electronics

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Optimal Home Energy Demand Management Based Multi-Criteria Decision Making Methods

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Received: 26 March 2019; Accepted: 7 May 2019; Published: 10 May 2019

Abstract: From the growth of residential energy demands has emerged new approaches for load scheduling to realize better energy consumption by shifting the required demand in response to cost changes or incentive offers. In this paper, a hybrid method is proposed to optimize the load scheduling problem for cost and energy saving. The method comprises a multi-objective optimization differential evolution (MODE) algorithm to obtain a set of optimal solutions by minimizing the cost and peak of a load simultaneously, as a multi-objective function. Next, an integration of the analytic hierarchy process (AHP) and a technique for order preferences by similarity to ideal solution (TOPSIS) methods are used as multi-criteria decision making (MCDM) methods for sorting the optimal solutions' set from the best to the worst, to enable the customer to choose the appropriate schedule time. The solutions are sorted based on the load peak and energy cost as multi-criteria. Data are for ten appliances of a household used for 24 h with a one-minute time slot. The results of the proposed method demonstrate both energy and cost savings of around 47% and 46%, respectively. Furthermore, the results are compared with other recent methods in the literature to show the superiority of the proposed method.

Keywords: residential demand response; optimal load scheduling; time-of-use; differential evolution; multi-criteria decision making

1. Introduction

The demand for energy consumption is rapidly growing due to an increase in the world wide population, urbanization, climate changes and technological developments [1]. In addition, more devices have been added to the traditional customers' devices list that place a high demand on the available generation capacity, such as electric vehicles [2,3]. The traditional solution for meeting the required energy demand is building new generation capacities [4,5]. However, increasing the generation capacity faces many problems such as the depletion of fossil fuel, air pollution and climate change [6]. Furthermore, the new renewable energy resources such as photovoltaic (PV) and wind turbine have some barriers such as the intermittent problem and high initial cost [7,8]. Therefore, demand response (DR) plays an essential role in balancing the available generation capacity against the demanded energy [9,10]. DR refers to the change in customer consumption profile related to the change in energy price or incentive offers [11]. Meanwhile, the developments in information and communication technologies (ICT) provide smart residential homes that provide optimal control for easier monitoring by connecting all household sensors and appliances through a home area network (HAN) [12,13]. On the other hand, the available varied pricing tariffs leads to the provision of flexible DR schemes. Therefore, there is a great opportunity for customers to manage the load scheduling by using the available smart home technologies [14]. In addition, informing consumers about recent effective programs like DR and applying load management strategies realize the desire of electricity companies for increasing their incomes [15]. Accordingly, dynamic and optimal load scheduling is required to manage the customer load for cost and energy saving [16].

Recently, several studies have addressed the necessity of load scheduling in DR systems. In Reference [17], aggregated multi-objective load scheduling is proposed for household appliances using mixed integer nonlinear programming (MINLP). A time-of-use (ToU) pricing scheme is considered in this work. The outcomes in Reference [17] showed a cost saving of about 24%. A multi-objective genetic approach is presented in Reference [18] for domestic load scheduling for cost saving. The interruption risk of the supplied energy and the ideal time slots of load operation are considered as customer dissatisfaction factors. The model presented in this work aimed to minimize these factors of customer dissatisfaction and energy bills as a multi-objective problem formulation. Non-dominated sorting genetic algorithm II (NSGA-II) is used to solve the formulated multi-objective problem. The results showed about 24% as a maximum cost saving. In Reference [19], historical data for energy consumption are used by smart meter to learn and predict the behaviour of appliances' consumption. Based on this behavioural energy consumption, the expected appliances load scheduling is presented. The cost savings for two residential houses that are tested in this work were about 24% and 17%, respectively. Wang et al. [20] presented a household load scheduling approach based on a robust optimization approach and considered uncertainty in the PV system output power. The results showed cost savings of about 25% and 12% for high and low PV output scenarios, respectively. Reference [21] proposed an adaptive level pricing scheme for dynamic residential load scheduling. Based on a given permitted consumption allowance, the customers were encouraged to schedule their load for ideal energy and cost saving. The results explained that ToU represented about 31% and 35% for cost and energy savings, respectively. Gruber et al. [22] presented a method for optimal scheduling regarding aggregated customer demand based on an economic criterion. By using the aggregated demand profile and energy pricing predication, an aggregator participates directly in the day-ahead market to maximize the cost saving. In Reference [23], an experimental analysis of the scheduling problem regarding home appliances is proposed, which is based on a realistic aspect. A binary integer linear programming (BILP) optimization method is presented for load scheduling. Seeking an efficient energy management scheduling for household appliances, a distributed real-time demand response is suggested in Reference [24]. The energy supply, energy demand and battery energy constraints are considered to form a temporally-spatially coupled optimization problem. This problem is decomposed into several independent sub-problems to mitigate an issue caused by temporally-spatially coupled constraints.

The aforementioned research discussed optimization methods and customer load modelling to solve load scheduling. On the one hand, several recent proposals deal with single or aggregated multi-objective functions of customer load modelling to formulate the load scheduling problem. In general, most of the methods do not provide a set of optimal solutions for certain trade-off constraints. They provide only one solution for the whole search space that might not be a global minimum point. Furthermore, sorting the solutions' set from the best to the worst and selecting the best optimal solution is not addressed in the literature.

Multi-criteria decision-making methods (MCDM) are used in various research fields to make an optimal decision to sort a set of solutions for a specific problem, which is dominated by multiple criteria. In Reference [25], a multi-objective memetic algorithm is used to facilitate the scheduling schemes. A mixed-integer linear programming (MILP) model based on the network graph is formulated with both makespan, as well as total power consumption, criteria. Moreover, the TOPSIS decision method is used to determine the most satisfactory non-dominated solution. An analytic network process (ANP) method is presented in Reference [26] to solve a decision problem by selecting the optimal location and configuration of a wind farm. The ANP method is used to capture the complexity of the decision problem by taking into consideration dependencies between criteria. In Reference [27], an artificial neural network coupled with ensemble empirical mode decomposition (EEMD-ANN) is used to decompose the original price time series into several subseries and then to forecast each of them. A factor analysis and a technique for order of preference by similarity to ideal solution (FA-TOPSIS), as an integrated evaluation method, is used to comprehensively evaluate the quality parameters. In Reference [28], a multi-objective optimization model is used to maximize the minimum power of multiple power grids. The TOPSIS method is utilized to handle this multi-objective optimization, where the complex minimum and maximum objective function is transformed into a group of linear formulations. Nonlinearities of the hydropower system are described approximately as polynomial formulations. In Reference [29], a novel method based on a multi-objective optimization algorithm and hybrid multi-criteria decision making methods proposed the configuration of a standalone off-grid photovoltaic system. An integration between TOPSIS and AHP methods is used to sort the configurations of the system. TOPSIS is an effective MCDM method which has been widely used to solve problems that are dominated by multi-dimensional multi-criteria [30].

