TÜBİTAK

Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2023) 31: 263 – 281
© TÜBİTAK
doi:10.55730/1300-0632.3983

Development of two-stage optimization-based demand response technique for smart homes under real-time pricing

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Received: 31.05.2022 • **Accepted/Published Online:** 18.01.2023 • **Final Version:** 23.03.2023

Abstract: Residential load management deals with two major objectives viz. minimizing the cost of monthly electricity bill and peak demand of power consumption. Both objectives can be achieved by effective operational scheduling of smart home appliances. These two objectives are conflicting in nature because rescheduling of appliances in order to minimize one objective may result in the rise of another. To achieve both objectives concurrently, an algorithm is suggested in this paper based on artificial intelligent techniques like cuckoo search, hybrid GA-PSO, and adaptive cuckoo search. The proposed algorithm is tested successfully on seven households of different monthly power consumption and real data of dynamic pricing options for electricity applicable in two utilities. To reduce the risk associated with real-time price, a cost function based on inclining block rates (IBR) is also suggested for both the utilities. A novel approach to find the threshold limit of hourly power consumption is also suggested in this paper. The proposed algorithm solves the optimization problem in two stages and validates its performance by successfully achieving both objectives simultaneously.

Key words: Demand response, dynamic pricing, optimal scheduling, smart homes

1. Introduction

With technological advancement, now it is possible for smart home residents to actively participate in load management by effective scheduling of household appliances. The energy consumption pattern of appliances is altered by a home energy management system (HEMS), installed in smart homes in response to dynamic pricing [1]. Managing the power demand of the residential consumers is considered difficult because it depends on consumers' behavior and their different consumption schedules. There are two major objectives of residential load management: the first one is the reduction of electricity bill cost and the second objective is the reduction of peak power consumption [2, 3]. The above two objectives of residential load management may be achieved with the help of demand side management (DSM). It is a way consumers can help the power grid in the management of power demand. DSM can modify the consumer's behavior of power consumption by various methods such as financial rebates/ incentives, differentiated tariffs, and demand response (DR) [4]. In the demand response, each smart home resident is expected to respond independently to the dynamic pricing by shifting the operational time of their household appliances. Objectives for shifting the operational time of appliances can be different for different stakeholders. Objective for power suppliers may be to minimize the appearance of high peak power demand or a longer power demand valley [5, 6]. It is desired that the load curve be as flat as possible. Flattening of the load curve is the reduction of power consumption at peak load hours and increasing the consumption

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during the low load periods [7]. To flatten the load curve, some of the home appliances that are deferrable can be arranged to operate at off-peak or midpeak hours to get the real load curve as similar to the target load curve as possible. Reducing the power demand during peak hours and minimizing the peak power demand in the load curve of a day are two different objectives of DSM. The former objective can be achieved by implementing dynamic pricing (high price during peak hours) and shifting the load from peak hours to off-peak/midpeak hours [8, 9]. As a consequence, this shifting may result in increased power demand during off-peak/midpeak hours. In order to minimize the power demand during peak hours, the objective becomes to reduce the difference between real and targeted load curves. On the other hand it is required to minimize the peak-to-average ratio (PAR) in order to minimize the peak power demand [10].

1.1. Related prior work

Various problems of HEMS have been formulated in numerous studies like reduction of power demand in peak hours [5, 7, 11], peak to average ratio (PAR) [3, 10], electricity expense [12, 13], operational waiting time of appliances [14], emission dispatch [11, 15], and maximizing user comfort [8] in a centralized and distributed manner. There are various advanced techniques proposed for the solution of HEMS problems available in the literature like machine learning, game theory approach [16], and numerous artificial-intelligence-based algorithms. These algorithms are very popular for solving real-world optimization problems and they are broadly classified into deterministic and stochastic algorithms. Deterministic algorithms such as quadratic programming (QP) [17], linear programming (LP) [5], and mixed integer linear programming (MILP) [18] have been implemented in the literature to optimize various objectives of HEMS like minimization of peak load and customer's bill payments individually for single and multiusers; and maximization of user's comfort or customer's satisfaction level. In stochastic metaheuristic optimization algorithms like simulated annealing or evolutionary algorithms, some random rules are applied during the search, and different final solutions may be obtained from the same initialization. In contrast, deterministic algorithms lead to the same final solution using a particular set of inputs. As a result, deterministic algorithms are unable to consider uncertainties, whereas stochastic optimization algorithms can do so with the help of appropriate probability distributions. To increase the likelihood that the technique will identify the global optimum of the objective function, stochastic optimization approaches offer an alternate strategy that permits less optimal local decisions to be taken during the search phase. Deterministic algorithms also have limitations in their application to smooth and unimodel objective functions. To overcome these limitations of nonstochastic algorithms, artificial intelligence technique-based metaheuristic algorithms are implemented to obtain global optimal solutions to HEMS objectives [17, 20]. Some of these are genetic algorithm (GA) [10, 14], genetic harmony search algorithm (GHSA) [11], whale optimization algorithm (WOA) [7], Jaya algorithm, earliglow algorithm, strawberry algorithm [15], and grasshopper optimization algorithm [19].

Implementation of dynamic pricing can be beneficial for all the stakeholders in different ways like monetary benefits for customers and actual cost recovery for suppliers. It has been implemented by various researchers with different strategies of DSM for different objective functions in their study. Authors in [10] proposed an efficient home energy management controller with real-time pricing (RTP) and critical peak pricing (CPP). The optimization problem of load management is also solved for single and multiple households using an evolutionary algorithm with time-of-use (ToU) price [5, 9]. A comparative evaluation for the performance of home energy management controllers designed on the basis of heuristic algorithms with ToU and CPP is also given in [15]. Various researchers had studied minimization of cost and PAR as multiobjective models or a composite function of cost with predetermined electricity prices. Authors of this paper have also studied minimization of both the objectives individually with ToU price and hourly-ahead real-time price (HA-RTP) [21]. It was observed that minimization of electricity cost and PAR are conflicting in nature.

