of appliance a. By considering each one hour as five identical time slots with the fixed energy consumption of $\frac{P_a}{5}$ during each time slot, the energy consumption schedule of appliance a is calculated by [35,36]:

$$E_a = \begin{cases} e_a^t | e_a^t = \frac{P_a}{5}, & t \in [X_a, X_a + \gamma_a - 1], \\ e_a^t = 0, & t \in H[X_a, X_a + \gamma_a - 1] \\ H = \{1, 2, ..., T\}, & X_a \in [\alpha_a, \beta_a \gamma_a + 1] \end{cases} \tag{36}$$

where e_a^t denotes the energy consumption of appliance a during time slot t. Pursuant to the energy consumption of appliances and the day-ahead real-time electricity price, the minimization formulation of electricity cost is:

$$\min_x f_2(x), \tag{37}$$

$$f_2(x) = \sum_{t=1}^{T} prc_t . l_t(x), \tag{38}$$

$$l_t(x) = \sum_{a=1}^{n} e_a^t, \tag{39}$$

$$X = \{X_1, X_2, ..., X_a, ..., X_n\}, \tag{40}$$

subject to:

$$X_a \in [\alpha_a, \beta_a - \gamma_a + 1], \text{ where } a = \{1, 2, ..., n\}, \tag{41}$$

where prc_t is the real-time electricity price at time slot t and l_t is total energy consumption of all the time-adjustable appliances during time slot t, which can be obtained after determining the start time slots of all appliances X. Energy consumption of every appliance is scheduled by Eq. (36).

3.1.3. Operational delay of appliances

Figure 3 illustrates that operational delay of an appliance is the delay time from α_a, the earliest start time of the operation. The longest delay occurs exactly when the appliance reaches the deadline to complete its operation, i.e., the appliance starts at the time slot $\beta_a - \gamma_a + 1$. For a home including n time-adjustable appliances [35,36], the formulation of operational delay minimization is as follows:

$$\min_x f_3(x), \tag{42}$$

$$f_3(x) = \sum_{a=1}^{n} \sigma_a^{DTR_a(X_a)}, \tag{43}$$

$$DTR_a(X_a) = \frac{x_a - \alpha_a}{\beta_a - \gamma_a + 1 - \alpha_a}, \tag{44}$$

$$X = \{X_1, X_2, ..., X_a, ..., X_n\}, \tag{45}$$

subject to:

$$X_a \in [\alpha_a, \beta_a - \gamma_a + 1], \text{ where } a = \{1, 2, ..., n\}, \tag{46}$$

where DTR_a indicates the delay time rate of appliance a. $\sigma_a > 1$ shows the delay parameter of appliance a. The higher the value of σ_a, the higher the cost of operational delay will be [36].

3.1.4. Peak to Average Ratio (PAR)

Supporting stability of the entire electricity network is an important issue that can be achieved by minimizing the PAR. PAR is the rate of maximum daily power demand to average daily power demand. Minimization formulation of PAR is presented as follows:

$$\min_x f_4(x), \tag{47}$$

$$f_4(x) = \frac{\max_x l_t(x)}{\sum_{t=1}^{T} l_t(x)}, \tag{48}$$

$$l_t(x) = \sum_{a=1}^{n} e_a^t, \tag{49}$$

$$X = \{X_1, X_2, ..., X_a, ..., x_n\}, \tag{50}$$

subject to:

$$X_a \in [\alpha_a, \beta_a - \gamma_a + 1], \text{ where } a = \{1, 2, ..., n\}. \tag{51}$$

3.1.5. CO_2 emission

During day and night, various renewable and non-renewable sources with different CO_2 footprints are used for electricity generation, leading to a dynamic CO_2 emission footprint during hours of a day. By shifting operation of the appliances to the hours of the day with low CO_2 emissions, the total CO_2 emissions of households will be reduced. The minimization formulation for total CO_2 emission is presented as follows:

$$\min_x f_5(x), \tag{52}$$

$$f_5(x) = \sum_{t=1}^{T} l_t(x).C_t, \tag{53}$$

$$l_t(x) = \sum_{a=1}^{n} e_a^t, \tag{54}$$

$$X = \{X_1, X_2, ..., X_a, ..., X_n\}, \tag{55}$$

subject to:

$$X_a \in [\alpha_a, \beta_a - \gamma_a + 1], \text{ where } a = \{1, 2, ..., n\}, \tag{56}$$

where C_t is the carbon emission in time slot t.

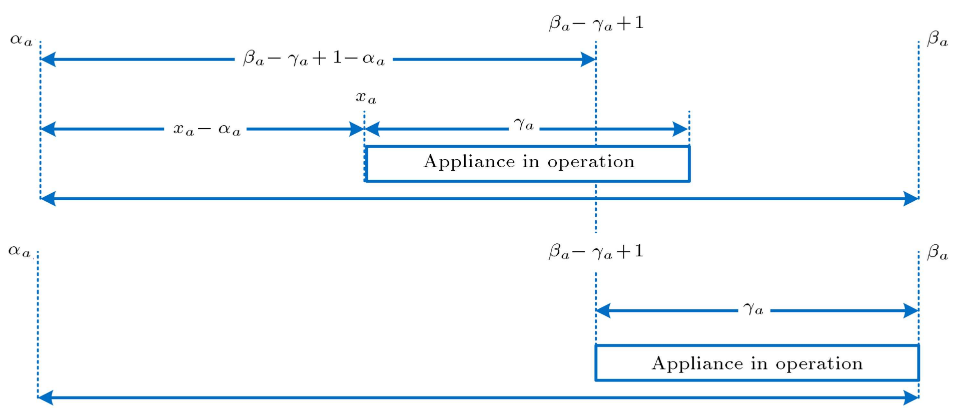


Figure 3. Representation of the delay time rate concept.

4. Implementation of the proposed system

4.1. Numerical example

To verify and show effectiveness of the proposed appliance scheduling system in order to unify the ER approach and MOALO for solving SHEMS, a benchmark of smart home, first proposed by Zhao et al. [36], is adopted and the interrelations among different objectives are investigated. Du et al. [35] altered the data to consider the safety of appliances. In this study, eight common appliances were recognized and some of them were used more than once during the day. The corresponding parameters are illustrated in Table 1.

Du et al. [35] considered the at-home and awake statuses of users, as shown in Figures 4 and 5. The electricity price data [47] and CO_2 footprint data [48] are shown in Figures 6 and 7, respectively. Both the unsafety (ρ_a) and delay (σ_a) parameters are considered to be 2. It is worth mentioning that the at-home status and awake status of the users in Figures 4 and 5 are demonstrated to show how statuses of the users are

Table 1. Parameters of appliances.

Appliance	Operation Time Interval (OTI)	Length of Operation Time (LOT)	Power (kW)
Rice cooker^1	1–40	2	0.5
Rice cooker^2	56–65	2	0.5
Rice cooker^3	71–90	2	0.5
Water heater	86–105	3	1.5
Dishwasher	101–120	2	0.6
Washing machine	1–60	5	0.38
Electric kettle^1	1–40	1	1.5
Electric kettle^2	81–90	1	1.5
Clothes dryer	71–90	5	0.8
Oven	71–90	3	1.9
Electric radiator^1	56–65	5	1.8
Electric radiator^2	81–110	20	1.8

$*^1$, $*^2$, and $*^3$ indicate that appliance * is used three times within various OTIs in a day.

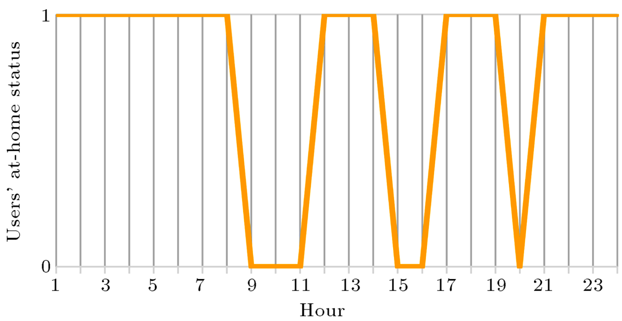


Figure 4. At-home status of the users.

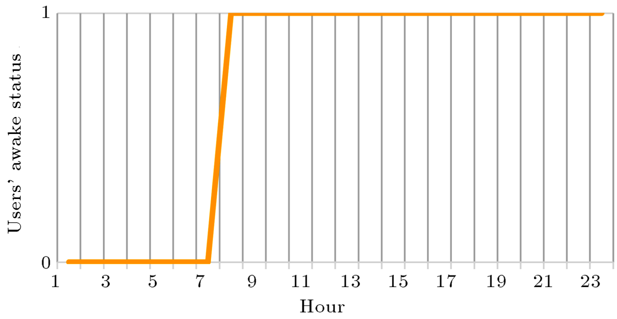


Figure 5. Awake status of the users.