The contribution of the present research can be described by presenting a hybrid multi-objective optimization differential evolution (MODE) model and integrated MCDM methods to solve the load scheduling problem for cost and energy saving. The MODE algorithm deals with the load scheduling problem as a multi-objective optimization problem. The multi-objectives are the cost and peak of the load that are simultaneously minimized, which is rarely done in the literature and leads to a Pareto-optimal set of solutions. Next, hybrid MCDM methods are presented to sort the obtained set of Pareto-front solutions for given constraints. The results show the superiority of the proposed method as compared to other recent work in the literature.

2. Problem Formulation

A company has an active connection to the smart meter where the HAN network provides the proposed load scheduling system with access to each device. For each time slot t the total load will be denoted as l^t. For a given customer, the set of household appliances will be referred to as E and these devices include items such as a washing machine, stove, refrigerator or any connected device. For a given appliance e, the one-slot energy consumption scheduled at time slot t is referred to as l_e^t. The first objective of the multi-objective functions of the MODE algorithm is the cost of energy that is consumed by the household. In the meantime, the peak of the load is considered the second objective. The goal of the MODE algorithm is to schedule the load to save energy cost and peak concurrently.

The utility company provides the energy pricing function that is denoted by EP_t for each time slot. An effective customer load schedule is expressed by way of decreasing peak consumption and minimizing the energy cost. The customer's energy bill (EB) can then be expressed as:

$$EB = \sum_{t}^{T} EP_t \sum_{e \in E} l_e^t \tag{1}$$

Subject to:

$$Pomin \leq l^t \leq Pomax \tag{2}$$

where $Pomin$ and $Pomax$ denotes the minimum and maximum load consumption, respectively. Equation (1) refers to customer preferences of allowable time operation for each appliance. The steps of the proposed MODE algorithm are discussed in detail in the next subsection.

2.1. Multi-Objective Optimization Differential Evolution (MODE)

In general, evolutionary algorithms (EAs) are being utilized to solve optimization problems with multi-objectives that are traced back to its ability to process a number of solutions and yields an optimal Pareto front with fast convergence and high diversity [31]. The MODE algorithm model is mainly based on a conventional differential evolution algorithm that can resolve multi-objective optimization

(MOO) problems. For this research, the MODE algorithm has been utilized to optimize the starting time of 10 operative appliances as a bi-objective real optimization problem. To optimize the load scheduling problem, the cost and peak load have been utilized as the two objectives. In general, the main significance of MOO algorithms is to offer a set of ideal solutions, as denoted by the Pareto front [32,33]. In addition, in the selection stage of single-objective optimization algorithms, the parent solution is exchanged for the candidate (child) solution when the last one is better than the parent solution in terms of objective function. Meanwhile, in MOO algorithms, the replacement's decision is not straightforward like a single-objective optimization algorithm because there are many objective functions that dominate the problem. The Pareto optimality (dominance) principle can be considered one of the most rigid techniques that are adapted to realize the replacement between the parent and child solutions in the selection stage. The details of the MODE model are depicted by the following algorithm.

Step 1: The first phase of MODE is creating an initial population set with P individual vectors and Q decision variables as follows:

$$POP^G = \begin{bmatrix} s_{11} & \cdots & s_{1P} \\ \vdots & \vdots & \vdots \\ s_{Q1} & \cdots & s_{QP} \end{bmatrix} \tag{3}$$

where, S_i is the target vector and G is an index which points to the counts of generation $(G = 1, 2, \ldots\ldots, G_{max})$, $i \in [1,\ P]$ and $j \in [1,\ Q]$ are two indices, which refer to the number of individual vectors (solutions) and number of decision variables that comprises each solution, respectively. Here, the initial values of Q elements of each individual vector are randomly chosen and uniformly distributed in the search space. Furthermore, the search space is bounded by the upper $(S_{j,H})$ and lower $(\ S_{j,L})$ bounds. The elements of the initial individual vector are selected as below,

$$DS^0_{j,\ i} = (S^0_{j,\ H} - S^0_{j,\ L})_i \tag{4}$$

$$S^0_{j,i} = (S^0_{j,\ L})_i + RND * DS^0_{j,\ i},\ \text{where } RND \in (0,\ 1) \tag{5}$$

where RND is a pseudo-random number that is generated by using a uniform distribution and belongs to the interval (0, 1). After that, the corresponding objective functions to current target vector are computed and saved in vectors to use them in the next steps.

Step 2: The mutant vector is generated in MODE by adding the third individual vector with the weighted difference between two individual vectors [34]. Therefore, a mutant vector $\hat{S}^G_i$ for any individual vector S_i, is generated as below:

$$DF^G = S^G_{r2} - S^G_{r3} \tag{6}$$

$$\hat{S}^G_i = S^G_{r1} + MSF * DF^G \tag{7}$$

where, S^G_{r1}, S^G_{r2} and S^G_{r3} vectors are selected in a random fashion from the population set and they are not equal to the current individual vector S^G_i. The values of $r1,\ r2\ and\ r3$ are indices that have values in the range of [1, P]. The base vector here is defined as S^G_{r1} while the mutation scaling factor is indicated as MSF, which is basically picked up within the interval [0, 1] [35].

Step 3: Within the next step of the MODE algorithm, the trial vector $X^G_{j,i}$ is generated by using the mutant vector $\hat{S}^G_i$ and the target vector X^G_i. In this step, two numbers are randomly selected to dominate the selection process between the mutant and the target vectors. The first one, RND is randomly belongs to (0, 1) interval, while the second one is I_i, which is chosen in a random fashion from the interval that is in the range [1, Q]. The trial vector equals to the mutant vector if the RND number is less than or equal to the crossover control factor (CCF) or the value of I_i equals to the current index (j) that refers to the decision variable. Otherwise, the trial vector equals to the corresponding target vector and the mutant vector is neglected. It is worth to mention that the CCF is selected in a random fashion in the range of $[0,\ 1]$ [35].

Step 4: The elements of the trial vector must be analysed to determine whether these elements are within the permitted search space or not and to validate that these are realistic values. If any element is outside the allowed limits of the search space, then the element is exchanged with a new element, which is computed using Equation (5).

