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An Intelligent Load Management System With Renewable Energy Integration for Smart Homes

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ABSTRACT Demand side management (DSM) will play a significant role in the future smart grid by managing loads in a smart way. DSM programs, realized via home energy management systems for smart cities, provide many benefits; consumers enjoy electricity price savings and utility operates at reduced peak demand. In this paper, evolutionary algorithms-based (binary particle swarm optimization, genetic algorithm, and cuckoo search) DSM model for scheduling the appliances of residential users is presented. The model is simulated in time of use pricing environment for three cases: 1) traditional homes; 2) smart homes; and 3) smart homes with renewable energy sources. Simulation results show that the proposed model optimally schedules the appliances resulting in electricity bill and peaks reductions.

INDEX TERMS Appliance scheduling, binary particle swarm optimization, genetic algorithm, cuckoo search algorithm, energy management system, electricity pricing, smart grid.

I. INTRODUCTION

Global energy demand is increasing rapidly in comparison to the steady growth of energy generation and transmission setups. Consequently, widening the demand and supply gap. In traditional grids, utilities cater this situation by increasing the total generation capacity as a function of peak demand. However, the resulted system (generation and distribution) by a large part is unutilized [1], [2]. Recently, two parallel approaches are developed to handle such situations: (i) using and promoting energy efficient technologies to reduce the aggregated power consumption, and (ii) developing strategies to control the aggregated power demand. Collectively, the two parallel approaches make DSM whereas the later approach is known as Demand Response (DR) [3], [4].

United States household electricity usage data show that 42% of energy is consumed by household appliances [5]. Major forces are creating a new paradigm on residential electricity markets as energy optimization becomes an increasingly important challenge in our society. New technologies are being deployed, including advanced meters, controllable appliances [6], distributed energy generation and storage systems, i.e., plug-in hybrid electric vehicle batteries, stand-alone storage systems, and communications capabilities. New laws are being proposed to allow electricity consumers to access pricing information. New dynamic pricing policies are likely to be implemented at the retail level over the next years [7], [8]. Energy management controllers [9] are primarily designed to control load within a single home. They often take into account the utility data like load forecasts or ToU pricing for scheduling the household appliances. On the customer side, customers have the incentive to shift their electricity usage from high peak hours to low peak hours so that their electricity bills can be reduced [10], [11].

DR is defined as "changes in electricity usage by end customers from their normal consumption patterns in response to changes in the price of electricity over time". Price based DR programs consider flattening demand fluctuations as an objective. Both the customer and the utility will get benefits from DR. It encourages the customer to reduce the peak demand in response to the incentives [12]. A DR strategy coordinates the requirements between the energy provider and the customer [13]. On the utility side, by reducing high peaks, DR programs are helpful in protecting grid from the risk of outages, reduce the usage of spinning reserves

TABLE 1. Nomenclature.

Symbol	Description	Symbol	Description
$\aleph \in N$	set of appliances	H	observation period
$\mathbf{I}$	interruptible load	$\mathbf{B}$	base load
$\alpha_i \in A$	shiftable appliances	h	total no. of time slots
ζ	appliance delay	β	length of operation time
ϕ_1	upper limit of appliance delay	ϕ_2	upper limit of appliance delay
β_{min}	minimum delay	β_{max}	maximum delay
E_T	total energy demand of a household	E_{RES}	energy production from photovoltaic module
E_{cost}	total electricity cost	$E_{h,load}$	total load during "h" hour
EP_h	electricity price during time slot "h"	E_{grid}	energy provided by grid
σ	boolean integer showing appliance ON/OFF state	M	total no. of swarm particles
S_i	position vector of swarm particles	V_i	velocity vector of swarm particles
P_{lbest}	position of best swarm particle	P_{gbest}	position of best swarm particle
t	current iteration	t_{max}	maximum iteration
$V_i^{h+1}(j)$	velocity of i^{th} particle in $t+1^{th}$ iteration	j	total no. of elements in velocity vector
S_i^h	position of i^{th} particle in t^{th} iteration	$r_1 \& r_2$	random variables
$c_1, \& c_2$	pulls for the local and global positions (constants)	w	weight of the particle's momentum
$w_{initial}$	initial weight of particle's momentum	w_{final}	final weight of particle's momentum
sig	sigmoid function used in PSO	$r_{i,j}$	random number between "i" and "j" limits
V_{min}	minimum velocity of particles	V_{max}	maximum velocity of particles
$Pvel$	random velocity of particles	P_{pos}	random position of particles
$E_{maxcost}$	maximum energy cost	$E_{Tot_{RES}}$	total amount of renewable energy
P_c	crossover rate in GA	P_m	mutation rate in GA
η^{PV}	energy conversion efficiency (%) of PV system	A^{PV}	area of the generators (m^2)
$T_{(r,t)}$	solar irradiance	T_a	outdoor temperature

during peak load periods, balance the supply demand ratio, and improve the grid reliability [14]–[16]. Further DR benefits include: (i) lower electricity price in wholesale market, (ii) adequacy saving and operational security, (iii) integrated resource planning studies, and (iv) improved choice for using DR [17], [18].