Implementation of dynamic pricing schemes is limited due to the risk associated with hourly variation of dynamic pricing plans. Many programs have limited this risk by joining dynamic pricing options with inclining block rates (IBR) and assigning customers a threshold limit of power consumption. The electricity price for purchase of power below this limit is as usual, but above this limit, customers have to pay a high price of fixed rate [12]. The concept of IBR was first adopted in the 1980s by some utilities viz. San Diego Gas & Electric, Pacific Gas & Electric Companies, and Southern California Edison. In the British Columbia Hydro Company, Canada, currently, a two-level price structure is used for residential load, wherein the first level (lower level) actual price is applicable and in the second level (higher level) 40% high price is received. In this price structure, a rebate can also be received for reducing the power consumption below the threshold level [22]. In the literature, IBR scheme has been implemented with RTP in order to minimize electricity cost as well as PAR using optimization algorithms like GA [12] and linear programming [16]. In these papers, base price is RTP and above the threshold limit a high price of fixed percent of base is applied, but these papers also lack the method of deciding the threshold limit.

1.2. Contribution of this research work

In the literature, a lot of attention has been given to minimizing the electricity bill cost and power demand during peak hours, i.e. high price hours. Moreover, it is important to minimize the power peaks during low price hours. Actually, in an aim to minimize the electricity cost, the start time of most appliances are rescheduled at low cost time periods which may result in increased power demand during the low cost time periods. With this motivation, this research work aims to achieve both objectives simultaneously. Our contribution in this research paper is different from the existing literature. Key contributions of this research work are summarized as follows:

- Proposes an electricity cost function based on inclining block rates (IBR) using time varying pricing which can benefit consumers as well as utilities both.
- Uncertainty of demand and price is considered in the study through real-time electricity prices viz. day-ahead real-time price (DA-RTP) and hourly-ahead real-time price (HA-RTP).
- Implementation of single interval programming (SIP) for the predetermined electricity prices, e.g., ToU or DA-RTP and multiinterval programming (MIP) for HA-RTP to find optimal scheduling of appliances.
- Optimum scheduling of smart home appliances is obtained by two-stage optimization using multiinterval programming (MIP) with the help of proposed cost function.
- A novel approach to find the threshold limit of hourly power consumption.

The proposed energy management system (EMS) will be able to optimize the consumer's bill cost as well as peak demand of electricity simultaneously by shifting the power drawn from grid. The optimal scheduling of household appliances considering consumer's preferences will also reduce the energy consumption during peak hours.

The paper starts with a brief introduction to HEMS and its objectives, followed by the related research work available in the literature and limitations in the implementation of dynamic pricing. The contribution of this research work is given in Section 1.2. Section 2 deals with the problem formulation, objective functions, and operational constraints of the system architecture developed for residential loads. The proposed cost functions to achieve both objectives are also given in Section 2.1. Section 3 deals with the artificial-intelligence-based algorithms used for optimal scheduling. Information on the electricity pricing schemes and household appliances considered in this study is given in Section 3.4. Simulation results and optimal solutions obtained for objective functions of electricity cost, PAR, and proposed cost functions in scenarios 1, 2, and 3 are given in Section 4. Finally, Section 5 presents a conclusion and suggestions for future research work in this direction.

2. Mathematical formulation

It is difficult and confusing for the consumers to manually respond to the dynamic pricing that changes on an hourly basis. To manage this requirement, a home energy management system (HEMS) is proposed using artificial-intelligence-based algorithms. HEMS installed in smart homes consist of home energy controller and smart home appliances. All the appliances under HEMS are categorized into three main classes on behalf of their inherent characteristics viz. time deferrable, power deferrable, and nondeferrable appliances [23]. It is anticipated that each household is supplied power by the utility that offers a variety of fixed and time-varying electricity prices. The system architecture of the model is given in Figure 1. Here, smart home residents can also define their preferences to energy controller. This study is divided into three scenarios:

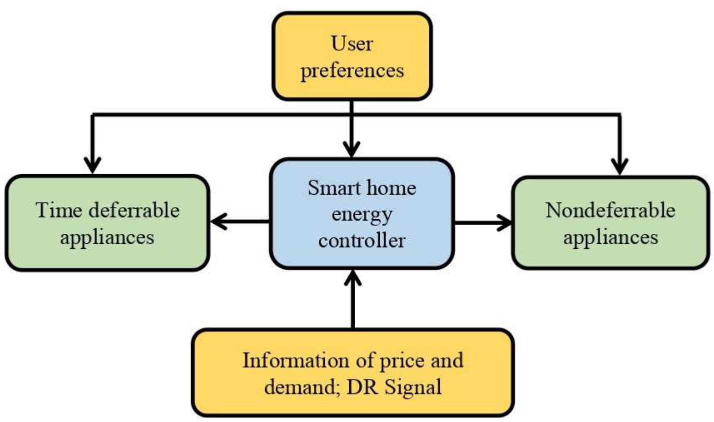

Figure 1. System architecture.

- **Scenario-1:** Individual smart home resident reschedules his/her household appliances in order to minimize the electricity bill cost.
- **Scenario-2:** Individual smart home resident reschedules his/her household appliances in order to minimize the peak-to-average ratio (PAR).
- **Scenario-3:** Individual smart home resident reschedules his/her household appliances in order to achieve both the objectives together through proposed electricity cost function.

2.1. Objective function

If the electricity price during time interval t is denoted by p^t. The vector p(d) accumulates electricity prices for all the intervals on day $d \in N$. Let the energy consumption scheduled in time slot t of day $d \in N$ is x_l^t(d), whereas the power demand scheduled for the load $\ell \in £$ in a time interval t is y_l^t. Here, £ designates the total number of existing loads. The total cost of electricity for 24 h of a day is calculated by the following equations [21]:

$$Minimize \;\; C_{DEC} = \sum_{t=1}^{T} x^t(d) \;\; p^t(d) \qquad where \;\;\; T = 24, \tag{1}$$

$$x^t(d) = \sum_{\ell=1}^{£} \xi_\ell^t \;\; y_\ell^t(d) \;\; T_\ell. \tag{2}$$

Here, ξ_ℓ^t is the ON/OFF state and T_ℓ denotes the operational time of the load $\ell \in £$ in time interval t, $t \in T$. T is the total number of time intervals, i.e. 24 with each being 1 hour.