Step 5: The last step of the MODE algorithm is the selection step, which is applied after generating P child solutions. The selection process between the child solution (CS) and the current parent solution (PS) is started by creating a temporary population (T_P). The individual vectors of the temporary population are chosen from both CS and PS. PS is rejected from T_P if PS is dominated by the corresponding CS and vice versa. Under other conditions, each of CS and PS are expressed as an element of T_P once the child and parent solutions are not dominating each other. Temporary population's size is usually expected between P and $2P$. Accordingly, the temporary population's size is minimized to reach the value of P solutions so as to prepare it for the next generation. The size of reduction depends on the next two sub steps [36]:

Step 5.1: In this sub step, the solution of temporary population is classified into many front levels (FL_i), where $i = 1,\ 2,\ \ldots,\ K$ [37,38]. The first front level FL_1 is made up from solutions that are non-dominated by other solutions and these solutions are ranked as 1. The solutions are non-dominated by other solutions except by the ones that belong to front level FL_1, which are ranked as 2 to form the second front level F_2 and so on. Meanwhile, solutions dominated only by other solutions belong to the front levels $FL_1 \cup FL_2 \cup \ldots \cup FL_{K-1}$ will be ranked as K with FL_K front level. Upon the completion of a non-dominated sorting algorithm, the newest population which has been arranged for the next generation is to combine different solutions that apply to various non-dominated front levels. To fill the new population, the non-dominated front level solution of rank 1 is chosen first. Then, it is tracked by solutions that belong to front levels 2, 3 and so on. Since the temporary population's size is within the range $[P,\ 2P]$, then not all T_P solutions must be included in the new population's P slots. Solutions that have been eliminated in the population of the next generation are excluded. A related point to consider is solutions that belong to the last allowable rank can be larger than other slots remained in the next generation's population. With such scenario, in order to choose solutions that lie in the least crowded region, a crowding distance ranking model is utilized. This will in turn increase solutions' diversity instead of arbitrarily discarding some solutions.

Step 5.2: In the MODE algorithm, the diversity of optimal solutions is increased by applying the crowding distance rank principle that presented in non-dominated sorting genetic algorithm-II [39]. The solutions' density surrounding a solution i can be estimated by computing along each objective the average distance which corresponds with two solutions on the right and left sides of a solution i. Thus, the circumference of a rectangle with the right and left vertices of neighbor solutions is said to be the crowding distance of any given solution i. The best solutions are the ones that have a high crowding distance rank, since these solutions offer much diversity in the population [37]. Along zth objective function, a crowding distance of ith solution is calculated as:

$$CDR_i^z = \left(Of_{i+1}^z - Of_{i-1}^z\right) / \left(Of_{max}^z - Of_{min}^z\right) \tag{8}$$

where CDR_i^z refers to the value of a single crowding distance of the ith solution that relates to zth objective function. Of_{i+1}^z is zth objective function for $i+1$ solution and Of_{i-1}^z is zth objective function for $i-1$ solution. In addition, Of_{min}^z is the minimum and Of_{max}^z is the maximum values of the zth objective function. In the meantime, by obtaining the summation value of all individual crowding distances along each objective, the total value of a crowding distance of every solution can be determined and is represented as follows:

$$CDR_i = \sum_{z=1}^{Z} CDR_i^z \tag{9}$$

The model that is applied to calculate the crowding distance rank for every solution belongs to an ith front level (FL_i) with bi-fitness functions is illustrated in the pseudo code of MODE model (Appendix A), which is proposed to optimize the starting time of operating electrical devices with minimum cost and load peak.

2.2. Hybrid AHP-TOPSIS Model Load Scheduling

In this work, an AHP-TOPSIS model is utilized to sort the optimal solutions' set of load scheduling system that obtained by the MODE algorithm and ranked from the best solution to the FL_i appropriate weights for each criterion according to the evaluation of evaluators (expert). For the second, the TOPSIS approach has been utilized with predefined weights, in order to sort the solutions of the problem. The proposed hybrid AHP-TOPSIS model that obtains the optimal set of time operation of customer load is depicted in Figure 1. The details of the proposed model will be discussed in the following subsection.

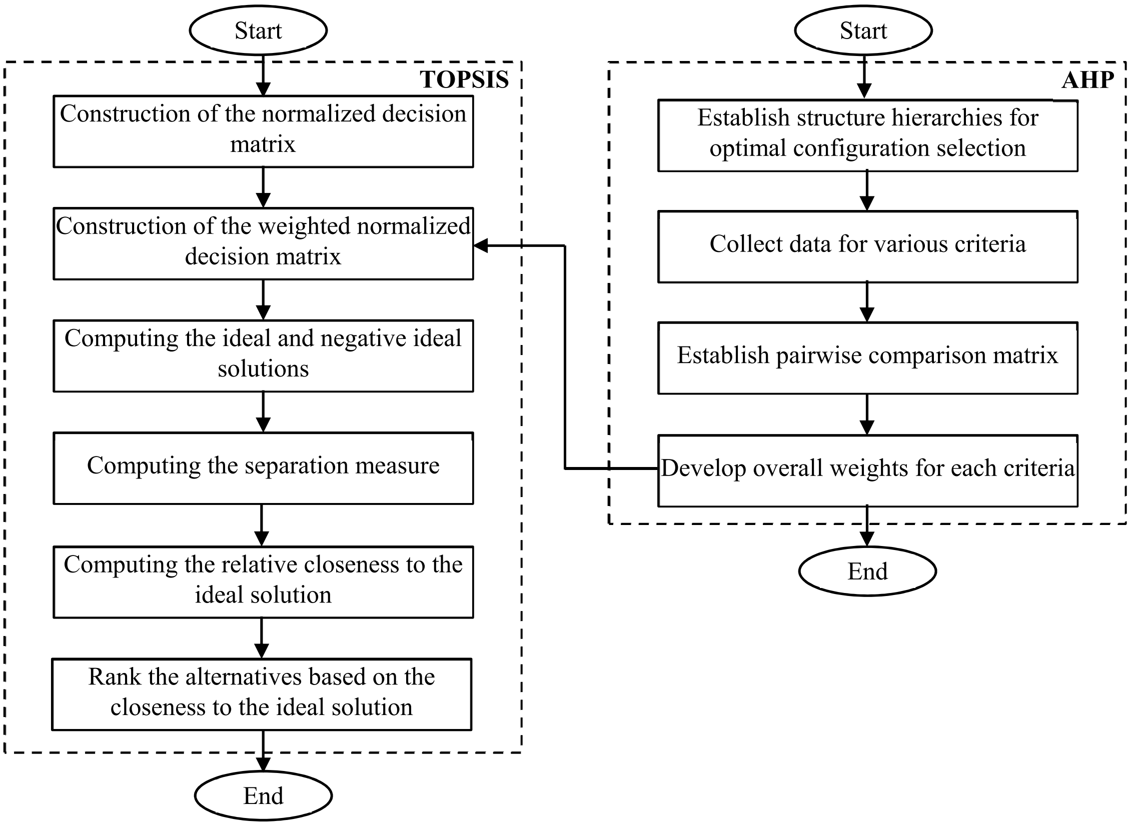

Figure 1. Integrated analytic hierarchy process - technique for order preferences by similarity to ideal solution (AHP-TOPSIS) model for selection optimal solution of load scheduling problem.