In contrast to DR programs, integration of renewable energy into residential units provides reliable, efficient and most attractive solution now a days. It can curtail electricity cost at residential premises and flatten the peaks at utility premises. The work presented in [5] and [6] uses various types of battery storage systems for electricity cost reduction alongwith grid stability. Whereas, the impact of uncertainty in renewable energy production on day-ahead market pricing is presented in [19]. In another work [20], authors analyze the impact of line limits/losses on electricity prices which later on are used for residential energy management [8].

In this paper, we present a cost efficient appliance scheduling model for residential users. Our appliance scheduling model aims at optimizing the operation time of electrical appliances. The model also takes into account the RES generated energy jointly with grid generated energy. The model uses EAs (GA, BPSO and Cuckoo [21], [22]) for generating the optimized schedules and it is simulated in ToU pricing environment. Results validate that the proposed model performs well in scheduling the household electrical appliances and provides benefits to the users by significantly reducing their electricity bills.

The rest of the paper is organized as follows. Section II describes the related work and provides motivation. Section III presents the proposed approach in detail. Section IV discusses the simulation settings and results. Section V deals with performance tradeoffs. Section VI concludes the paper. The variables used in this work are listed in table 1.

II. RELATED WORK AND MOTIVATION

Smart grid is a network of technologies that delivers electricity from power plants to the end user and connects all supply, grid and demand elements via an effective communication system. The system is the amalgamation of engineering, information and communication technologies, and management of the power grid. The improvements in these technologies can be applied to enhance automation, foster integration of distributed generation from renewables, secure the power system architecture, and enable efficient demand-side energy management. Recently, residential energy management has become an active topic with respect to research and also has a need of an implementation on the real test bed. In Energy Management System (EMS), appliance scheduling is one of the main and important parameter that needs proper attention. Several appliance scheduling strategies have been proposed by different researchers. Some of the authors designed an automatic controlling devices for scheduling the appliances to provide an optimum cost to the users. while, others used the AI techniques to schedule the appliances in an automated way [23].

EMS is deployed in a home to schedule the electricity consumption in such a way that peaks and electricity cost is reduced to the maximum extent [9]. The EMS includes

Advanced metering infrastructure, smart meters, home gateway, energy management controller, home appliances and in-home display devices. The advance metering infrastructure is like the nervous system of the EMS architecture which communicates in both ways between utility and smart meter. An optimization approach based on Real Time Pricing (RTP) combined with the inclining block rate pricing scheme is used for the power consumption of all the automatically operated appliances in the home. GA is used to optimize the operation start time of such type of appliances [24]. The GA randomly creates a solution population that consists of a certain number of individuals. Each individual contains a solution set of all kinds of variables which are represented as chromosomes. We can get the new solutions by calculating the fitness value, selecting individuals, crossover and mutation that include both old and new individuals.

The objective of the DSM strategy is to increase the use of RES, increase the economic benefit and reduce the power imported from the main distribution grid or minimize the peak load demand [5]. The objective load curve is taken as an input by the DSM system and demands for the control action in order to meet the desired load consumption. The algorithm is completely independent of the criteria that is used for generating the objective load curve. The connection moments of each shiftable device are scheduled by DSM. DSM algorithm needs to be designed in order to handle the complexities,i.e., operation time interval of electrical appliances more than one hour and able to process a large number of controllable appliances of various characteristics,i.e., different power consumption characteristics. Moreover, the aim of the DSM scheme is to get the final load curve as closer as possible to the objective load curve [25].