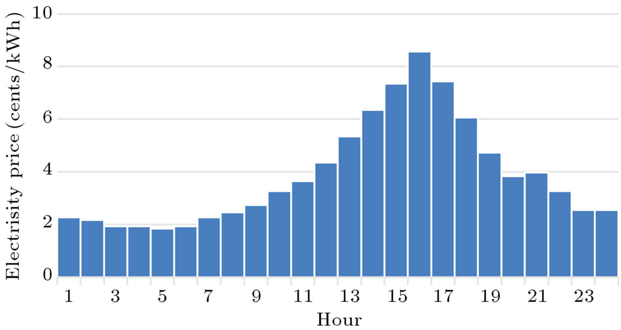


Figure 6. Electricity price data.

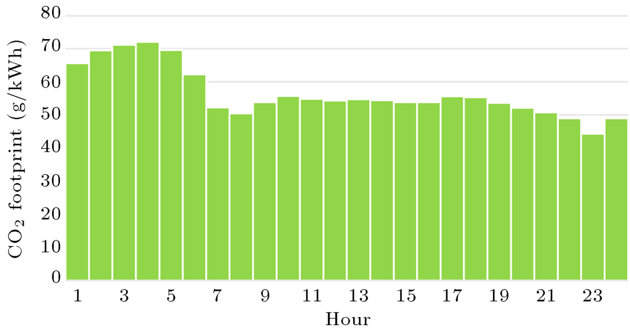


Figure 7. CO_2 footprint data.

considered in operational unsafety of the appliances. The users individually define the at-home status and awake status.

Regarding the effect of parameter setting on the performance of metaheuristic algorithms, the Taguchi method [49] is hired. Before calibration of the applied algorithms, some preliminary tests are run to find the proper parameter levels. To achieve more accurate and better sustained results for the proposed algorithm, the population number and iteration parameters are configured.

4.2. Parameter configuration

Due to the effect of parameter configuration on the performance of metaheuristics, the Taguchi method of Design-Of-Experiment (DOE) [49] is performed for the configuration of the MOALO parameters. The MOALO contains two key parameters, namely the maximum number of iterations (T) and the number of antlions (n). Before calibration of the used algorithms, some preliminary tests are run to find appropriate parameter levels and 5 levels are considered for each of the two parameters. For each run, the maximum number of iterations is set to $MaxIt = \{1000, 2000, 3000, 4000, 5000\}$ and the number of ants is set to $n = \{100, 150, 200, 250, 300\}$. The performance indicators of multi-objective algorithms differ from single-objective algorithms. In the single-objective case, the optimal solution has the global optimum of a particular objective function, whereas, in the multi-objective case, there may not exist a unique solution that is optimal in terms of all objective functions. Hence, a different method is required for comparing the performance of each test of the algorithm. Therefore, relative performance metrics are used (spread of non-dominance solutions, diversification matrix, mean ideal distance, rate of achievement to two objectives simultaneously, and quality metric) are employed to analyse the results of test runs quantitatively. These metrics are well-known and available in several books and papers. Hence, they are not explained here for brevity. For a thorough explanation of this method and its enhanced version, the interested reader may refer to Jolai et al. [50]. All test results are calculated using the Taguchi method; the mean of S/N (Signal per Noise) ratio is shown in Figure 8. Taguchi is a well-known method of DOE and widely applied in many papers and books. Again, for brevity, it is not repeated in here and for a thorough explanation, the interested reader may refer to [50]. As demonstrated in Figure 8, the second level of iteration numbers and the fourth level of population numbers have better performance. Thus, in this case, the iteration number is set to 2000 and the population number set to 250.

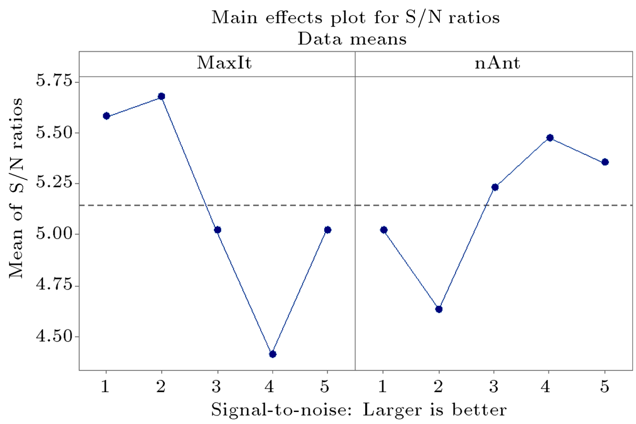


Figure 8. Diagram of the mean effect of the Signal per Noise (S/N) ratio.

4.3. Pareto selection

Table A.1 (Appendix) presents the acquired Pareto solutions to the benchmark instance of SHEMS. The utility scores of the solutions for each objective are also provided in the table. Figure 9 shows the plot for the parallel coordinates of the Pareto solutions. The data can be used in the prospective research studies. As it can be seen in Figure 10, except for cost-unsafety and CO_2 emission-unsafety objective pairs, which have no clear relationship, the relationships between all other objective pairs are oppositional and a Pareto diagram can be plotted for them.

4.4. Determining the weights

Shannon's entropy technique determined the weights for all objectives (see Section 2.3.1). The PAR objective possessed the highest value of normalized weight by 41.65%, which for delay, unsafety, cost, and CO_2 emission was equal to 36.65%, 16.49%, 4.91%, and 0.3%, respectively. Table 2 shows that the PAR objective forces a higher impact on the associated uncertainty in the acquired results and possesses a higher weight. It is clear that these weights will change daily by changing the day-ahead CO_2 footprint and day-ahead electricity price. This is the advantage of this weighting method over the previously developed methods.

4.5. Ranking solutions

The acquired Pareto solutions should now be ranked based on their overall performance, indicating the satisfactory degree of every alternative by taking into account all the criteria simultaneously. In order to assess the overall performance of each solution, a hierarchical structure is required to associate unsafety of the appliances, electricity cost, delay of appliances, PAR, and CO_2 emission attributes with their related normalized weights as the indicator of the overall performance, as given in Figure 11. The belief structure of each attribute is determined as demonstrated in Figure 12. The x-axis shows the grades ('Worst,' 'Poor,' 'Moderate,' 'Good,' and 'Best') and the corresponding values of the attributes. For example, consider the 40th alternative. The delay of 18.9562 lies between 'Worst' and 'Poor' grades with the values of 22.6271 and 20.0001, respectively. Therefore,

Table 2. Normalized weights of the objectives by Shannon's entropy.

Objectives	Unsafety	Cost	Delay	PAR	CO_2 emission
Normalized weights	0.1649	0.0491	0.3665	0.4165	0.0030