Minimization of PAR helps the utility to retain the stability and ultimately leads to the cost reduction. PAR is the reciprocal of load factor. It is minimized to reduce the peak power demand with the help of the following equation [15]:

$$Minimize \;\; PAR = \frac{\max(load)}{avg(load)}. \tag{3}$$

Here, average load is considered equal to the sum of power consumed by all nondeferrable loads in any time slot. Mathematical expression for PAR can be given by equation (4):

$$Minimize \;\;\; PAR = \frac{\max\{\sum_{\ell=1}^{£} \xi_\ell^t \;\; y_\ell^t(d)\}}{\frac{1}{T}\sum_{t=1}^{T}\sum_{\ell=1}^{£} \xi_\ell^t \;\; y_\ell^t(d)}. \tag{4}$$

Objective functions given by equation (1) and equation (4) are used to minimize the monthly cost of power consumption and peak demand individually in scenario-1 and scenario-2, respectively, while in scenario-3 smart home appliances are scheduled by two-stage optimization in order to achieve both objectives at the same time. To achieve both objectives simultaneously IBR-based cost function is proposed for Alectra Utilities Corp., Canada to calculate total electricity bill. The proposed function of electricity cost is given by equation (5) in which ToU and HA-RTP pricings are used to calculate the total bill cost. As per equation (5), for the power consumption below hourly threshold limit ToU rates are applicable, and for the power consumption above this limit HA-RTP rates are applicable.

$$Minimize \; C_{Total} = \sum_{d=1}^{N}\sum_{t=1}^{T} \begin{array}{l} x^t(d) \;\; p_{ToU}^t, if 0 \le x^t(d) \le P_{Th}^t \\ x^t(d) \;\; p_{HA-RTP}^t, if P_{Th}^t \le x^t(d) \end{array} \tag{5}$$

Similarly, cost function proposed for the case of ComEd Northern Illinois Power Company, USA, is given by equation (6) in which DA-RTP and HA-RTP pricings are used to calculate the total bill cost. As per the equation (6), DA-RTP rates are applicable for the power consumption below hourly threshold limit, and for the power consumption above this limit, HA-RTP rates are applicable.

$$Minimize\ C_{Total} = \sum_{d=1}^{N}\sum_{t=1}^{T} \begin{matrix} x^t(d)\ p^t_{DA-RTP}, if 0 \leq x^t(d) \leq P^t_{Th} \\ x^t(d)\ p^t_{HA-RTP}, if P^t_{Th} \leq x^t(d). \end{matrix} \tag{6}$$

Here, P^t_{Th} is the threshold power consumption for time slot t. Optimal values of P^t_{Th} for 24 time slots are obtained in the first stage by maximizing the objective function of load factor (L.F.) given in equation (7) [20]. While in the second stage, objective function given by equations (5) and (6) are optimized in order to reduce the cost of electricity bill.

$$Minimize\ L.F. = \frac{\frac{1}{T}\sum\limits_{t=1}^{T}\sum\limits_{\ell=1}^{£}\xi^t_\ell\ y^t_\ell(d)}{\max\{\sum\limits_{\ell=1}^{£}\xi^t_\ell\ y^t_\ell(d)\}}. \tag{7}$$

2.2. Operational constraints

1. Energy consumption of appliances other than their operational time T_ℓ will be zero [23].

$$x^t_\ell(\mathrm{d}) = 0 \quad where\ \ t \notin T_\ell. \tag{8}$$

2. The power is deferrable for loads that consume energy within a certain power limit [18].

$$x^{\min}_\ell \leq x^t_\ell(\mathrm{d}) \leq x^{\max}_\ell \quad where\ \ t \in T_\ell. \tag{9}$$

3. Only ON-OFF control is allowed for loads that consume a fixed power P_ℓ.

$$x^t_\ell(\mathrm{d}) \in 0,\ \xi^t_\ell = 0\mathrm{P}_\ell,\ \xi^t_\ell = 1 \quad where\ \ t \in T_\ell. \tag{10}$$

4. Sum of energy consumption after rescheduling of all appliances should be equal to the requirement of energy for a day DR_ℓ [19].

$$\sum_{t=1}^{24} x^t_\ell(d) = DR_\ell. \tag{11}$$

3. Solution methods

In this research work, objective functions of total cost of power consumption and peak-to-average ratio (PAR) are optimized in both cases by cuckoo search (CS) method, hybrid GA-PSO algorithm, and adaptive cuckoo search (ACS) method. These three optimization algorithms are implemented as core algorithms with SIP and MIP.

3.1. Cuckoo search (CS) method

Cuckoo search method is a metaheuristic type stochastic algorithm. Metaheuristic algorithms can help to find the global search solution for an optimization problem due to their unique feature of randomization. This algorithm is inspired by obligate brood parasitism of cuckoo species. It is named after the sweet sound made by these birds. The step-by-step procedure of the CS method to find the optimal solution is given in Figure 2 [24].

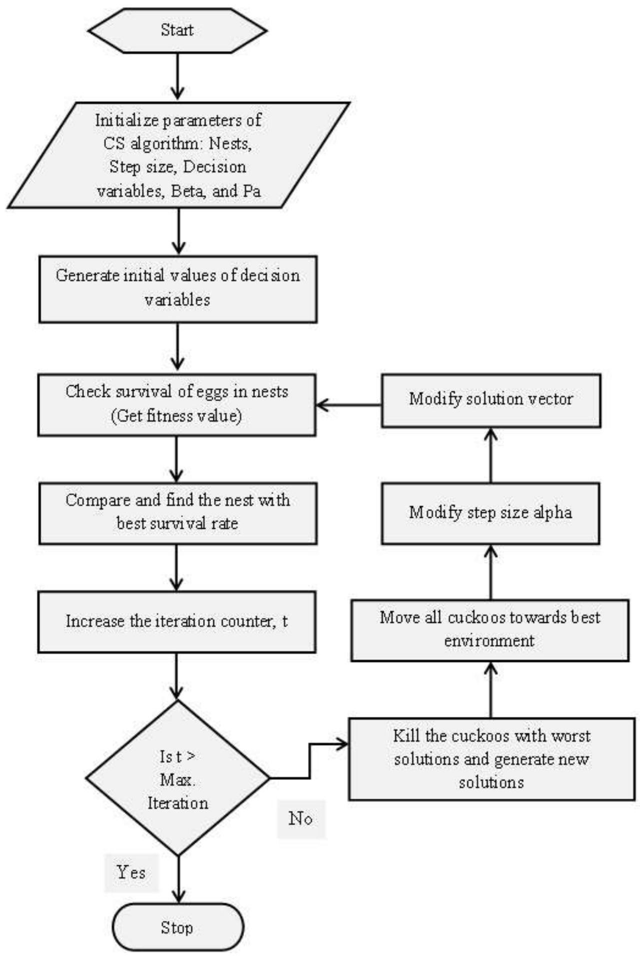

Figure 2. Optimization procedure of the CS method.