2.2.1. AHP Approach for Deriving Weights of Criteria

Each criterion has a degree of importance to dominate the performance of the MCDM problem. The degree of importance can be presented by weight value, where the weight's sum of total criteria of the MCDM problem must be controlled by

$$\sum_{j=1}^{n} w_j \tag{10}$$

where n is the entire criteria's count that dominates the MCDM problem and w_j is the weight of jth criteria. Saaty in 1977 [40] proposed the AHP model to derive the appropriate weights for each criteria in the MCDM problem. The AHP method depends on the comparisons between a pairwise criteria. However, the total number of pairwise comparisons for n-criteria problem is $n(n-1)/2$. The pairwise comparison is achieved by using the Saaty scale which was presented by Saaty [41]. The Saaty scale comprises nine preference points to enable the evaluator to specify the number of times a single criterion is more or less important than another. A questioner which depends on the expertise of three experts (evaluators) is realized to accomplish a comparison between a pairwise criteria of MCDM problem. The evaluations of experts are tabulated in Tables 1–3. The preference of evaluators is done as three steps whereas, the first evaluator does not give preference for each criterion. In the meanwhile, the second and third evaluators are strong and slightly favour the cost criterion over the peak criterion, respectively.

Table 1. First evaluators' comparison according to Saaty's scale.

Criteria	Extremely Favor	Very Strong Favor	Strong Favor	Slightly Favor	Equal	Slightly Favor	Strong Favor	Very Strong Favor	Extremely Favor	Criteria
	9	7	5	3	1	3	5	7	9	
cost					✔					peak

Table 2. Second evaluators' comparison according to Saaty's scale.

Criteria	Extremely Favor	Very Strong Favor	Strong Favor	Slightly Favor	Equal	Slightly Favor	Strong Favor	Very Strong Favor	Extremely Favor	Criteria
	9	7	5	3	1	3	5	7	9	
cost			✔							peak

Table 3. Third evaluators' comparison according to Saaty's scale.

Criteria	Extremely Favor	Very Strong Favor	Strong Favor	Slightly Favor	Equal	Slightly Favor	Strong Favor	Very Strong Favor	Extremely Favor	Criteria
	9	7	5	3	1	3	5	7	9	
cost				✔						peak

According to the evaluator preferences, Table 4 depicts the construction of a comparison matrix. The comparison matrix is normalized by dividing each element belongs to a column by the sum of the column's elements. After that, the elements of each row of the normalized matrix are aggregated and finally divided by the sum of them to acquire weights of each criteria.

Table 4. Analytic hierarchy process (AHP) processing matrix for calculating the criteria's weights.

Evaluators	Criteria	Original Matrix		Normalized Matrix		Aggregation	Weight
		Cost	Peak	Cost	Peak		
First evaluator	Cost	1	1	0.5	0.50	1.00	0.50
	Peak	1	1	0.5	0.50	1.00	0.50
	Sum	2	2	-	-	2.00	-
Second evaluator	Cost	1	5	0.83	0.83	1.67	0.83
	Peak	0.2	1	0.17	0.17	0.33	0.17
	Sum	1.2	6	-	-	2.00	-
Third evaluator	Cost	1	3	0.75	0.75	1.50	0.75
	Peak	0.33	1	0.25	0.25	0.50	0.25
	Sum	1.33	4	-	-	2.00	-

2.2.2. Technique for Order Preferences by Similarity to Ideal Solution (TOPSIS)

Yoon and Hwang proposed TOPSIS in 1980 to solve multi-dimensional MCDM problems [30]. In this method, the shortest and fastest distances from the negative ideal and ideal solutions play an important role in sorting the alternatives. For simplicity, the MCDM problem may be presented in a matrix with m alternatives and n criteria which have variables weight (w_j, where $j = 1, 2, \ldots, n$) that have been previously derived by the AHP method. The decision matrix (DM) that represents the MCDM (Equation (11)) comprises of the performance (a_{ij}) of ith alternative (A_i) in terms of jth criteria (C_j), where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. The TOPSIS technique can be expressed according to the next steps:

$$DM = \begin{array}{c c} & \begin{array}{ccc} C_1 & \ldots\ldots\ldots & C_n \\ w_1 & \ldots\ldots\ldots & w_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} a_{11} & \ldots\ldots\ldots & a_{1n} \\ \vdots & \ldots\ldots\ldots & \vdots \\ a_{m1} & \ldots\ldots\ldots & a_{nm} \end{bmatrix} \end{array} \tag{11}$$

Step 1: Constructing normalized decision matrix:

In general, DM's criteria differ in measuring units (multi-dimension criteria). Therefore, the elements of DM should be normalized using the following formula.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m}\left(a_{kj}\right)^2}} \tag{12}$$

Accordingly, normalized decision matrix (R) can be defined as

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{13}$$

Step 2: Constructing normalized weighted decision matrix:

The normalized weighted decision matrix (V) is constituted by utilizing the normalized decision matrix (R) with weights that have been acquired through AHP model. The elements of V are computed by multiplying the elements of R by the corresponding weight as given by;

$$v_{ij} = w_j r_{ij}, \text{ for } i = 1,\ 2,\ \ldots,\ m \text{ and } j = 1,\ 2,\ \ldots,\ n \tag{14}$$

Thus, the obtained matrix from step 2 can be described by

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} \tag{15}$$

Step 3: Calculating the negative ideal and ideal solutions:

In steps 3, ideal (A^*) and negative (A^-) solutions are computed as follow

$$A^* = \left\{\left(max_i\ v_{ij}\middle|j \in J\right), \left(min_i\ v_{ij}\middle|j \in J^-\right),\ i = 1,\ 2,\ \ldots,\ m\right\} = \left\{v_1^*,\ v_2^*,\ \ldots,\ v_n^*\right\} \tag{16}$$

$$A^- = \left\{\left(min_i\ v_{ij}\middle|j \in J\right), \left(max_i\ v_{ij}\middle|j \in J^-\right),\ i = 1,\ 2,\ \ldots,\ m\right\} = \left\{v_1^-,\ v_2^-,\ \ldots,\ v_n^-\right\} \tag{17}$$

where J is a set of benefit criteria with period [1, n] and J^- is the complement set of J with period [1, n], which refers to the cost criterion. Above all, the most preferable solution (alternative) is the ideal solution (A^*). On the other hand, the least preferable solution is the negative ideal solution (A^-).

Step 4: Separation measure's calculation process:

In this step, the n-dimension Euclidean distance has been utilized to calculate the separation distance between each alternative in matrix V and the negative ideal and ideal solutions. Where the distance (S_{P_i}) of an alternative (A_i) from the ideal solution (v_j^*) can be indicated by

$$S_{P_i} = \sqrt{\sum\nolimits_{j=1}^{n} (v_{ij} - v_j^*)^2}, \text{ for } i = 1,\ 2,\ \ldots,\ m \tag{18}$$

Similarly, the distance (S_{N_i}) between an alternative (A_i) and the negative ideal solution (v_j^-) can be computed by

$$S_{N_i} = \sqrt{\sum\nolimits_{j=1}^{n} (v_{ij} - v_j^-)^2}, \text{ for } i = 1,\ 2,\ \ldots,\ m \tag{19}$$

However, at the end of step 4 every alternative belongs to matrix V poses two distance values, which are S_{P_i} and S_{N_i} to express the nearest and farthest of alternative from the negative ideal and ideal solutions.