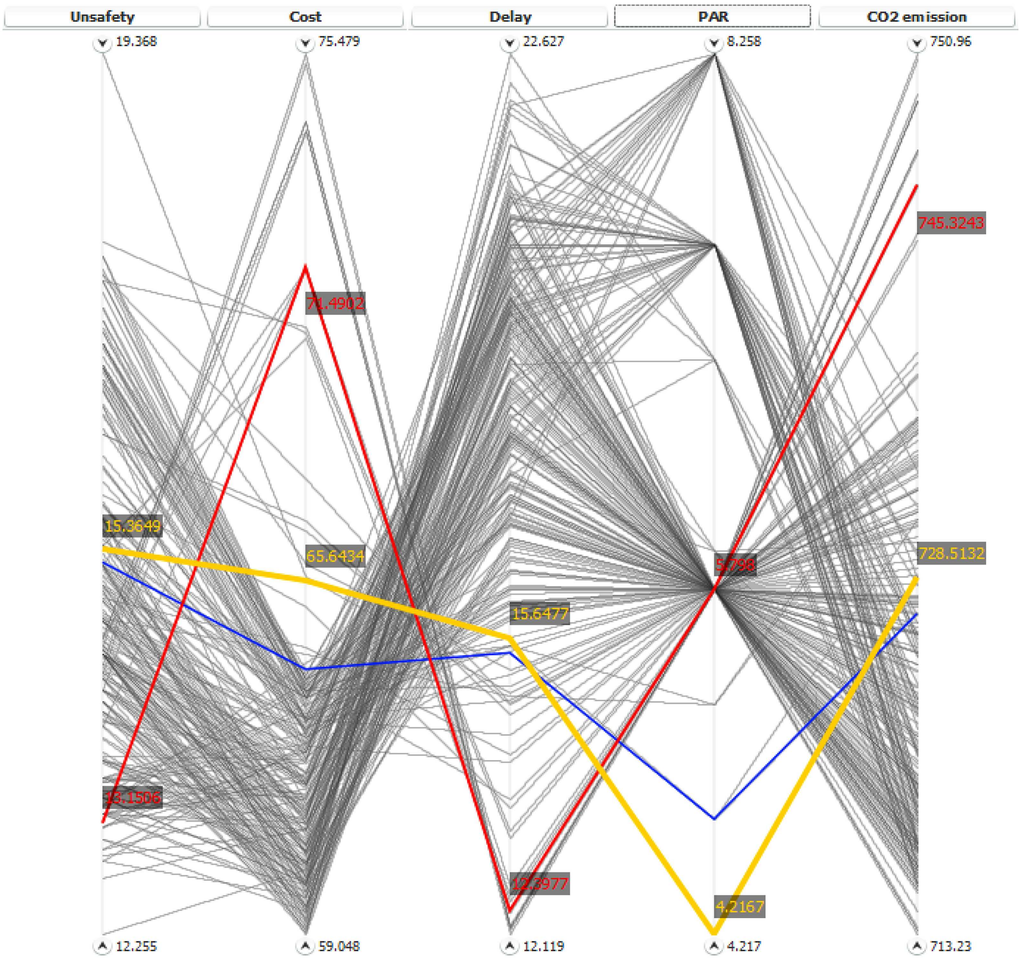


Figure 9. Plot for the parallel coordinates of the Pareto solutions.

Table 3. Belief structures of the attributes of the 40th alternative.

	Grades (%)				
	Worst	**Poor**	**Moderate**	**Good**	**Best**
Unsafety	0	0	0	35.84	64.16
Cost	0	0	0	46.50	53.50
Delay	60.26	39.74	0	0	0
PAR	100	0	0	0	0
CO_2 emission	0	0	0	93.22	6.78

attribute of the 40th alternative belongs to the grade of 'Worst' with 60% belief and to the grade of 'Poor' with 40% belief. An identical procedure is adopted for all other attributes. The acquired belief structures for all attributes are presented in Table 3. Figure 13 shows the overall performance utility assessment of all solutions. The solutions are sorted based on their acquired overall performance utility scores. The first solution is recommended to the users. In this case, the 6th Pareto solution is selected as the best one because it has the highest utility score (79.52%) among all the Pareto solutions. That is, this appliance scheduling alternative satisfies the overall performance by concurrently regarding all objectives with the utility score of 79.52%. However, the overall performance might be insufficient for the final decision on the best solution schedule, because every schedule should be reviewed in terms of its weakness and strength points in considering utility score of every objective. As can be observed, the 6th alternative has the best utility score for the PAR objective, which is equal to 100%, and other objectives of this alternative have good levels of utility score. In fact, the ER provides the users with an obvious perception of the performance of each

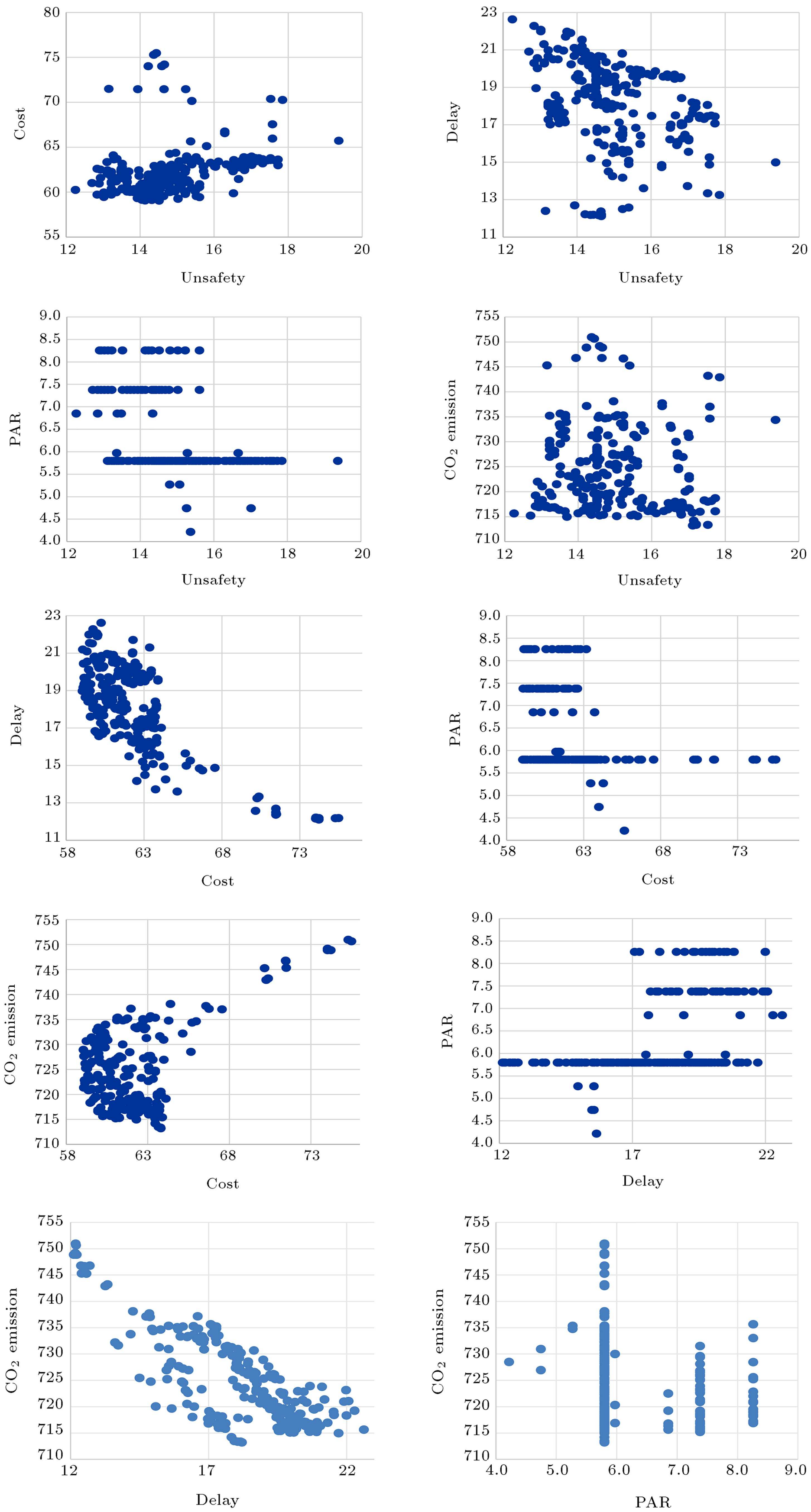


Figure 10. Obtained Pareto optimal solutions shown for each pair of objectives.

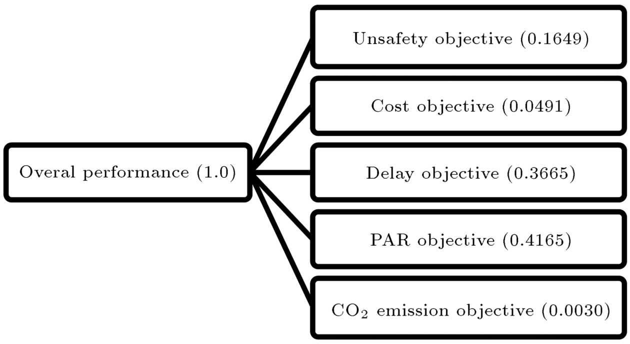


Figure 11. Hierarchical structure of objective weights.

alternative for each single criterion and enables them to investigate schedules quickly.