3.2. Adaptive cuckoo search (ACS) method

It is very challenging to find the global optimal solution to an optimization problem. Quality of solution depends on choice and accurate use of optimization technique. In general, a global optimization technique has some characteristics like good balance between exploration and exploitation; fast convergence; least control parameters; and global optimum solution in each run. Performance of CS method is improved in ACS method by adding new equations for adaptive adjustments of inertia weight (w); step size (α); and skewness parameter (λ) as by equations (12)–(14), respectively [25, 26].

$$w = 1 - e^{-\frac{1}{t}}, \tag{12}$$

$$\alpha_i(t) = 0.5 + 1.5(\frac{1}{\sqrt{t}}) \left| \frac{f^t_{best} - f^t_i}{f^t_{best} - f^t_{worst} + \varepsilon} \right|, \tag{13}$$

$$\lambda_i(t) = 0.5 + 0.1 \left| \frac{f^t_{best} - f^t_i}{f_{best} - f_{worst} + \varepsilon} \right|^t. \tag{14}$$

Here, w= inertia weight; t= number of iteration; f^t_{best} is the best fitness value of function f in iteration count t; f^t_{worst} is worst fitness value of function f in iteration count t; f_{best} and f_{worst} are global best and global worst fitness values, respectively. (ϵ) is a smallest constant used to avoid error by zero value in denominator. Figure 3 represents the pseudocode to implement ACS.

```
Begin
objective function f(X),  X=(x1, x2,......., xD)T
generate initial population Yi of n host nest (i=1,2,......,n)
evaluate the fitness and find best nest (P_best)
        while (t < max iterations)
        t=t+1
        generate new solutions randomly from (P_best)
        evaluate fitness of new solutions
        choose randomly a nest among n nests (say, j)
if (Fi < Fj),   i = j
        replace j by new solution
end if
        A fraction of worst nests (Pa) are abandoned
        new solution are built
        evaluate the fitness
        keep the better solutions
        rank the solutions and find global best (G_best)
        end while
post process results and visualization
End
```

Figure 3. Pseudocode for the ACS method.

3.3. Hybrid GA-PSO algorithm

This algorithm is structured by amalgamation of genetic algorithm (GA) and particle swarm optimization (PSO). In this algorithm, the best features of GA like mutation and crossover are combined to improve the performance of PSO [27]. Figure 4 represents the flow chart of the hybrid GA-PSO algorithm.

Table 1 provides the information of parameters set for all three algorithms. In this research work, single interval programming (SIP) has been implemented with the CS, ACS, and hybrid GA-PSO algorithms as core optimization techniques for the minimization of electricity cost (scenario-1) and peak demand (scenario-2) with the pricing schemes known to the consumers for the whole day in advance like ToU and DA-RTP. So in SIP, the number of decision variables (D) is 24 to find the optimal values of power consumption for 24 h of the day. However, in the case of hourly-ahead real-time pricing (HA-RTP), the signal for the price of the electricity is sent to the consumer at the beginning of the hour. Therefore, in such a case, SIP cannot be implemented and multiinterval programming (MIP) is required. So in scenarios 1 and 3, the objective functions of cost with the HA-RTP scheme are minimized by implementing MIP and considering the number of decision variables (D): 1. In this case, the optimization algorithm finds one optimal value in each run. In the literature, the number of decision variables is considered to be 24 for all schemes of electricity pricing [7, 9]. Initial velocities of particles in hybrid GA-PSO are considered zero for searching solutions from the initial generation of the population. Inertia weight (w) in the CS algorithm is unity and remains constant, but in the ACS algorithm it is updated in each iteration using equation (11). In the ACS algorithm, w varies in a range of 0 to 1 [26]. Other parameters of CS, ACS, and hybrid GA-PSO algorithms are considered as given in [24, 27].

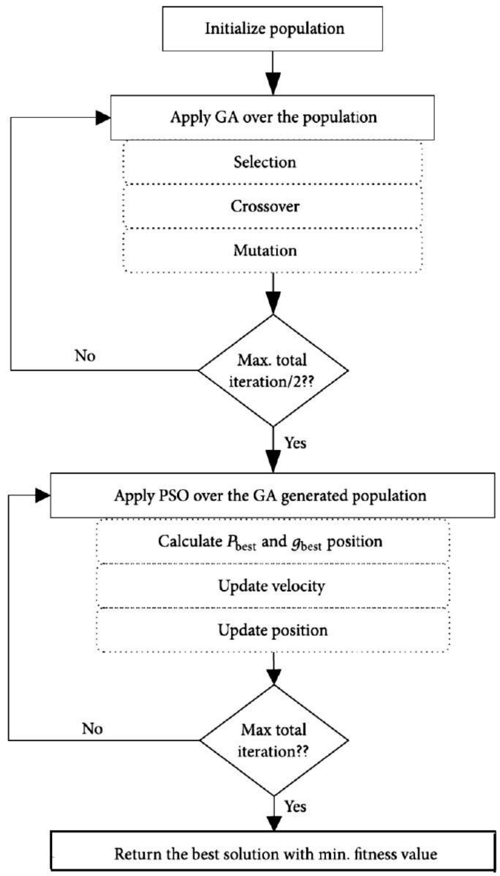

Figure 4. Flow chart to implement hybrid GA-PSO.

Table 1. Parameters set for algorithm.