Step 5: Calculating the relative closeness to the ideal solution:

For this stage, relative closeness of alterative (A_i for $i = 1, 2, \ldots, m$) as regards to ideal solution (A_i^* for $i = 1, 2, \ldots, m$) can be computed by

$$C_I = \frac{S_{N_i}}{S_{N_i} + S_{P_i}}, \text{ where } i = 1,\ 2,\ \ldots,\ m \tag{20}$$

In addition, C_i^* values are within the range [0, 1], where $C_I = 1$ if and only if $S_{P_i} = 0$ $\left(\text{i.e., } A_i = A_i^*\right)$ and $C_I = 0$ iff $S_{N_i} = 0$ $\left(\text{i.e., } A_i = A_i^-\right)$.

Step 6: Sorting the solution according to the closeness to the ideal solution:

The set of solutions (A_i for $i = 1, 2, \ \ldots, m$) in matrix V are organized in descending order depending on its closeness's value to the ideal solution (C_I) that computed in previous step. Thus, the best alternative is the one which has the biggest closeness value (i.e., it has the longest distance from the A_i^- and the shortest distance to A_i^*).

3. Results and Discussion

3.1. Case Study

A new load scheduling approach is proposed based on the hybridization of a multi-objective optimization algorithm and integrated MCDM methods to obtain the optimal load scheduling for various appliances. A MODE algorithm is presented to minimize the cost and peak of load simultaneously based on optimality of the Pareto front. After that, seeking to sort the preferred solutions, hybrid multi-criteria decision making techniques have been utilized to sort according to the suggested weights that were developed by the developers (experts). The weights reflect the priority of one criterion relative to another one. Thus, the decision matrix (*DM*) of the TOPSIS method comprises the solutions (starting of operation time for each appliance). The various solutions represented in *DM* are dominated by the criteria, which are the cost and peak of load. The actual customer load data adopted from Reference [17], which studied a typical household in South Africa containing 10 appliances. The rated power of each appliance, duration to complete its operation and the allowable starting and ending time (t^S, t^E) are mentioned for each appliance and shown in Table 5.

Table 5. The appliances data [17].

S/No.	Appliances Name	Duration (slot/day)	Power Rate (W)	Allowance Time	
				t^S (slot)	t^E (slot)
1	Teakettle	10	1900	05:30	07:30
2	Teakettle	10	1900	17:40	20:00
3	Pop-up toaster	10	1010	05:00	07:00
4	Steam Iron	48	1235	16:00	21:00
5	Water heater	120	2600	04:00	08:10
6	Water heater	120	2600	16:00	22:00
7	Oven	10	1230	16:00	19:00
8	Dryer	30	3300	16:00	20:20
9	Dishwasher	150	2500	20:00	24:00
10	Stove	30	3000	05:00	07:00
11	Stove	50	3000	16:00	20:00
12	Cloth washing	45	3000	16:00	22:00
13	Cleaner	30	1200	08:00	10:20

These customer data have been collected within one month and for all weekdays. In a typical working-class household, the majority of activities happen in the morning and after work. Based on Table 5, device 1 (a teakettle) managed to operate two times a day for 10 min in the evening and in the morning. In addition, appliance 2 (pop-up toaster) is managed to operate once a day for 10 min as illustrated in Table 5. The proposed technique has a 24 h optimization period and a 1 min sampling time, which encourages a shorter waiting period for behaviour change.

The pricing scheme that has been considered in this work is a ToU tariff, same as in Reference [17]. In a normal period, a tariff of 0.4554 R/kWh is applied and in the peak period, 1.4452 R/kWh tariff is utilized. R denotes the South African currency, ZAR or rand. The normal periods of consumption per day are supposed to be 19 h from 20:00 to 01:00, 01:00 to 07:00 and 10:00 to 18:00. In addition, the periods of peak consumption are considered to be 5 h, from 18:00 to 20:00 and 7:00 to 10:00. The search space of each appliance is the permitted period of operation, which is represented in Table 5 as the allowance time.

For the best MODE performance in terms of convergence to global optimal solution, the *MSF* and *CCF* values are recommended by Reference [35] to be 0.75 and 0.5, respectively. Based on Reference [42] and to increase the diversity of solutions, the preferred P value belongs to the range [5Q, 10Q] and is chosen to be 10Q, where Q is the count of appliances (decision variables). Based on several extensive simulation tests, the maximum generation number is found to be 50, which is adequate for obtaining optimal solutions while minimizing both objectives.

The optimal Pareto front points, which relates the cost and peak of load objectives, are tabulated in Table 6. Table 6 comprises 130 points that relate the multi-objectives in three columns. According to these results, the minimum peak of load is 4900 W with cost R18.446. On the contrary, the maximum peak of load is 8100 W with R13.447 as cost. In the meanwhile, the minimum cost (R12.987) is obtained with 7535 W, as peak of load. On the other hand, the maximum cost is R21.948 with peak of load is 5600 W.

Table 6. Optimal Pareto front solutions of the multi-objective optimization differential evolution (MODE) algorithm.

Cost (Of_1)	Peak (Of_2)	Cost (Of_1)	Peak (Of_2)	Cost (Of_1)	Peak (Of_2)
12.98692	7535	16.76540	5600	13.75072	7235
13.36800	7500	16.84450	6300	13.81011	5900
13.49626	7230	16.85704	5600	14.06424	6300
13.49626	7230	16.93977	6000	14.09385	7535
13.61875	7235	16.99429	5600	14.39087	7230
13.73637	6830	17.11983	5500	14.41224	6835
13.74577	5600	17.14722	5600	14.58760	6300
13.75732	5765	17.26781	5600	14.67833	5600
13.92228	5600	17.28958	5600	14.74423	6830
14.05591	5600	17.29989	5100	14.75586	6300
14.07092	5600	17.29989	5100	14.89064	8100
14.11744	6300	17.39442	5600	15.01618	5600
14.23217	7235	17.44317	5100	15.16803	5600
14.31820	6610	17.71536	5600	15.57269	6300
14.37924	6300	17.71759	5100	15.74871	6000
14.40745	6300	17.76667	6610	16.01406	5600
14.45480	6610	17.77186	5500	16.16806	6300
14.47657	6300	17.99457	5600	16.22505	6000
14.51748	6610	18.07804	6000	16.24881	5600
14.53151	6300	18.09668	5600	16.77975	6610
14.57225	5600	18.16416	5600	16.85919	6300
14.64566	5600	18.19385	5100	17.03215	5600
14.70645	6300	18.30380	5600	17.27169	5900
14.74877	6300	18.44567	4900	17.30988	5600
14.76691	5600	18.68537	5600	17.75776	5600
14.84610	5600	18.82254	5900	17.87051	6610
14.96677	5600	18.87805	5600	18.02501	6300
15.15953	5600	19.20048	6300	18.15063	6000
15.48122	8100	19.32676	5735	18.34009	5600
15.48996	7500	19.37278	5465	18.69032	5600
15.49161	5600	19.85193	5900	18.90288	5600
15.62895	5900	20.02605	5600	19.33839	6000
15.64346	6835	20.07109	5100	19.38128	5600
15.67918	7535	20.16710	5500	19.95347	6300
15.72925	5600	20.20281	5100	20.16710	5500
15.79424	5600	20.50503	6830	20.35623	5600
16.07535	6300	20.56211	5510	20.64492	6610
16.09885	6610	20.80304	5510	20.80824	6000
16.14933	6000	20.87777	5500	21.08077	5500
16.18398	5600	20.87777	5500	21.94791	5600
16.23627	5600	21.54894	5510	13.44718	8100
16.25046	5100	21.69791	5500	14.62356	6300
16.53181	7500	13.36470	8100	-	-
16.58435	5600	13.61561	7535	-	-