4.6. Discussion

Among the Pareto solutions, the 6th, 40th, 99th, 137th, 181st, and 230th alternatives (Pareto solutions) were chosen to show the procedure of the overall assessment. Figure 14 illustrates the correspondent utility score of every objective along with the overall performance of every alternative. The 181st alternative possesses 21% overall utility score, which is quite low to be selected, and does not present satisfactory performance in terms of the unsafety objective. By careful investigation into the best solutions, the users are able to select the most suitable scheduling alternative. ER expedites the investigation into the overall performance of scheduling alternatives by providing more pieces of information about the performance of each scheduling alternative concerning each objective. The presumptions of the users about the performance of each alternative makes them more confident to perform their preferred appliance schedule. Therefore, energy control becomes more efficient in the smart home. As remarked before, the ER approach achieves informative data about the weaknesses of each scheduling alternative at any desirable level. This study divides the overall performance into five grades including 'worst grade,' 'poor grade,' 'moderate grade,' 'good grade,' and 'best grade,' which are spaced equally within the range of [0,1]. These grades can be utilized to show the combined degree of belief β_n (Figure 15). Accordingly, overall performance of the 6th solution is believed to pertain to the 'best' grade by a degree equal to 79.52%. As well, the 6th alternative has no belief degree on the 'worst' grade, while the 40th, 137th, and 181st alternatives have belief degrees of the 'worst' grade with the values of 46.05%, 18.10%, and 47.58%, respectively. Consequently, the users decide to select the 6th alternative as the best one. If the first alternative is not suitable, the

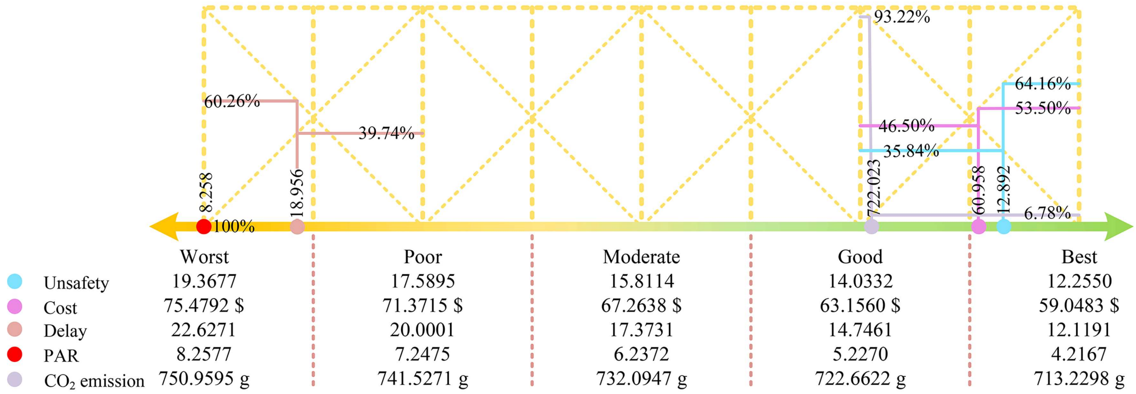


Figure 12. Transfer of each attribute to the belief structure.

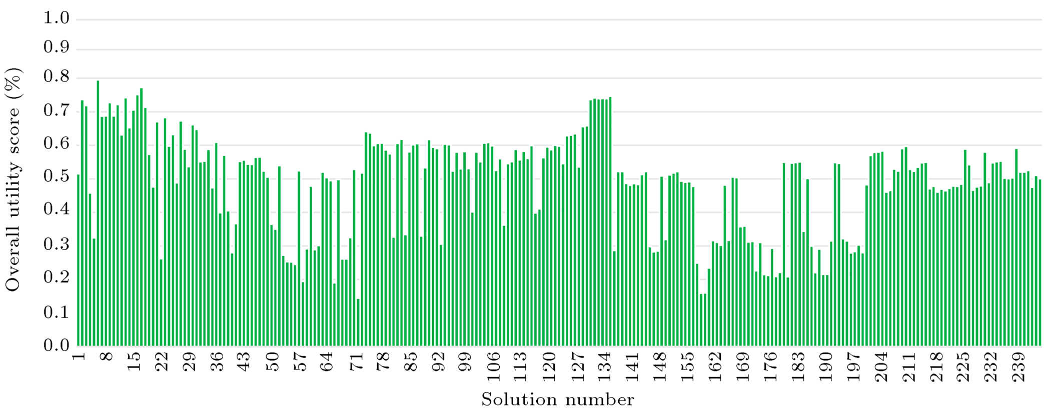
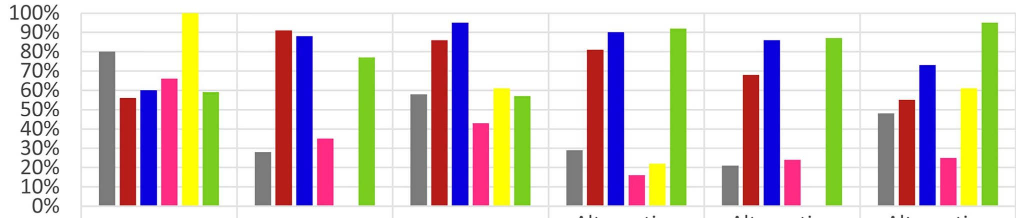
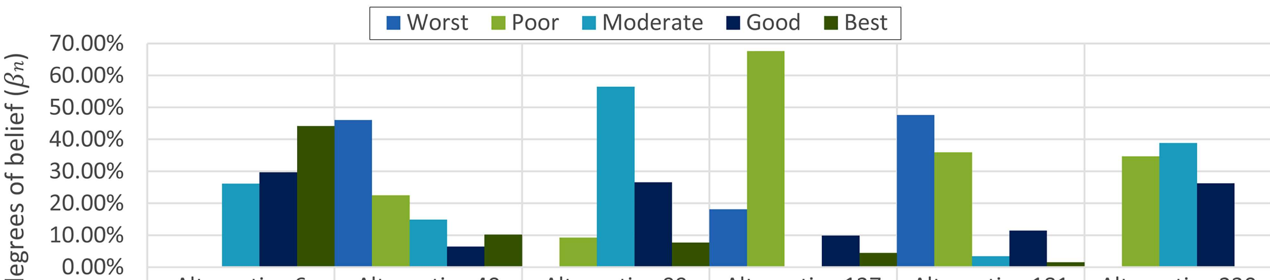


Figure 13. Overall performance utility assessment of all solutions.



	Alternative 6	Alternative 40	Alternative 99	Alternative 137	Alternative 181	Alternative 230
Overall Performance	80%	28%	58%	29%	21%	48%
Unsafety	56%	91%	86%	81%	68%	55%
Cost	60%	88%	95%	90%	86%	73%
Delay	66%	35%	43%	16%	24%	25%
PAR	100%	0%	61%	22%	0%	61%
CO2 emission	59%	77%	57%	92%	87%	95%

Figure 14. The utility scores of the 6th, 40th, 99th, 137th, 181st, and 230th alternatives concerning each objective.



	Alternative 6	Alternative 40	Alternative 99	Alternative 137	Alternative 181	Alternative 230
Worst	0.00%	46.05%	0.00%	18.10%	47.58%	0.00%
Poor	0.00%	22.49%	9.23%	67.60%	35.98%	34.72%
Moderate	26.10%	14.83%	56.48%	0.00%	3.42%	38.89%
Good	29.70%	6.42%	26.57%	9.86%	11.48%	26.24%
Best	44.20%	10.20%	7.72%	4.44%	1.54%	0.14%

Figure 15. Combined belief degrees (β_n) for the 6th, 40th, 99th, 137th, 181st, and 230th alternatives concerning the overall performance.

users could start investigating other alternatives. In this case, there is no incomplete assessment, so the incompleteness assessment is considered to be zero, $\beta_H = 0$.

In general, ER is highly effective in determining the performance of each alternative and it empowers the users to make a practical and transparent decision on the best scheduling alternative. Employing the ER procedure in smart home appliance scheduling makes a more efficient electrical energy control system possible and provides the users with higher confidence in their decisions, because they have a transparent knowledge on the performance of each scheduling alternative. In some cases, an inappropriate alternative from the point of view of the users may have the highest value of utility score. In such cases, the next alternative could be investigated.

Concerning the goal of achieving a trade-off, a solution that reaches a balance among unsafety, cost, delay, PAR, and CO_2 emission is preferred. In comparison to other solutions, the 6th solution provides a suitable trade-off among the objectives by concurrently satisfying them to an acceptable degree. The best schedule is obtained in this paper and the relative objectives are shown in Figure 16. If the user recognizes that the schedule cannot satisfy their preference in terms of unsafety or delay of appliances, they are able to change the relative ρ_a or σ_a of the appliance.