S. No.	Parameter	Value
1	Numbers of cuckoo's nests in CS and ACS (N)	30
2	Rate of discovery (pa) in CS and ACS	25%
3	Inertia weight (w) in CS	1.00
4	Inertia weight (w) in ACS	0.0 < <1.0
5	Population size (p) in hybrid GA-PSO	20
6	String length (n) in hybrid GA-PSO	10
7	Probability of mutation (pm) in hybrid GA-PSO	0.02
8	Probability of crossover (pc) in hybrid GA-PSO	0.80
9	Inertia weight (w) in hybrid GA-PSO	0.4–0.9
10	Constants C1 and C2 in hybrid GA-PSO	2.0
11	Initial velocity vector (v) in hybrid GA-PSO	0.0
12	Numbers of decision variables (D) in SIP	24
13	Numbers of decision variables (D) in MIP	01
14	Penalty factor in ACS & hybrid GA-PSO (k)	10
15	Max. iterations count in ACS & hybrid GA-PSO	200

3.4. Applicability of the proposed model

The proposed model is implemented for seven residential households with different monthly power consumption. All the seven households have a different set of appliances and separate usage preferences of appliances. Information of monthly power consumption for all the seven households is provided in Table 2 [28]. Table 3 contains further information of appliances', like their power rating and category (NDL: nondeferrable; TDL: time deferrable; PDL: power deferrable) [20, 21].

Table 2. Household power consumption and appliance information.

House hold no.	Range (kWh/month)	Power consumption (kWh/Month)	Total appliances	Deferrable appliances
1	<600	558.60	8	3
2	601–750	654.60	9	3
3	751–1000	947.40	14	6
4	1001–1250	1142.40	14	6
5	1251 –1500	1312.50	12	7
6	1501–2000	1732.50	14	9
7	2001–2500	2392.50	15	10

Table 3. Information of power rating and category of appliances.

S. No.	Appliances	Power rating (kW)	Category
1	Light	0.5	NDL
2	Refrigerator	0.125	NDL
3	Personal computer	0.20	NDL
4	TV	0.14	TDL
5	Hairdryer	1.0	TDL
6	Washing machine	1.5	TDL
7	Vacuum cleaner	1.0	TDL
8	Electric stove	1.5	NDL
9	Water heater	1.5	NDL
10	Iron	1.0	TDL
11	Air conditioner	1.0-1.5	PDL
12	Water pump	2.0	TDL
13	Dish washer	1.0	TDL
14	Air heater	1.5	NDL
15	Cloth dryer	1.5	TDL
16	Fan	0.12	NDL

In this research, real data on pricing schemes available with two utilities, viz., Alectra Utilities Corp., Canada, and ComEd, Northern Illinois Power Company, USA, is considered to verify the performance of the proposed model. Alectra Utilities Corporation, founded in 2017 and headquartered in Ontario, Canada, provides various utility services to customers. It serves approximately one million homes and businesses across a territory comprising seventeen communities, including Brampton, Hamilton, Alliston, and Vaughan. The pricing options applicable for retail consumers under Alectra Utilities Corp. are ”two-tiered” and ”time-of-use” (ToU) pricing. Both of these prices are considered for the time period May 1 through October 31, 2019. To consider the uncertainty of demand and price in this study, the HA-RTP proposed by [21] for Alectra Utilities Corp. is also considered. Here, real-time price data is taken for September 1–September 30, 2019 [29]. In Alectra Utilities Corp., the standard schedule of power consumption for billing by ToU price is assumed to be 64% of monthly power consumption in off-peak hours, 18% in midpeak hours, and 18% in peak hours, whereas Commonwealth Edison Company (ComEd) provides electric service to more than four million customers across northern Illinois. ComEd is a subsidiary of Exelon Corporation (NASDAQ: EXC). In this case, the pricing options are flat rate tariff, HA-RTP, and day-ahead real time price (DA-RTP). In this case, the pricing data for the flat rate tariff is considered for the time period of October 2019 to May 2020, and the RTP is considered for the month of April 2020 [30].

The price of electricity is determined in real-time and managed by the Independent Electricity System Operator (IESO). As electricity supply is offered to the market at its operating cost, the IESO prioritizes it from the lowest to the highest cost. Where supply meets demand is the market clearing price (MCP). The MCP is set every five minutes. The 12 MCP that make up one hour are averaged to make the hourly-ahead real-time price.

4. Simulation results and analysis

4.1. Case study-1: Alectra Utilities Corp., Canada

4.1.1. Scenario-1: Individual smart home resident reschedules his/her household appliances in order to minimize the electricity bill cost

In the scenario-1, an analysis of electricity bill cost before and after optimization is given. Cost of monthly electricity bill before optimization given in Table 4 is calculated by two-tiered price, HA-RTPü and ToU price with estimated scheduling of appliances. In Table 4, electricity cost by standard scheduling as assumed by Alectra Utilities Corp. with ToU price is also given. From the results given in Table 4, it can be perceived that monthly cost of power consumption is the lowest by two-tiered price before optimization, but standard scheduling resulted in reduced bill cost for the households having power consumption more than 1000 kWh. This saving in monthly bill cost can be further improved by optimal scheduling of smart home appliances.

Table 4. Cost of power consumption before optimization for September 2019.

House hold no.	Two-tiered price ($)	HA-RTP price ($)	With ToU price ($)	
			Random scheduling	Standard scheduling
1	85.41	93.99	100.62	88.60
2	96.30	105.45	112.67	99.15
3	130.54	140.90	144.72	131.25
4	153.42	163.64	170.12	152.96
5	173.50	183.95	183.40	171.30
6	223.10	234.07	243.85	217.36
7	299.52	312.82	334.81	290.43

Table 5 gives a comparative analysis of electricity cost obtained by optimization on behalf of consumer's preferences using all three algorithms with time of use price and HA-RTP with or without participation incentive (PI). By the analysis of optimal results given in Table 5, it is found that optimum scheduling with ToU price obtained by CS, hybrid GA-PSO, and ACS algorithms reduced the cost of power consumption by 10.85%, 10.96%, and 11.20% on an average for all the households as compared to bill cost with ToU price before optimization. On the other hand, these results by HA-RTP with PI are 9.20%, 9.75%, and 10.45% for all the houses.

Peak to average ratios and peak demand resulting from estimated and optimal scheduling achieved by ACS algorithm is given in Table 6. By a comparative study of the results given in Table 6, it is noted that rescheduling of appliances to minimize the cost of bill may result in increased peak power consumption due to scheduling of various appliances during low-cost time slots.