Following an earlier discussion, the MODE algorithm candidate is an optimal solutions' set of load scheduling problems, which is defined by an optimal Pareto front. Next, the set of optimal solutions is utilized as an input for the hybrid AHP-TOPSIS model to order the of optimal solutions' preference. To summarize, the first ten scoring solutions of the load scheduling of every evaluator are listed in Tables 7–9, respectively. The first 13 rows of each table present the start of the appliance's operation time. The fourteen (S_P) and fifteen (S_N) rows represent the measurements of separation for every alternative (solution) in *DM* which are relative to both ideal solutions and negative ideal solutions, respectively. The sixteen row (C_I) refers to the closeness degree to the ideal solution. The last two rows present the criteria that are used in the MCDM method. According to Tables 7–9, the set of the starting time slot for the operation of 10 appliances (380 (i.e., 06:20), 990 (i.e., 16:30), 1051 (i.e., 17:31), 356 (i.e., 05:56), 1074 (i.e., 17:54), 325 (i.e., 05:25), 976 (i.e., 16:16), 555 (i.e., 09:15), 276 (i.e., 04:36), 1191 (i.e., 19:51), 1277 (i.e., 21:17), 1201(i.e., 20:01) and 1043 (i.e., 17:23) is better efficient to offer an acceptance balance between the cost and peak of load. The score of closeness for the previous starting time set is 0.83771 with a cost and peak of load about R13.74577 and 5600 W, respectively. In fact, the integrated AHP-TOPSIS implies the optimal and best solutions according to the evaluators' weights. Moreover, the weights of the first, second and third developers for the cost criterion were 0.5, 0.83 and 0.75, respectively. In the meantime, the weights of the first, second and third developers for the peak of load criterion were 0.5, 0.17 and 0.25, respectively. The weight differences make the sorting configuration of the first developer different to those of second and third evaluators. That is traced to the second developer which gives equal weights for each criterion.

Based on the integrated AHP-TOPSIS approach, the average scores of closeness to the ideal solution and the distance between an alternative and ideal and negative ideal solutions are obtained. These scores, for all developers, with a starting time for all appliances as well as their associated cost and peak of load are tabulated in Table 10. The set of operation starting times for the 10 appliances (380, 990, 1051, 356, 1074, 325, 976, 555, 276, 1191, 1277, 1201 and 1043) still has the highest closeness score to the ideal solution at around 0.87994.

Table 7. Scores based on integrated analytic hierarchy process-technique for order preferences by similarity to ideal solution (AHP-TOPSIS) for first developer.

Device		Starting Time of Operation for Each Device (Each Column Represents an Alternative)									
Appliances	Teakettle	356	399	437	344	402	348	419	379	402	412
	Teakettle	1074	1092	1156	1146	1104	1096	1130	1070	1104	1128
	Pop-up toaster	325	344	318	380	319	400	365	350	319	398
	Steam Iron	976	1023	962	1038	1000	973	1042	1025	1000	1006
	Water heater	276	278	246	251	255	255	282	312	255	279
	Water heater	1191	1192	1190	1196	1200	1181	1198	1187	1200	1195
	Oven	1051	1012	1063	978	1014	970	997	1121	1044	1061
	Dryer	1043	1028	1046	1040	996	1002	968	1037	996	1040
	Dishwasher	1277	1263	1280	1252	1269	1289	1279	1254	1269	1286
	Stove	380	312	371	365	337	369	308	306	337	302
	Stove	990	972	968	963	1038	1034	1014	968	1038	979
	Cloth washing	1201	1216	1226	1197	1219	1210	1191	1198	1185	1181
	Cleaner	555	512	585	543	581	571	543	486	568	525
MCDM indices	SP	0.00388	0.00432	0.00443	0.00482	0.00487	0.00492	0.00655	0.00669	0.00668	0.00694
	SN	0.03323	0.03303	0.03257	0.03271	0.03207	0.03201	0.03143	0.03122	0.03014	0.02987
	CI	0.89536	0.88428	0.88024	0.87163	0.86817	0.86679	0.82744	0.82357	0.81867	0.81141
Criteria	Cost	13.7458	13.7573	13.9223	13.8101	14.0559	14.0709	14.0642	14.1174	14.5723	14.6457
	Peak	5600	5765	5600	5900	5600	5600	6300	6300	5600	5600

Table 8. Scores based on integrated AHP-TOPSIS for second developer.

Device		Starting Time of Operation for Each Device (Each Column Represents an Alternative)									
Appliances	Teakettle	356	402	399	407	437	344	350	377	348	419
	Teakettle	1074	1104	1092	1095	1156	1146	1094	1082	1096	1130
	Pop-up toaster	325	319	344	388	318	380	328	346	400	365
	Steam Iron	976	1000	1023	1209	962	1038	1176	1183	973	1042
	Water heater	276	255	278	274	246	251	259	258	255	282
	Water heater	1191	1200	1192	971	1190	1196	1197	1196	1181	1198
	Oven	1051	1014	1012	1013	1063	978	1117	1028	970	997
	Dryer	1043	996	1028	979	1046	1040	1039	1041	1002	968
	Dishwasher	1277	1269	1263	1237	1280	1252	1241	1254	1289	1279
	Stove	380	337	312	300	371	365	378	313	369	308
	Stove	990	1038	972	1025	968	963	996	966	1034	1014
	Cloth washing	1201	1219	1216	1271	1226	1197	966	1027	1210	1191
	Cleaner	555	581	512	580	585	543	589	556	571	543
MCDM indices	SP	0.00388	0.00432	0.00443	0.00482	0.00487	0.00492	0.00655	0.00669	0.00668	0.00694
	SN	0.03323	0.03303	0.03257	0.03271	0.03207	0.03201	0.03143	0.03122	0.03014	0.02987
	CI	0.89536	0.88428	0.88024	0.87163	0.86817	0.86679	0.82744	0.82357	0.81867	0.81141
Criteria	Cost	13.7458	13.7573	13.9223	13.8101	14.0559	14.0709	14.0642	14.1174	14.5723	14.6457
	Peak	5600	5765	5600	5900	5600	5600	6300	6300	5600	5600

Table 9. Scores based on integrated AHP-TOPSIS for third developer.