5. Concluding remarks and future works

In this research, for the first time, unsafety of the appliances, electricity cost, delay of appliances, Peak to Average Ratio (PAR), and CO_2 emission were considered as the objectives of a smart home appliance scheduling model and jointly optimized. Moreover, a comprehensive Multi-Criteria Decision Making (MCDM) framework for ranking the acquired Pareto solutions was tailored and evaluated for making

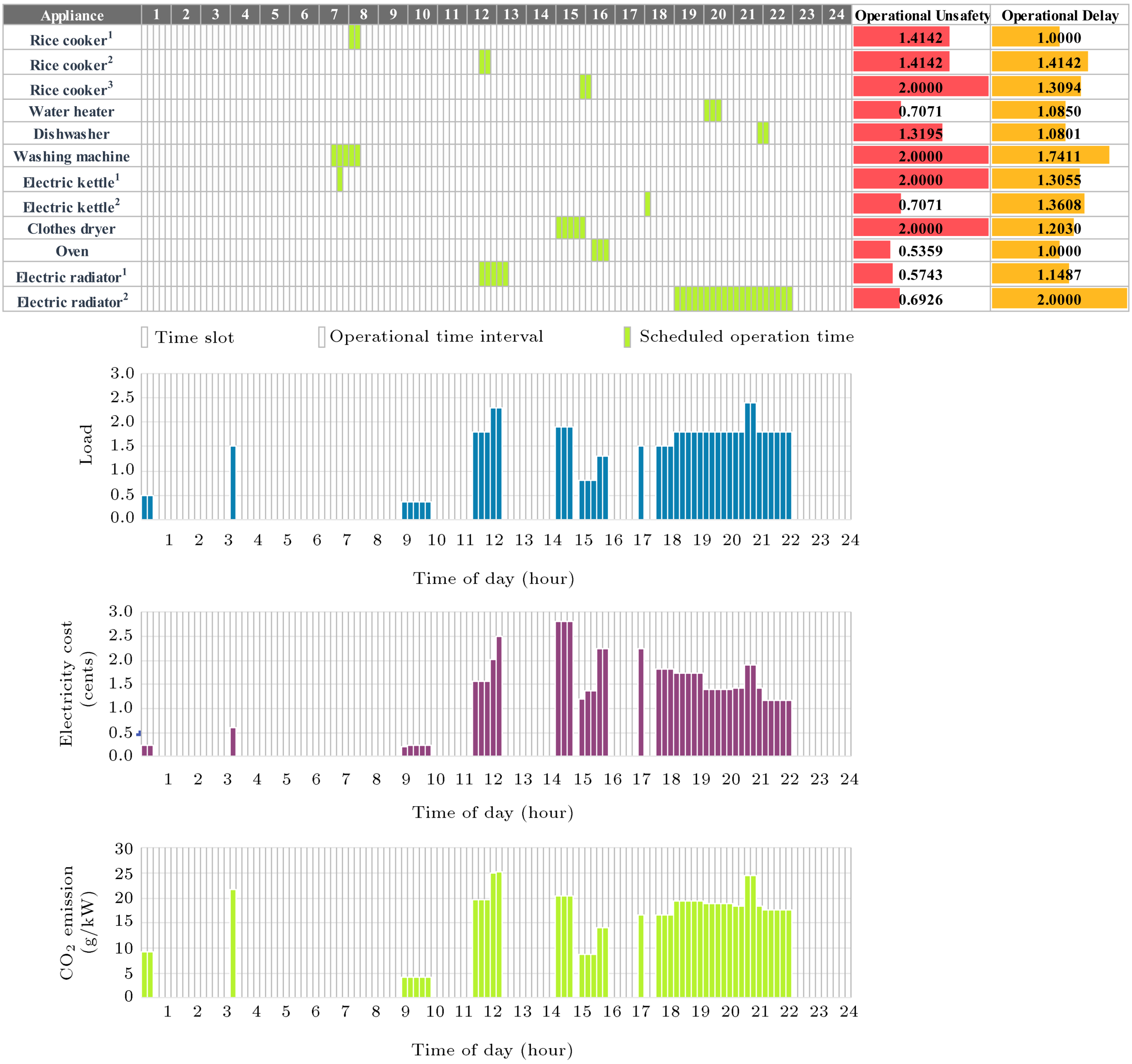


Figure 16. The best solution acquired in this research.

a trade-off between objectives. A Multi-Objective Ant Lion Optimizer (MOALO) was designed to solve Smart-Home Energy Management System (SHEMS) and then, applied to a benchmark appliance scheduling instance from the literature. After that, an Evidential Reasoning (ER) approach was adopted to rank the optimal Pareto solutions employing the weights acquired by Shannon's entropy. The proposed ER approach helps users to identify the efficiency of every alternative in a panoramic view to all the attributes and, consequently, to select one of the Pareto solutions with higher assurance. A comprehensive framework to integrate MCDM techniques into an Evolutionary Multi-Objective Optimization (EMOO) was employed to facilitate the process of making a trade-off among objectives. The proposed approach to employing the MCDM technique made it possible to select the most efficient appliance schedule. The ER approach gives a transparent and comprehensive sense of efficiency of the alternatives and the users can find the strengths and weaknesses of each alternative. The implementation of the developed SHEMS will need easy access to the data of day-ahead electricity cost and CO_2 emission.

In future works on the basis of this study, the authors intend to provide a user-friendly API utilizing social media and BIM to help automatize the process of smart home appliance operation scheduling. Considering the multi-user nature of smart homes, integrating the developed system with game theory concepts may be beneficial. Testing several metaheuristics for solving this problem will also be an interesting topic.

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Appendix

Pareto solutions of the MOALO for smart home benchmark

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark.