Table 5. Electricity bill cost after optimization for September 2019.

S. No.	Optimization by Hybrid GA-PSO			Optimization by CS			Optimization by ACS		
	ToU price	HA-RTP		ToU price	HA-RTP		ToU price	HA-RTP	
		Without PI	With PI		Without PI	With PI		Without PI	With PI
1	88.50	87.58	86.61	88.55	87.73	88.51	88.40	87.30	85.33
2	99.00	98.50	96.15	99.05	98.65	96.48	98.88	98.32	95.69
3	131.00	129.54	127.25	131.17	130.56	128.39	130.85	128.85	126.95
4	152.40	150.42	145.80	152.54	150.56	146.23	152.17	149.50	145.00
5	170.35	167.82	165.15	170.58	168.23	165.89	170.00	167.50	162.40
6	216.70	213.65	210.36	216.87	215.63	212.03	216.04	213.25	208.14
7	286.40	280.10	279.80	286.85	280.95	280.32	285.10	279.50	279.40

Table 6. PAR of optimized schedule with different pricing schemes in scenario-1.

House hold no.	PAR with estimated scheduling	PAR with optimal scheduling		Resulting peak (kW) by optimal scheduling	
		ToU price	HA-RTP	ToU price	HA-RTP
1	2.990	2.552	3.389	2.38	2.63
2	3.203	4.440	4.440	4.04	4.04
3	2.689	2.700	2.729	3.55	3.59
4	2.325	2.596	2.092	4.12	3.32
5	2.184	2.468	2.468	4.50	4.50
6	2.450	3.480	3.770	8.37	9.07
7	1.983	3.724	3.724	12.37	12.37

4.1.2. Scenario-2: Individual smart home resident reschedules his/her household appliances to minimize the peak to average ratio (PAR)

Individual smart home residents reschedule their appliances in order to reduce the peak demand using objective function given by equation (4). Optimal values of PAR and peak demand obtained by the ACS algorithm for all seven households are given in Table 7. From this table, it can be observed that optimal scheduling with ToU price reduced the PAR and peak demand by 25.25% and 21.74% on an average for all the households. From the results given in Table 7, it is found that rescheduling of appliances in scenario-2 may also result in raised cost of electricity bill. Here rescheduling of appliances in order to minimize PAR resulted in raised monthly cost of power consumption for all the households by 9.23% on an average.

Table 7. Comparative results of minimized PAR with ToU price using the ACS algorithm in scenario-2.

S. no.	House hold no.	Estimated scheduling			Optimal scheduling using ACS		
		PAR	Peak demand (kW)	Monthly electricity cost ($)	PAR	Peak demand (kW)	Monthly electricity cost ($)
1	1	2.990	2.33	100.62	1.796	1.98	109.59
2	2	3.203	2.92	112.67	2.457	2.24	125.63
3	3	2.689	3.35	144.72	1.823	2.27	158.58
4	4	2.325	3.68	170.12	1.779	2.82	187.23
5	5	2.184	3.98	183.40	1.563	2.85	200.02
6	6	2.450	5.88	243.85	2.114	5.18	260.92
7	7	1.983	6.59	334.81	1.672	5.42	363.15

Figures 5 and 6 display power consumption patterns for household-4 and household-5, respectively, resulting in scenario-1 (shown by black and blue colors) and scenario-2 (shown by red color). Data tips given on scheduling curves shows the peak power consumption. Here, X shows the time slot and Y gives the value of peak demand. From these figures, it can be observed that the peak demands for households-4 and 5 are positioned in the off-peak or midpeak hours in scenario-1 in order to minimize the cost. However, in scenario-2, peak demands for households-4 and 5 are positioned in the peak hours and off-peak hours, respectively, as shown by data tips in power consumption curves.

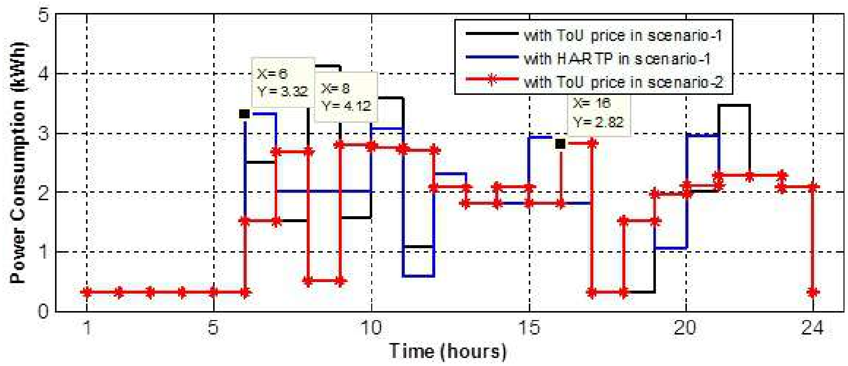

Figure 5. Comparison of power consumption scheduling of household-4.

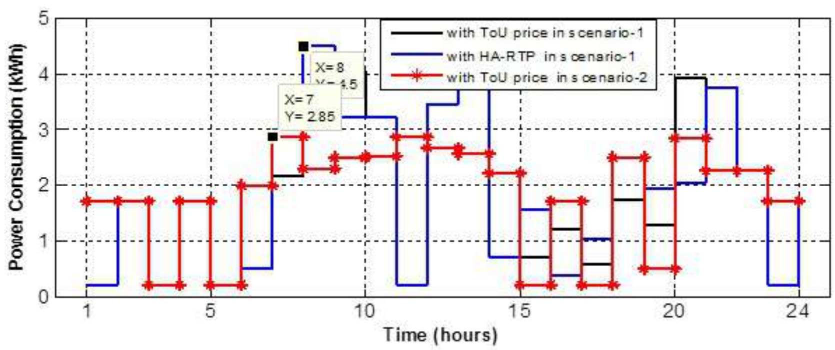

Figure 6. Comparison of power consumption scheduling of household-5.