Device		Starting Time of Operation for Each Device (Each Column Represents an Alternative)									
Appliances	Teakettle	356	402	407	399	437	344	407	397	397	397
	Teakettle	1074	1104	1095	1092	1156	1146	1078	1063	1063	1063
	Pop-up toaster	325	319	388	344	318	380	332	383	328	382
	Steam Iron	976	1000	1209	1023	962	1038	1209	1000	1176	1176
	Water heater	276	255	274	278	246	251	274	259	259	285
	Water heater	1191	1200	971	1192	1190	1196	971	1197	1197	1197
	Oven	1051	1014	1013	1012	1063	978	1071	973	995	1011
	Dryer	1043	996	979	1028	1046	1040	979	1024	1039	1031
	Dishwasher	1277	1269	1237	1263	1280	1252	1237	1262	1241	1231
	Stove	380	337	300	312	371	365	300	382	339	300
	Stove	990	1038	1025	972	968	963	1025	992	997	997
	Cloth washing	1201	1219	1271	1216	1226	1197	1201	966	966	966
	Cleaner	555	581	580	512	585	543	580	589	589	589
MCDM indices	SP	0.00370	0.00394	0.00431	0.00439	0.00492	0.00498	0.00572	0.00644	0.00610	0.00610
	SN	0.03593	0.03582	0.03554	0.03518	0.03461	0.03455	0.03559	0.03871	0.03655	0.03655
	CI	0.90675	0.90089	0.89179	0.88917	0.87552	0.87397	0.86157	0.85743	0.85694	0.85694
Criteria	Cost	13.7458	13.7573	13.8101	13.9223	14.0559	14.0709	13.7364	12.9869	13.4963	13.4963
	Peak	5600	5765	5900	5600	5600	5600	6830	7535	7230	7230

Table 10. Average scores based on integrated AHP-TOPSIS for all developers.

Device		Starting Time of Operation for Each Device (Each Column Represents an Alternative)									
Appliances	Teakettle	356	399	402	437	344	407	348	419	379	402
	Teakettle	1074	1092	1104	1156	1146	1095	1096	1130	1070	1104
	Pop-up toaster	325	344	319	318	380	388	400	365	350	319
	Steam Iron	976	1023	1000	962	1038	1209	973	1042	1025	1000
	Water heater	276	278	255	246	251	274	255	282	312	255
	Water heater	1191	1192	1200	1190	1196	971	1181	1198	1187	1200
	Oven	1051	1012	1014	1063	978	1013	970	997	1121	1044
	Dryer	1043	1028	996	1046	1040	979	1002	968	1037	996
	Dishwasher	1277	1263	1269	1280	1252	1237	1289	1279	1254	1269
	Stove	380	312	337	371	365	300	369	308	306	337
	Stove	990	972	1038	968	963	1025	1034	1014	968	1038
	Cloth washing	1201	1216	1219	1226	1197	1271	1210	1191	1198	1185
	Cleaner	555	512	581	585	543	580	571	543	486	568
MCDM indices	SP	0.00433	0.00480	0.00493	0.00518	0.00522	0.00554	0.00674	0.00698	0.00708	0.00736
	SN	0.03235	0.03176	0.03199	0.03132	0.03127	0.03156	0.02961	0.02937	0.02927	0.02898
	CI	0.87994	0.86692	0.86370	0.85655	0.85537	0.84745	0.81386	0.80756	0.80474	0.79705
Criteria	Cost	13.74577	13.92228	13.75732	14.05591	14.07092	13.81011	14.57225	14.64566	14.67833	14.76691
	Peak	5600	5600	5765	5600	5600	5900	5600	5600	5600	5600

A comparison of the load scheduling before and after applying the proposed method is presented in Figure 2. The peak load consumption was about 10.5 kW, while the best optimal solution based on MODE-AHP-TOPSIS is 5.6 kW (i.e., 47% energy saving). The cost of energy consumption before using the proposed scheduling method was about R25.37, while after applying the proposed method it decreased to R13.74 (i.e., a 46% cost saving).

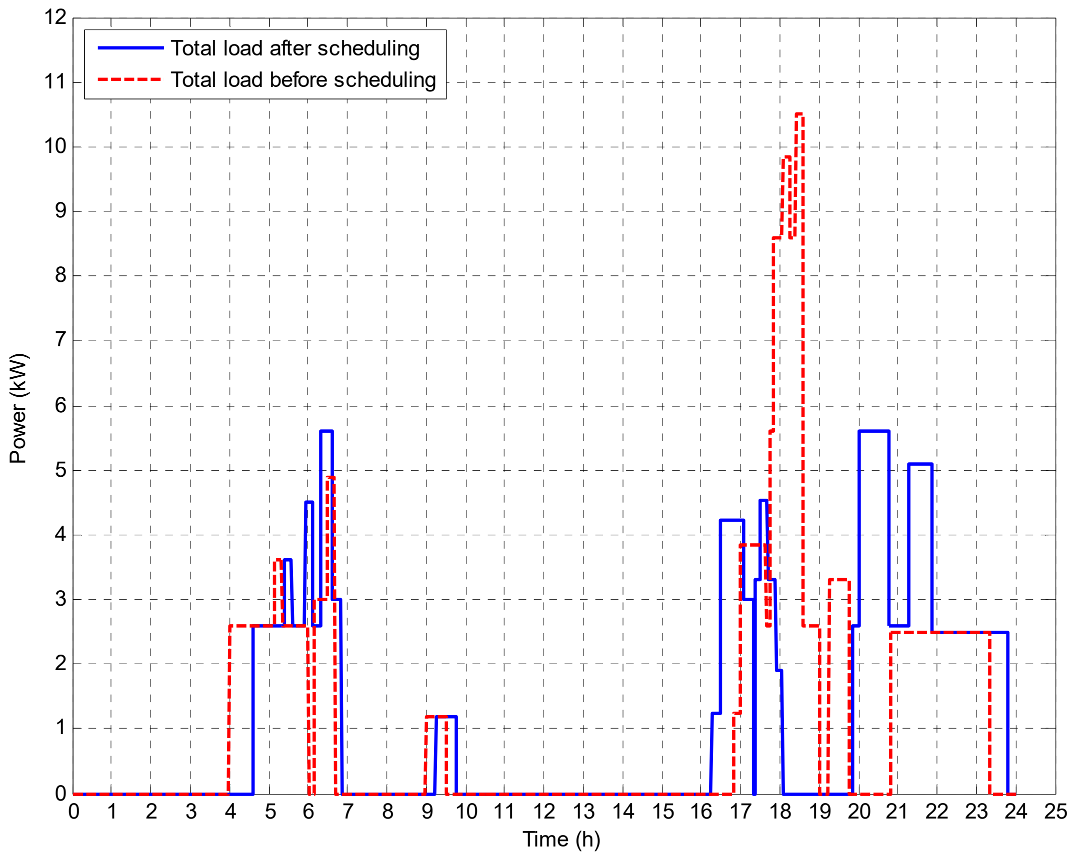

Figure 2. Total load before and after load scheduling.