#	Objectives					Utility scores in terms of					
	Unsafety	Cost	Delay	PAR	CO_2 emission	Overall performance	Unsafety	Cost	Delay	PAR	CO_2 emission
1	17.1417	63.4492	17.8280	5.7980	714.1940	52%	31%	73%	46%	61%	97%
2	14.6435	71.4542	12.3762	5.7980	746.8006	74%	66%	24%	98%	61%	11%
3	15.2293	71.4569	12.4987	5.7980	746.6918	72%	58%	24%	96%	61%	11%
4	13.6921	62.2955	21.7105	5.7980	714.9864	46%	80%	80%	9%	61%	95%
5	12.2550	60.2432	22.6271	6.8521	715.6594	32%	100%	93%	0%	35%	94%
6	15.3649	65.6434	15.6477	4.2167	728.5132	80%	56%	60%	66%	100%	59%
7	14.9617	64.3873	14.2542	5.7980	738.1254	69%	62%	68%	80%	61%	34%
8	15.2293	62.5355	14.1747	5.7980	733.7811	69%	58%	79%	80%	61%	46%
9	14.7989	64.2737	14.9529	5.2709	734.7895	73%	64%	68%	73%	74%	43%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives						Utility scores in terms of				
	Unsafety	Cost	Delay	PAR	CO_2 emission	Overall performance	Unsafety	Cost	Delay	PAR	CO_2 emission
10	14.8493	63.0491	14.5018	5.7980	725.4890	69%	64%	76%	77%	61%	68%
11	17.0116	63.9736	15.5519	4.7438	730.9634	72%	33%	70%	67%	87%	53%
12	15.2226	63.5840	15.6671	5.7980	719.6484	63%	58%	72%	66%	61%	83%
13	13.9364	71.4542	12.6965	5.7980	746.8006	74%	76%	24%	95%	61%	11%
14	15.3974	63.5847	15.0823	5.7980	720.0563	65%	56%	72%	72%	61%	82%
15	15.0665	63.4514	15.5510	5.2709	735.3550	71%	60%	73%	67%	74%	41%
16	15.2570	63.9868	15.4740	4.7438	726.9526	75%	58%	70%	68%	87%	64%
17	13.1506	71.4902	12.3977	5.7980	745.3243	77%	87%	24%	97%	61%	15%
18	15.3970	70.1594	12.5776	5.7980	745.2823	71%	56%	32%	96%	61%	15%
19	15.1382	61.8578	17.1284	5.7980	718.4045	57%	59%	83%	52%	61%	86%
20	13.1063	63.3554	21.3051	5.7980	716.9784	48%	88%	74%	13%	61%	90%
21	16.9856	63.7382	13.7257	5.7980	731.6613	67%	33%	71%	85%	61%	51%
22	13.0207	59.9607	22.0699	7.3792	721.0676	26%	89%	94%	5%	22%	79%
23	15.7953	65.1334	13.6117	5.7980	732.1948	68%	50%	63%	86%	61%	50%
24	14.7750	62.6034	16.7423	5.7980	723.3095	60%	65%	78%	56%	61%	73%
25	15.3871	63.1638	15.5615	5.7980	727.7293	63%	56%	75%	67%	61%	62%
26	13.2207	62.2586	20.9829	5.7980	719.8696	49%	86%	80%	16%	61%	82%
27	14.3759	62.9120	15.2081	5.7980	731.2745	67%	70%	76%	71%	61%	52%
28	15.7184	62.3380	16.4147	5.7980	718.0575	59%	51%	80%	59%	61%	87%
29	17.7241	62.9968	17.0731	5.7980	718.7073	54%	23%	76%	53%	61%	85%
30	15.3974	63.0814	14.9029	5.7980	724.7709	66%	56%	75%	74%	61%	69%
31	14.9617	62.0403	15.4956	5.7980	725.2368	65%	62%	82%	68%	61%	68%
32	14.8214	62.9751	18.0663	5.7980	717.8952	55%	64%	76%	43%	61%	88%
33	16.5320	63.5697	17.0100	5.7980	717.1116	55%	40%	72%	53%	61%	90%
34	13.2907	63.6540	17.6197	5.7980	716.8579	59%	85%	72%	48%	61%	90%
35	13.3738	63.7130	17.5972	6.8521	716.8148	47%	84%	72%	48%	35%	90%
36	13.2768	64.1006	17.0175	5.7980	719.1450	61%	86%	69%	53%	61%	84%
37	13.5136	61.6662	17.8799	7.3792	725.0781	40%	82%	84%	45%	22%	69%
38	13.5136	61.5659	18.3079	5.7980	723.5365	57%	82%	85%	41%	61%	73%
39	14.3358	61.0696	18.9242	6.8521	722.5242	41%	71%	88%	35%	35%	75%
40	12.8923	60.9583	18.9562	8.2577	722.0227	28%	91%	88%	35%	0%	77%
41	14.5812	60.7093	18.2616	7.3792	726.5390	37%	67%	90%	42%	22%	65%
42	14.2213	60.4876	18.6142	5.7980	726.1011	55%	72%	91%	38%	61%	66%
43	14.6813	61.8451	18.0378	5.7980	723.8403	56%	66%	83%	44%	61%	72%
44	14.2213	61.5587	18.8636	5.7980	720.6617	54%	72%	85%	36%	61%	80%
45	14.2213	61.4180	18.8964	5.7980	721.1667	54%	72%	86%	36%	61%	79%
46	13.4135	61.6166	18.5765	5.7980	721.4916	56%	84%	84%	39%	61%	78%
47	13.9742	61.8152	18.2966	5.7980	721.8166	57%	76%	83%	41%	61%	77%
48	15.3923	60.5147	18.7253	5.7980	722.8884	52%	56%	91%	37%	61%	74%
49	14.6363	59.5679	19.8617	5.7980	721.1451	51%	67%	97%	26%	61%	79%
50	14.7812	60.6823	18.2502	7.3792	723.3192	37%	64%	90%	42%	22%	73%
51	14.5136	59.4906	18.7327	7.3792	723.3209	35%	68%	97%	37%	22%	73%
52	14.3136	59.5317	18.9923	5.7980	722.9183	54%	71%	97%	35%	61%	74%
53	14.1336	59.0726	21.1977	7.3792	721.3806	27%	74%	100%	14%	22%	78%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives					Overall performance	Utility scores in terms of				
	Unsafety	Cost	Delay	PAR	CO_2 emission		Unsafety	Cost	Delay	PAR	CO_2 emission
54	13.8252	60.0048	21.9048	7.3792	720.9801	25%	78%	94%	7%	22%	79%
55	13.7279	60.0275	21.9785	7.3792	723.1382	25%	79%	94%	6%	22%	74%
56	14.1336	59.5729	19.3477	8.2577	721.0120	25%	74%	97%	31%	0%	79%
57	14.0505	59.1530	19.6956	5.7980	722.2769	52%	75%	99%	28%	61%	76%
58	14.3136	59.1240	20.4415	8.2577	722.8441	19%	71%	100%	21%	0%	75%
59	13.9279	59.9384	20.6726	7.3792	723.9357	29%	76%	95%	19%	22%	72%
60	13.9279	59.3325	21.1022	5.7980	723.8097	48%	76%	98%	15%	61%	72%
61	14.3136	59.9450	20.5745	7.3792	716.8616	29%	71%	95%	20%	22%	90%
62	14.4110	59.4418	20.1251	7.3792	720.8947	30%	70%	98%	24%	22%	80%
63	14.6161	62.2988	19.3456	5.7980	719.4611	52%	67%	80%	31%	61%	83%
64	14.4282	62.4868	19.9747	5.7980	719.6376	50%	69%	79%	25%	61%	83%
65	15.2777	61.3393	19.0967	5.9736	720.3384	49%	58%	86%	34%	57%	81%
66	14.2213	59.3630	20.5508	8.2577	720.8116	19%	72%	98%	20%	0%	80%
67	14.1336	60.1509	20.4066	5.7980	721.2573	50%	74%	93%	21%	61%	79%
68	14.1336	59.5069	21.5452	7.3792	718.4550	26%	74%	97%	10%	22%	86%
69	14.1336	59.6788	21.5244	7.3792	719.0413	26%	74%	96%	10%	22%	85%
70	12.8408	59.7234	22.2827	6.8521	719.2443	33%	92%	96%	3%	35%	84%
71	13.9645	62.4396	19.5292	5.7980	719.9357	53%	76%	79%	29%	61%	82%
72	13.0207	59.4680	21.9931	8.2577	718.3342	14%	89%	97%	6%	0%	86%
73	16.6578	61.4601	17.5023	5.9736	730.0047	52%	38%	85%	49%	57%	56%
74	16.2847	66.7463	14.7403	5.7980	737.1302	64%	43%	53%	75%	61%	37%
75	16.2847	66.5647	14.8513	5.7980	737.7221	64%	43%	54%	74%	61%	35%
76	15.1550	62.6959	16.4547	5.7980	733.6621	60%	59%	78%	59%	61%	46%
77	15.7036	62.8599	15.9773	5.7980	733.3305	61%	52%	77%	63%	61%	47%
78	15.2151	62.2222	16.2553	5.7980	733.4252	61%	58%	81%	61%	61%	46%
79	16.5080	62.3312	16.2180	5.7980	733.2398	59%	40%	80%	61%	61%	47%
80	15.5877	60.5352	16.8389	5.7980	730.8753	58%	53%	91%	55%	61%	53%
81	13.5136	62.7928	17.2595	8.2577	733.0318	33%	82%	77%	51%	0%	48%
82	17.5776	65.9606	15.2584	5.7980	734.6493	61%	25%	58%	70%	61%	43%
83	17.5776	67.5448	14.8774	5.7980	737.0504	62%	25%	48%	74%	61%	37%
84	13.5136	63.1664	17.0801	8.2577	735.6544	33%	82%	75%	53%	0%	41%
85	13.2207	61.1238	18.0882	5.7980	726.9711	58%	86%	87%	43%	61%	64%
86	13.2207	61.7535	17.2806	5.7980	735.2347	60%	86%	84%	51%	61%	42%
87	13.6764	60.4028	17.1293	5.7980	733.9633	61%	80%	92%	52%	61%	45%
88	14.0505	60.3698	19.3792	7.3792	726.0636	33%	75%	92%	31%	22%	66%
89	14.0505	60.5958	19.3735	5.7980	726.1201	53%	75%	91%	31%	61%	66%
90	14.2254	61.9653	16.6060	5.7980	737.1763	62%	72%	82%	57%	61%	37%
91	13.4883	62.5930	17.3593	5.7980	733.5048	59%	83%	78%	50%	61%	46%
92	19.3677	65.7170	14.9940	5.7980	734.3737	59%	0%	59%	73%	61%	44%
93	13.2207	61.8930	18.0217	8.2577	728.4742	31%	86%	83%	44%	0%	60%
94	13.6484	61.1524	17.1547	5.7980	735.3783	60%	80%	87%	52%	61%	41%
95	14.5441	60.3545	16.8152	5.7980	732.2314	60%	68%	92%	55%	61%	50%
96	14.5136	59.1926	19.4110	5.7980	725.2773	52%	68%	99%	31%	61%	68%
97	13.3555	60.0092	18.1028	5.7980	727.4578	58%	85%	94%	43%	61%	62%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives					Overall performance	Utility scores in terms of				
	Unsafety	Cost	Delay	PAR	CO_2 emission		Unsafety	Cost	Delay	PAR	CO_2 emission
98	15.0524	60.6945	18.7427	5.7980	724.4386	53%	61%	90%	37%	61%	70%
99	13.2207	59.8390	18.1093	5.7980	729.2846	58%	86%	95%	43%	61%	57%
100	14.5136	59.0930	19.1686	5.7980	727.6424	53%	68%	100%	33%	61%	62%
101	13.2207	60.3757	17.9799	7.3792	729.4188	40%	86%	92%	44%	22%	57%
102	13.2207	59.7321	18.1703	5.7980	730.2261	58%	86%	96%	42%	61%	55%
103	14.5136	59.7548	18.4267	5.7980	728.5667	55%	68%	96%	40%	61%	59%
104	14.5441	60.3401	16.6917	5.7980	732.3622	61%	68%	92%	56%	61%	49%
105	14.5441	61.4770	16.6261	5.7980	734.8168	61%	68%	85%	57%	61%	43%
106	13.6484	60.2172	17.2796	5.7980	732.2641	60%	80%	93%	51%	61%	50%
107	14.5136	59.1566	19.3477	5.7980	726.1765	53%	68%	99%	31%	61%	66%
108	14.8065	60.0030	17.8386	5.7980	731.3030	56%	64%	94%	46%	61%	52%
109	14.5136	59.4036	18.4209	7.3792	728.1273	36%	68%	98%	40%	22%	61%
110	14.5136	59.2375	18.6406	5.7980	730.6881	55%	68%	99%	38%	61%	54%
111	15.5183	59.5558	17.6075	5.7980	731.4037	55%	54%	97%	48%	61%	52%
112	13.6484	60.0652	17.6483	5.7980	730.7418	59%	80%	94%	47%	61%	54%
113	14.9413	60.0796	17.8576	5.7980	729.7118	56%	62%	94%	45%	61%	56%