4.1.3. Scenario-3: Individual smart home resident reschedules his/her household appliances in order to achieve both objectives together through the proposed electricity cost function

In scenario-3, individual smart home residents reschedules his/her appliances in order to reduce the cost of electricity bill with the help of the proposed cost function given by equation (5). As per equation (5), electricity cost is calculated with ToU price for the power consumption up to threshold limit (P_{Th}^{t}) for each time slot and above this limit, HA-RTP is applicable. Here, cost of monthly power consumption is optimized by ACS algorithm using multiinterval programming. Optimal results of power consumption cost, resulting PAR, and peak power demands are given in Table 8. By comparing the optimal results, it is found that optimal scheduling in scenario-3 reduced the PAR and monthly power consumption cost by 12.25% and 7.29%, respectively, on an average for all the households.

Table 8. Results of power consumption cost minimization by proposed function in scenario-3.

House hold no.	Load factor	Optimal monthly electricity cost ($)	PAR with optimal scheduling	Peak (kW) with optimal scheduling
1	0.9676	96.11	2.564	2.05
2	0.9314	102.55	2.896	2.86
3	0.9937	136.42	2.153	3.01
4	0.9465	165.48	2.027	3.36
5	0.9306	171.76	1.995	3.75
6	0.9354	220.13	2.217	5.78
7	0.9654	291.21	1.756	11.19

4.2. Case study-2: ComEd Northern Illinois Power Company

4.2.1. Scenario-1: Individual smart home resident reschedules his/her household appliances in order to minimize the electricity bill cost

In this case study, cost of electricity bill before optimization is calculated with flat rate tariff, and mean values of real-time pricing (DA-RTP & HA-RTP). Tables 9 and 10 give cost of monthly bill for power consumption before and after optimal scheduling respectively. From Table 9, it can be observed that electricity bill cost is less with DA-RTP and HA-RTP pricing in comparison to flat rate tariff by 8.28% and 9.97%, respectively, on an average for all the seven households. Optimal results given in Table 10 show that rescheduling of smart home appliances with DA-RTP and HA-RTP further decreases the monthly bill cost respectively by 21.47% and 23.50% on an average for all the households. Table 11 gives PAR before and after rescheduling of smart home appliances in scenario-1. Here, it can be perceived that minimization of electricity cost with DA-RTP and HA-RTP leads to rise of PAR by 38.96% and 27.13% on an average for all the households.

Table 9. Electricity bill cost before optimization for April 2020 in case-2.

House hold no.	Monthly power consumption in (kWh)	Flat rate tariff ($)	DA-RTP price ($)	HA-RTP price ($)
1	558.6	44.63	40.91	40.08
2	654.6	52.26	47.89	46.96
3	947.4	75.52	69.20	67.97
4	1142.4	91.00	83.93	81.96
5	1312.5	104.52	95.77	94.17
6	1732.5	137.87	126.33	124.30
7	2392.5	190.30	174.35	171.65

Table 10. Optimized electricity bill cost for April 2020 in case-2.

House hold no.	Electricity cost with DA-RTP optimized by			Electricity cost with HA-RTP optimized by		
	CS	Hybrid GA-PSO	ACS	CS	Hybrid GA-PSO	ACS
1	34.50	33.95	33.15	32.85	32.45	32.50
2	41.56	41.32	40.23	40.31	40.21	39.97
3	57.27	56.96	56.03	56.89	56.78	55.83
4	72.89	72.17	71.26	72.48	70.85	70.25
5	87.42	85.69	84.23	85.69	83.56	82.98
6	108.78	106.47	105.56	105.79	104.57	104.32
7	156.69	153.48	151.26	148.23	146.61	145.72

4.2.2. Scenario-2: Individual smart home resident reschedules his/her household appliances to minimize the peak to average ratio (PAR)

In scenario-2, individual consumer optimally schedules his/her household appliances in order to reduce the peak demand similar to case-1. In this case, optimal scheduling is obtained with DA-RTP only because minimization of PAR required the pricing data for all the 24 time slots of a day in advance. From the optimal results given in Table 12, it can be observed that rescheduling of smart home appliances resulted in decreased PAR and peak demand by 15.97% and 19.75% on an average for all the households. From the optimal results of Table 12, it can be perceived that minimization of PAR resulted in raised electricity bill cost by 13.25% and 23.48% on an average for all the households as compared to the electricity cost before optimization with flat rate tariff and DA-RTP, respectively.

Table 11. PAR before and after optimization in scenario-1.

House hold no.	Before optimal scheduling		PAR with optimized scheduling		Resulting peak (kW) by optimal scheduling	
	PAR	Peak demand (kW)	HA-RTP	DA-RTP	HA-RTP	DA-RTP
1	2.990	2.33	3.248	3.389	2.52	2.63
2	3.203	2.92	4.441	4.443	4.04	4.04
3	2.689	3.35	2.462	1.967	3.24	2.59
4	2.325	3.68	1.983	3.039	3.05	4.67
5	2.184	3.98	2.894	3.436	5.08	6.05
6	2.450	5.88	3.564	4.207	8.57	10.12
7	1.983	6.59	3.724	3.724	12.37	12.37

Table 12. PAR with DA-RTP before and after optimization using ACS algorithm in scenario-2

House hold no.	Before optimal scheduling		Optimal scheduling using ACS		
	PAR	Electricity cost with DA-RTP in ($)	PAR	Peak demand in (kW)	Electricity cost with DA-RTP in ($)
1	2.990	40.91	2.552	1.98	48.26
2	3.203	47.89	2.320	2.10	62.53
3	2.689	69.20	2.220	2.38	95.40
4	2.325	83.93	2.089	3.20	99.05
5	2.184	95.77	1.739	3.17	118.22
6	2.450	126.33	2.367	5.03	147.87
7	1.983	174.35	1.621	5.38	208.27

4.2.3. Scenario-3: Individual smart home resident reschedules his/her household appliances in order to achieve both objectives together through the proposed electricity cost function

Similar to the case-1 in scenario-3, individual smart home residents reschedules their appliances in order to reduce the cost of electricity bill with the help of the proposed cost function given by equation (6). As per equation (6), electricity cost is calculated with DA-RTP price for the power consumption up to threshold limit, and above this limit, HA-RTP is applicable. Optimal results for cost of electricity, resulting PAR, and peak values of power demand in scenario-3 are given in Table 13. Optimal results of Table 13 illustrate that electricity cost in scenario-3 is reduced by 13.89% and 6.12% on an average as compared to the electricity cost before optimization with flat rate tariff and DA-RTP, respectively. By comparing the optimal results given in Tables 11 and 13, it is found that the peak power demand with optimal scheduling in scenario-3 (average values for 30 days) is reduced by 7.83% on an average for all the seven households. Figures 7 and 8 illustrate the power consumption pattern for household-1 and household-2 in all three scenarios. As it is shown in both figures, blue color is used for optimal scheduling with DA-RTP in scenario-1, red color is used for optimal scheduling in scenario-2, and black color is used for optimal scheduling with proposed cost function in scenario-3. Similar graphs can also be given for other households. Data tips provided on all the scheduling curves in these figures display the peak power consumption. Here, X shows the time slot and Y gives the value of peak power that can be verified with the peak power consumption given in Tables 11–13.