3.2. *Validation of The Proposed Scheduling Model*

To highlight the differences between the proposed method and the previously published methods, a comparison between the methods presented in References [17,21] and the proposed method is conducted. The same customer data and pricing scheme (ToU) are common for all methods. The comparison results of these methods are presented in Table 11. According to these results, and before applying any scheduling method, the total energy consumption and total cost are about 27.18 kWh and R25.37, respectively, while the peak load is about 10.5 kW. Before scheduling, all cited parameters are the same for all methods because scheduling is based on baseline customer data. While after scheduling, in Reference [17] the total cost reduces to R18.80 (i.e., a 25% cost reduction) and peak load decreases to 8.4 kW (a 20% peak load reduction). In Reference [21], the total cost and peak load become 17.38 (i.e., a 31% cost reduction) and 6.8 kW (i.e., a 35% peak reduction). For the proposed method, the total cost of customer consumption reduces to R13.74 (i.e., a 46% cost reduction) and the peak load decreases into 5.6 kW (i.e., a 47% peak reduction). According to these results, the proposed method provides higher reduction for both cost and peak load than two other methods, when the same total utility revenue for all method was assumed. The proposed method benefits both customers and utility companies to save energy and cost concurrently.

Table 11. Comparison results.

References	Before Scheduling			After Scheduling				
	Total Energy (kWh)	Peak Load (kW)	Total Cost (R)	Total Energy (kWh)	Peak Load (kW)	Total Cost (R)	Cost Reduction (%)	Peak Load Reduction (%)
[17]	27.18	10.5	25.37	27.18	8.4	18.80	25	20
[21]	27.18	10.5	25.37	27.18	6.8	17.38	31	35
Proposed method	27.18	10.5	25.37	27.18	5.6	13.74	46	47

4. Conclusions

Optimal and dynamic load scheduling is proposed to tackle the energy shortage crisis and supports effective cost and energy savings. A hybrid MODE algorithm and MCDM method is proposed to optimize the load scheduling problem. The MODE algorithm offers a set of optimal solutions, which are sorted by the integration of AHP-TOPSIS methods based on the cost of energy and the peak of load criteria. According to the results of the proposed method, the peak of load is reduced from 10.5 kW to 5.6 kW, which is about a 47% peak reduction. In the meantime, the cost of energy is reduced from R23.37 to R13.74 for a 46% cost reduction. The superiority of the approach is explained by verifying the acquired outcomes with the results of various techniques proposed in the literature. The presented load scheduling provides a holistic DR solution that encourages the customer to schedule their energy bill and allows the utility company to manage aggregated energy consumption.

Author Contributions: H.T.H collected the data. D.H.M and H.T.H conducted formal analysis, conceptualization, methodology, resources, software implementation, investigation and the writing of the original draft. Y.A.-N. and T.K. were involved in the conceptualization, investigation, paper editing and reviewing, and project administration.

Funding: This research received no external funding.

Acknowledgments: The authors would like to thank University of Mustansiriyah (www.uomustansiriyah.edu.iq) Baghdad-Iraq for its support in the present work.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Pseudo code of the MODE model:

Initialization the algorithm

Set parameter limits $[S_L, S_H]$, *population size (P), maximum number of generation* (G_{max}), *MSF, CCF and data of 10 appliances.*

Randomly generate initial population

for $i = 1$ *to P*
    for $j = 1$ *to Q*
        $DS^0_{j,\,i} = (S^0_{j,\,H} - S^0_{j,\,L})_i$
    end for
    compute Of_1, Of_2
    save Of_1 and Of_2 *in fitness function vectors*
end for
$G = 1$
While $G < G_{max}$
    for $i = 1$ *to P*
        Generate mutant vector
        Randomly choose three distinct individual vectors S^G_{r1}, S^G_{r2} *and* S^G_{r3} *from the current population*
        $DF^G = S^G_{r2} - S^G_{r3}$
        $\hat{S}^G_i = S^G_{r1} + MSF * DF^G$
        Generate the trial vector
        Choose I_i *randomly belongs to the range [1, Q] and* $RND \in (0,\ 1)$

for $j = 1$ *to* Q
if $(RND \le CCF)$ *or* $(j = I_i)$
$X^G_{j,i} = \hat{S}^G_{j,i}$
else
$X^G_{j,i} = S^G_{j,i}$
end if
end for
for $j = 1$ *to* Q
if $(X^G_{j,i} < S_{j,L})$ *or* $(X^G_{j,i} > S_{j,H})$
$DS^0_{j,\,i} = \left(S^0_{j,\,H} - S^0_{j,\,L}\right)_i$
$X^G_{j,i} = \left(S^0_{j,\,L}\right)_i + RND * DS^0_{j,\,i}$
end if
end for
Compute Of_1 and Of_2 *for trial vectors*
end for
Selection the best solutions to construct the new population
for $i = 1$ *to* P
if PS dominate CS
save PS in T_P *and discard CS*
elseif CS dominate PS
save CS in T_P *and discard PS*
else
save both CS and *PS in* T_P
end if
end for
if size of $T_P > P$
sort the solutions according to Of_1
if $Of_{1,i} = Of_{1,i+1}$
sort the i and i+1 solution based on Of_2
end if
Initialize the rank value, $r_k = 1$
for $i = 1$ *to* P
$R_{S_i} = r_k$
Remove solution S_i *from* T_P
$P = P - 1$
for $j = 1$ *to* P
if $Of_1(S_j) = Of_1(S_i)$ *and* $Of_2(S_j) = Of_2(S_i)$
$R_{S_j} = r_k$
elseif $Of_2(S_j) < Of_2(S_i)$
$R_{S_j} = r_k$
end if
$r_k = r_k + 1$
end for
end for
Fill the POP^{G+1} *by the solutions belong to the lowest rank front level*
if the number of the last front level's (F_L) *solutions>remaining slots in* POP^{G+1}
set NSL=number of solutions in F_L
for z = 1 to Z
sort the solutions of F_L *in ascending order* Of_z

set $CDR_1^z = CDR_{NSL}^z = \infty.$
for i = 2 to (NSL-1)
$CDR_i^z = \left(Of_{i+1}^z - Of_{i-1}^z\right) / \left(Of_{max}^z - Of_{min}^z\right)$
end for
end for
$CDR_i = \sum_{z=1}^{Z} CDR_i^z$
end if
else if
$POP^{G+1} = T_P$
end if
G=G+1
end while

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