114	13.3555	59.9869	18.0087	5.7980	728.2227	58%	85%	94%	44%	61%	60%
115	14.5136	59.7321	18.0644	5.7980	730.9709	56%	68%	96%	43%	61%	53%
116	15.2293	61.1173	16.4521	5.7980	735.3054	60%	58%	87%	59%	61%	41%
117	13.5136	60.3321	17.9319	7.3792	729.5955	40%	82%	92%	45%	22%	57%
118	13.5136	60.4125	17.6816	7.3792	731.5180	41%	82%	92%	47%	22%	52%
119	16.5222	59.8713	16.8378	5.7980	732.8086	56%	40%	95%	55%	61%	48%
120	15.2293	60.1073	16.5709	5.7980	732.9533	60%	58%	94%	58%	61%	48%
121	15.2293	59.9566	16.7661	5.7980	733.3702	59%	58%	94%	56%	61%	47%
122	13.6484	61.6413	17.2025	5.7980	734.9969	60%	80%	84%	52%	61%	42%
123	13.6484	61.1046	17.2761	5.7980	734.8627	60%	80%	87%	51%	61%	43%
124	14.5136	59.5796	18.6534	5.7980	726.5798	55%	68%	97%	38%	61%	65%
125	14.9996	62.7050	15.8599	5.7980	735.0816	63%	61%	78%	64%	61%	42%
126	14.5692	63.0770	16.0686	5.7980	735.2087	63%	67%	75%	62%	61%	42%
127	14.7320	62.7145	15.9001	5.7980	734.6931	63%	65%	78%	64%	61%	43%
128	14.5136	59.0483	18.9812	5.7980	728.9206	54%	68%	100%	35%	61%	58%
129	17.8452	70.2607	13.2550	5.7980	742.9204	66%	21%	32%	89%	61%	21%
130	17.5270	70.3729	13.3445	5.7980	743.2157	66%	26%	31%	88%	61%	21%
131	14.6562	74.2133	12.1999	5.7980	748.8843	74%	66%	8%	99%	61%	6%
132	14.3653	75.2809	12.1832	5.7980	750.9595	74%	70%	1%	99%	61%	0%
133	14.4361	75.4792	12.1973	5.7980	750.6642	74%	69%	0%	99%	61%	1%
134	14.5854	74.0150	12.1653	5.7980	749.1795	74%	67%	9%	100%	61%	5%
135	14.6562	74.2133	12.1191	5.7980	748.8843	74%	66%	8%	100%	61%	6%
136	14.2205	74.0222	12.2218	5.7980	748.8843	75%	72%	9%	99%	61%	6%
137	13.6355	60.6206	20.9640	7.3792	716.0881	29%	81%	90%	16%	22%	92%
138	15.4883	60.1020	18.7093	5.7980	726.3938	52%	55%	94%	37%	61%	65%
139	15.0741	60.5304	18.9947	5.7980	725.3321	52%	60%	91%	35%	61%	68%
140	14.4889	59.9507	20.5186	5.7980	716.6109	49%	69%	95%	20%	61%	91%
141	15.1923	60.1108	20.2116	5.7980	717.4020	48%	59%	94%	23%	61%	89%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives						Utility scores in terms of				
	Unsafety	Cost	Delay	PAR	CO_2 emission	Overall performance	Unsafety	Cost	Delay	PAR	CO_2 emission
142	14.7817	60.0392	20.3422	5.7980	716.7063	49%	64%	94%	22%	61%	91%
143	15.7413	61.8527	19.7089	5.7980	718.7407	48%	51%	83%	28%	61%	85%
144	15.3270	61.0949	19.1113	5.7980	721.7035	51%	57%	88%	33%	61%	78%
145	15.1062	60.7093	18.9790	5.7980	721.7106	52%	60%	90%	35%	61%	78%
146	14.3136	61.9817	20.1714	7.3792	715.7793	30%	71%	82%	23%	22%	93%
147	14.1336	60.2739	20.8586	7.3792	716.2160	28%	74%	93%	17%	22%	92%
148	14.3136	60.2350	20.6913	7.3792	716.0953	29%	71%	93%	18%	22%	92%
149	13.8408	60.3456	20.2310	5.7980	722.9539	51%	78%	92%	23%	61%	74%
150	14.0252	60.1744	19.7064	7.3792	722.6284	32%	75%	93%	28%	22%	75%
151	14.5142	60.7141	19.7164	5.7980	719.6693	51%	68%	90%	28%	61%	83%
152	14.8741	60.3285	19.2865	5.7980	719.6764	52%	63%	92%	32%	61%	83%
153	14.7817	60.5681	19.2197	5.7980	719.5987	52%	64%	91%	32%	61%	83%
154	15.6065	60.8887	19.5327	5.7980	718.0555	49%	53%	89%	29%	61%	87%
155	14.3555	61.2191	20.4670	5.7980	717.1479	49%	70%	87%	21%	61%	90%
156	14.2207	60.9932	20.5122	5.7980	717.0914	49%	72%	88%	20%	61%	90%
157	14.2207	60.8284	20.9273	5.7980	717.0842	48%	72%	89%	16%	61%	90%
158	15.6065	60.5588	18.6509	8.2577	725.2547	25%	53%	91%	38%	0%	68%
159	15.2207	59.8368	20.8187	8.2577	719.4964	16%	58%	95%	17%	0%	83%
160	15.2207	59.8044	20.7963	8.2577	719.5635	16%	58%	95%	17%	0%	83%
161	15.0207	59.2639	19.2798	8.2577	725.6042	23%	61%	99%	32%	0%	67%
162	15.6065	59.4557	19.2238	7.3792	726.0846	32%	53%	98%	32%	22%	66%
163	15.0207	59.2967	19.5771	7.3792	725.1592	31%	61%	98%	29%	22%	68%
164	13.2207	61.0038	20.6531	7.3792	716.7770	30%	86%	88%	19%	22%	91%
165	13.3555	61.1973	20.4932	5.9736	716.9006	48%	85%	87%	20%	57%	90%
166	14.7812	62.0419	19.4133	7.3792	719.2174	32%	64%	82%	31%	22%	84%
167	14.5136	61.3297	19.8860	5.7980	718.7829	51%	68%	86%	26%	61%	85%
168	14.7812	61.2792	19.7701	5.7980	719.0266	50%	64%	86%	27%	61%	85%
169	14.0505	60.9606	18.6518	7.3792	725.8881	36%	75%	88%	38%	22%	66%
170	14.4265	60.9960	18.4767	7.3792	726.8657	36%	69%	88%	39%	22%	64%
171	14.7812	61.8483	19.5491	7.3792	719.0938	31%	64%	83%	29%	22%	84%
172	14.7812	61.8159	19.4957	7.3792	719.1609	31%	64%	83%	30%	22%	84%
173	14.5136	61.8159	19.6197	8.2577	719.1609	23%	68%	83%	29%	0%	84%
174	13.1181	62.4439	20.3365	7.3792	717.2122	31%	88%	79%	22%	22%	89%
175	14.5136	62.4492	19.8929	8.2577	717.2666	22%	68%	79%	26%	0%	89%
176	14.5136	61.9126	19.9932	8.2577	717.1323	21%	68%	83%	25%	0%	90%
177	14.5136	60.4055	20.3002	7.3792	718.6664	29%	68%	92%	22%	22%	86%
178	12.9284	61.5858	20.5625	8.2577	716.8914	21%	91%	85%	20%	0%	90%
179	13.1181	62.0484	20.2701	8.2577	717.1133	22%	88%	82%	22%	0%	90%
180	14.9413	61.2790	18.0720	5.7980	727.6208	55%	62%	86%	43%	61%	62%
181	14.5136	61.3615	20.0766	8.2577	718.1755	21%	68%	86%	24%	0%	87%
182	14.5457	60.5910	18.5135	5.7980	726.0632	55%	68%	91%	39%	61%	66%
183	14.9413	61.3064	18.1093	5.7980	727.3524	55%	62%	86%	43%	61%	63%
184	14.5457	60.5910	18.4202	5.7980	726.0632	55%	68%	91%	40%	61%	66%
185	13.4821	62.2730	21.0476	6.8521	716.3638	34%	83%	80%	15%	35%	92%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives					Utility scores in terms of					
	Unsafety	Cost	Delay	PAR	CO_2 emission	Overall performance	Unsafety	Cost	Delay	PAR	CO_2 emission
186	13.4821	62.4377	20.4962	5.7980	716.3709	50%	83%	79%	20%	61%	92%
187	14.5136	61.7713	20.0256	7.3792	717.0970	30%	68%	83%	25%	22%	90%
188	14.8065	62.6212	19.5930	8.2577	718.8785	22%	64%	78%	29%	0%	85%
189	14.5136	61.8182	20.3324	7.3792	718.6522	29%	68%	83%	22%	22%	86%
190	14.8065	61.9225	19.7583	8.2577	719.0797	22%	64%	83%	27%	0%	84%
191	14.5136	62.0538	19.8999	8.2577	718.4546	22%	68%	82%	26%	0%	86%
192	14.5136	60.7659	19.5954	7.3792	722.7390	32%	68%	90%	29%	22%	75%
193	15.0631	61.1721	18.0313	5.7980	727.3383	55%	61%	87%	44%	61%	63%
194	15.2136	61.3981	17.9809	5.7980	727.3948	55%	58%	86%	44%	61%	62%
195	12.9284	62.5168	20.0203	7.3792	718.1382	32%	91%	79%	25%	22%	87%
196	12.8408	62.5973	20.3016	7.3792	717.0914	32%	92%	78%	22%	22%	90%
197	14.6786	61.2371	20.6427	7.3792	715.4032	28%	66%	87%	19%	22%	94%
198	14.3604	61.2371	20.6775	7.3792	715.4032	28%	70%	87%	19%	22%	94%
199	12.7025	61.0248	20.9104	7.3792	715.2125	30%	94%	88%	16%	22%	95%
200	14.5812	61.2508	20.6619	7.3792	715.2690	28%	67%	87%	19%	22%	95%
201	13.9954	60.7175	20.9286	5.7980	715.6962	48%	76%	90%	16%	61%	93%
202	16.9143	63.8164	16.4717	5.7980	720.0298	57%	34%	71%	59%	61%	82%
203	17.0170	63.7985	16.2233	5.7980	720.5454	58%	33%	71%	61%	61%	81%
204	17.0170	63.0336	16.2494	5.7980	722.6644	58%	33%	76%	61%	61%	75%
205	17.0170	63.3123	16.1666	5.7980	723.1146	58%	33%	74%	61%	61%	74%
206	16.6350	62.9733	19.6836	5.7980	716.7419	46%	38%	76%	28%	61%	91%
207	16.4350	63.0007	19.6884	5.7980	716.4735	47%	41%	76%	28%	61%	91%
208	17.4317	63.5465	17.3139	5.7980	718.2905	53%	27%	73%	51%	61%	87%
209	17.1099	63.4934	17.5999	5.7980	715.8325	52%	32%	73%	48%	61%	93%
210	16.6988	62.7554	16.0713	5.7980	727.2426	59%	38%	77%	62%	61%	63%
211	16.6988	63.0341	15.9150	5.7980	727.6929	60%	38%	76%	64%	61%	62%
212	17.3099	63.6615	17.3631	5.7980	715.9986	53%	29%	72%	50%	61%	93%
213	17.5241	63.5670	17.4538	5.7980	718.0009	52%	26%	72%	49%	61%	87%
214	17.0170	63.4589	17.3143	5.7980	716.7173	53%	33%	73%	51%	61%	91%
215	16.8488	63.5465	17.0416	5.7980	717.1675	55%	35%	73%	53%	61%	90%
216	16.8488	63.6916	16.9903	5.7980	716.8232	55%	35%	72%	54%	61%	90%
217	16.4509	62.7894	19.5575	5.7980	717.7272	47%	41%	77%	29%	61%	88%
218	16.0367	62.8235	19.6282	5.7980	717.3033	48%	47%	77%	29%	61%	89%
219	16.8037	63.8872	19.5354	5.7980	715.4207	46%	36%	71%	29%	61%	94%
220	16.6406	62.7620	19.4548	5.7980	717.9956	47%	38%	77%	30%	61%	87%
221	16.7872	63.0548	19.4907	5.7980	715.9776	46%	36%	76%	30%	61%	93%
222	16.3290	63.0908	19.5748	5.7980	716.1252	47%	43%	75%	29%	61%	92%
223	16.0108	63.0908	19.6325	5.7980	716.1252	48%	47%	75%	28%	61%	92%
224	15.9026	63.2819	19.7192	5.7980	716.1252	48%	49%	74%	28%	61%	92%
225	15.0473	63.4531	20.0844	5.7980	715.1278	48%	61%	73%	24%	61%	95%
226	16.7246	63.4485	16.0845	5.7980	724.5290	59%	37%	73%	62%	61%	70%
227	16.0170	62.8571	17.4775	5.7980	716.9415	54%	47%	77%	49%	61%	90%
228	16.1168	63.4053	19.8602	5.7980	715.6859	47%	46%	73%	26%	61%	93%
229	15.6102	63.4531	19.9504	5.7980	715.1278	48%	53%	73%	25%	61%	95%