Table 13. Results of power consumption cost minimization by proposed function in scenario-3 of case-2

House hold no.	Load factor	Optimal monthly electricity cost in ($)	PAR with optimal scheduling	Peak with optimal scheduling (kW)
1	0.9676	38.3	2.177	1.99
2	0.9314	45.43	2.761	2.51
3	0.9937	63.83	2.344	3.08
4	0.9465	77.55	2.564	3.43
5	0.9306	89.42	1.961	3.56
6	0.9354	119.6	2.085	5.02
7	0.9654	167.39	2.256	7.50

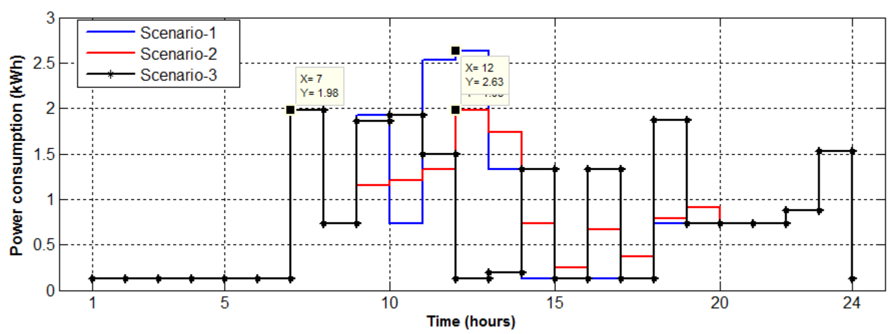

Figure 7. Comparison of power consumption scheduling for household-1 in scenario-1, 2, and 3.

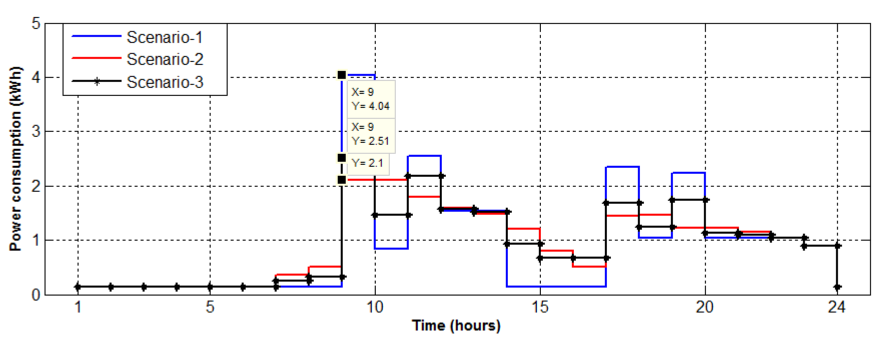

Figure 8. Comparison of power consumption scheduling for household-2 in scenario-1, 2, and 3.

The nutshell comparison of optimal results obtained in all three scenarios in case-1 and case-2 illustrates that in scenario-3, PAR is reduced by 26.40% as compared to the optimal results of scenario-1 obtained with ToU price and electricity cost is reduced by 15.12% in comparison of the optimal results of scenario-2 in the case study of Alectra Utilities Corporation. Similarly, in the case study of ComEd Northern Illinois Power Company in the scenario-3, PAR is reduced by 29.20% as compared to the optimal results (with DA-RTP) of scenario-1 and electricity cost is reduced by 23.70% in comparison of the optimal results of scenario-2. From the analysis of peak power consumption levels for all 30 days of September 2019 under the case study of Alectra Utilities Corporation, it is observed that peak levels of power demands for weekend days are higher as compared to weekdays. Because of ToU price for weekend days does not vary with the time and remains constant (6.5 Cents/kWh) for all the 24 hours. By comparing the results of the optimal scheduling in scenario-3 with estimated scheduling, it is also found that the peak power demand (average for 30 days) is reduced by 7.09% on an average for all the seven households.

5. Conclusion

The core objective of this research work is to minimize the cost of electricity bill and peak power demand simultaneously. Due to conflicting behavior of these two objectives, this study has been divided into three scenarios. The first two scenarios deal with individual minimization of electricity cost and peak to average ratio. In addition, their effects on each other have been studied in scenario-1 and scenario-2. In the third scenario, both objectives have been achieved by minimizing the cost function proposed for both utilities. The proposed approach to find the optimal threshold limit of hourly power consumption is implemented in scenario-3 with the help of two stage optimization. Optimal scheduling of smart home appliances is obtained in all three scenarios as per consumer's preferences with the help of CS, hybrid GA–PSO, and ACS as core algorithms of optimization. Here, SIP and MIP is implemented to find the optimum scheduling with respective electricity pricing options. From the results of simulations for both of the case studies, it is observed that optimal scheduling in scenario-1 minimized the cost of electricity bill but also resulted in raised PAR. On the other hand, in scenario-2, PAR was minimized but electricity bill cost was raised in comparison to the cost before optimal scheduling. However, optimal scheduling in scenario-3 reduced the PAR and monthly cost of power consumption both for all the houses. Optimal scheduling of smart home appliances in scenario-3 also reduced the energy consumption during peak hours in comparison to scenario-2 by 16.39% in case-1 and 18.61% in case-2 on an average for all the households. Comparative analysis of results demonstrated the competence of the proposed model to achieve both the objectives simultaneously. The future research direction in this area can be suggested as the implementation of other artificial intelligent techniques for optimization of electricity cost and peak power demand with dynamic pricing schemes available in other utilities as different case studies.

Acknowledgment

There is no conflict of interest and no funding is received for this research work.

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