Several variants of time pricing are discussed in this paper, e.g., ToU and RTP [26]. In ToU, prices are well known in advance may be a year ahead and establishes a variable price structure for peak, shoulder, and off-peak hours and low peak hours. RTP is discussed in this paper and vary on an hourly basis depending on the energy demand of the market. Variable peak pricing is a hybrid of the two, and establishes variable pricing in the day. Energy can be efficiently consumed and the power consumption can be efficiently minimized by voluntary reduction of home electric consumption based on energy awareness and automatic or manual reduction of home idle appliances. Smart meters and HEM are deployed so that consumers may respond according to the behavior of energy markets and reduce their energy consumption at peak prices. The highest developments in the home area communications and networking technologies for energy management in the smart grid are presented briefly in [27]. It also gives a review of the different objects used in smart grid, offered by different companies and also explains the various challenges in the design of future EMS such as network security, etc.

A GA based optimization approach combined with a two point estimate method is used to meet the heating ventilation air-conditioning load with a hybrid renewable energy generation and energy storage system [28]. Hybrid generation systems are inherently unpredictable because of the stochastic nature of the wind, solar irradiation and load attributes. Probability density function is used to characterize the uncertainties of wind and solar generation whose statistics are obtained from past data of wind speed and solar irradiance. Fuzzy C-Mean is used for the calculation of the seasonal variations in the data. To get the optimal capacity for solar energy, wind energy and energy stored in hybrid system, GA based tool is used.

In [29], a residential load management problem is formulated and solved in terms of cardinality optimization used to form sparse patterns for Nash equilibrium. The sparse patterns significantly reduce the user discomfort which is created when cost reduction is a primary objective of optimization program. As it is understood that with the objective of cost reduction, peak reduction constraint could be violated. To overcome this issue, a Newton method to accelerate coordination of DSM strategies is used. Generally, the DSM techniques are price driven where there is a minimal consumer interaction involved [30]–[33]. To achieve cost reduction object with utility benefits, consumers' activities are predicted using hidden Markov model. Then based on the information about consumers' activities, load demand, utility supply constraints, algorithm decides weather the load will be turned ON or OFF. A similar work where interactions among various energy retailers and mobile operators are investigated [34]. These interactions are made to achieve economical goals with reduction in carbon dioxide emissions.

In DSM, cost and comfort are two major objectives subject to price and user preferences. The works done in [6], [26], [32], and [33] use stationary strategies to minimize electricity cost and user discomfort of myopic consumers. In contrast, the work [35] uses repeated energy scheduling game to model interactions among foresighted and interested consumers. They prove that stationary strategies provide sub-optimal solutions in terms of long-term cost and comfort. In contrast, authors determine non-stationary DSM strategies where consumers have choice to select any strategy based on their energy demand and comfort requirements. In [36], an integer linear programming technique is used to schedule power and time shiftable appliances. At utility premises, integration of distributed RES can help independent system operators and aggregatorsto make foresighted decisions (i.e., procurement and energy purchase) for long term cost reduction [37].

Residential users are not much aware about the importance of DR program and most of them have not tools for taking part in DR. Moreover, the commercial and industrial customers have tools and therefore widely participate in the DR programs as compared to residential users. Home appliances and their consumption are monitored, controlled and managed by HEM system. It is the most prevalent response side for automation of appliance monitoring [38]. Distributed resources are used to describe mainly three new concepts, i.e., DR, distributed generation and electricity storage. These distributed resources are connected in low and medium voltage level inside of the grid. This connection of distributed