Table A.1. All the acquired Pareto solutions for the smart home appliance scheduling benchmark (continued).

#	Objectives					Utility scores in terms of					
	Unsafety	Cost	Delay	PAR	CO_2 emission	Overall performance	Unsafety	Cost	Delay	PAR	CO_2 emission
230	15.4350	63.4394	19.9664	5.7980	715.2620	48%	55%	73%	25%	61%	95%
231	16.8488	63.3073	16.2750	5.7980	726.9442	58%	35%	74%	60%	61%	64%
232	15.5108	63.8872	19.6028	5.7980	715.4207	49%	54%	71%	29%	61%	94%
233	16.8170	62.4509	17.0874	5.7980	717.8897	55%	36%	79%	53%	61%	88%
234	16.8170	62.8481	17.0022	5.7980	717.4218	55%	36%	77%	54%	61%	89%
235	16.8170	62.5599	16.9742	5.7980	717.7043	55%	36%	79%	54%	61%	88%
236	17.1135	63.7973	18.2044	5.7980	713.2298	50%	32%	71%	42%	61%	100%
237	17.5241	63.7836	18.0555	5.7980	713.3640	50%	26%	71%	44%	61%	100%
238	17.2059	63.7836	18.1527	5.7980	713.3640	50%	30%	71%	43%	61%	100%
239	16.7246	63.4580	16.0320	5.7980	724.7762	59%	37%	73%	63%	61%	69%
240	17.6215	63.5533	17.4930	5.7980	718.1351	52%	25%	73%	49%	61%	87%
241	17.7241	63.6313	17.4408	5.7980	716.1046	52%	23%	72%	49%	61%	92%
242	17.3099	63.2076	17.4845	5.7980	715.9986	53%	29%	75%	49%	61%	93%
243	15.7184	62.8775	19.9174	5.7980	716.7736	48%	51%	77%	26%	61%	91%
244	17.2072	63.6505	17.9371	5.7980	713.4983	51%	30%	72%	45%	61%	99%
245	16.8255	63.7301	18.4221	5.7980	717.6390	50%	36%	72%	40%	61%	88%

Biographies

Ali Kaveh was born in 1948 in Tabriz, Iran. After graduation from the Department of Civil Engineering at the University of Tabriz in 1969, he continued his studies on Structures in the Imperial College of Science and Technology at London University and received his MSc and PhD degrees in 1970 and 1974, respectively. He then joined the Iran University of Science and Technology. Professor Kaveh is the author of 620 papers published in international journals and 155 papers presented at national and international conferences. He has authored 23 books in Persian and 10 books in English published by Wiley, Research Studies Press, American Mechanical Society, and Springer. Professor Kaveh is a fellow of the Iranian Academy of Science, World Academy of Sciences, and European Academy of Sciences and Arts.

Yasin Vazirinia was born in Isfahan, Iran, in 1992. He completed his MSc at Iran University of Science and Technology, Tehran, Iran and is currently a PhD student in the field of Construction Management at the same university. His main research interests are optimization and applications in construction management.