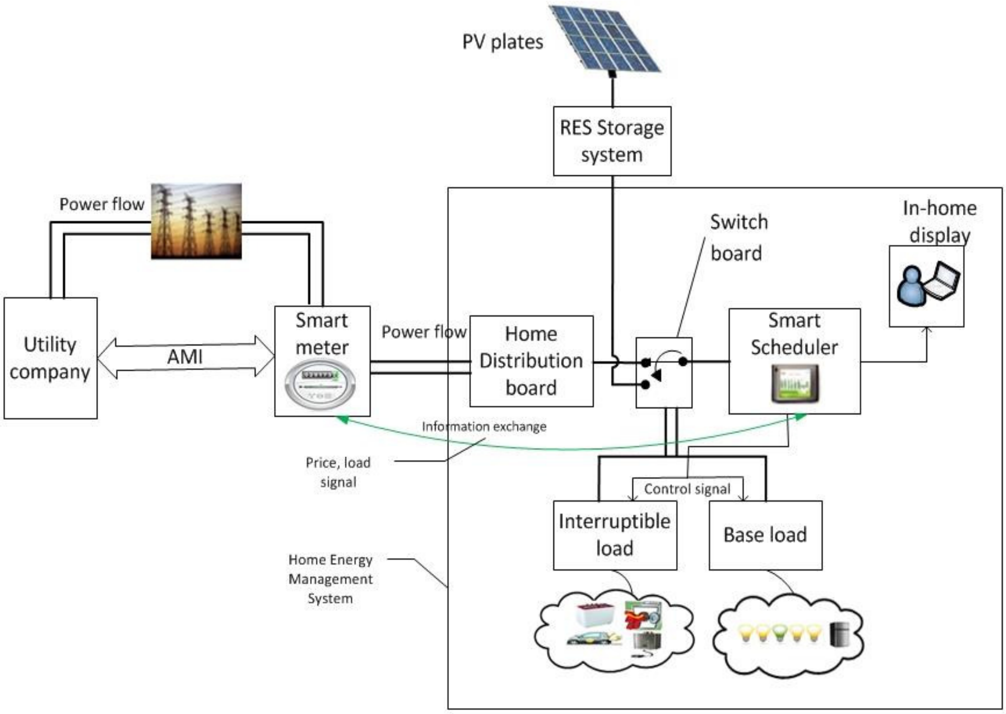

FIGURE 1. Proposed model.

resources inside of the grid represents a radical change for the operation [39]. An opportunistic scheduling scheme is proposed based on the optimal stopping rule for smart appliance automation control [6]. It calculates the best time for an appliance operation to minimize electricity bill reduction. The proposed scheme has low complexity, i.e., can be easily implemented, real time and distributed characteristics. It follows distributed threshold policy when no constraint is considered. Furthermore, if there exists a power constraint, the scheduling algorithm can be implemented in either a centralized or distributed fashion [39].

Smart grid gives opportunity to the end users to bi-directionally communicate with the utility in real time, so consumers can tailor their energy consumption based on individual preferences like price concern, user comfort, etc. Based on different usage patterns of energy, the smart grid offers differential pricing scheme in order to avoid different risk factors like blackout or load shedding, thus allows the user to curtail energy consumption during peak demand. The objective of appliance scheduling in differential pricing environment is to optimally schedule the ON-OFF cycles of appliances subject to end user electricity cost minimization. The contributions of work are listed as follows:

1) We propose a model for different types of users and loads and a simple way to model user preferences with the aim at cost and peak reductions. Then cost reduction objective function is formulated, mathematically.
2) BPSO, GA and Cuckoo search algorithms are used to solve centralized optimization problem. Control parameters of these algorithms are selected in such a way that an optimal solution is found within acceptable processing time.
3) To avoid the usage of peaking power plants during high demanding hours, on-site renewable energy and backup storage systems are used which further reduce electricity cost.

III. PROPOSED APPROACH TO OPTIMIZE ENERGY CONSUMPTION

In this section, an optimal approach for scheduling the power usage of smart appliances in a home is proposed based on the ToU pricing scheme. Accurate and reliable load management are a key element of the automation. Whereas, automation of appliances is a critical aspect of energy management in the residential sector, especially in the smart grid environment. The concept of load scheduling approach to monitor the electricity usage of appliances is introduced. Section III-A describes the conceptual model used in this work. Section III-C discusses the user categorization based on which the optimization algorithm works.

A. CONCEPTUAL MODEL

Fig. 1 shows a graphical representation of the proposed model that serves as the basis for the development of optimization algorithm. It consists of integrated power & renewable energy utility that is interested in serving all types of residential or commercial loads. The respective power grid and on-site RES act as a single node. The optimization program dispatches power to residential loads and storage system that could be utilized during high demanding hours. The energy demand of residential load is directly fulfilled by using grid energy, direct renewable energy or storage systems depending on the electricity price in particular hours. However, the on-site renewable energy source and storage system act as a ''first-choice'' for delivering energy to residential loads. In this way, the load management system reduces the energy obtained from utility which is presented and discussed in section V. Furthermore, the integration of on-site renewable energy and storage systems with HEM model is helpful in reducing high peaks on grid when energy demand is high.

B. ADVANCE METERING INFRASTRUCTURE

Rather than a single technology, advance metering infrastructure is an integration of multiple technologies such as smart metering, home area network, software interfaces, and data management applications. Alongwith these technologies, two way communication, sensors, and distributed computing make it feasible for both end users and independent system operators. The system composed of these technologies leads to make intelligent decision making, reliability, safety and ease of use [40], [41]. Regarding home area network, system includes smart meters, communicating thermostats, back-haul communication network, data centers, and data integration into new and old application platforms. According to Fig. 1, smart meter is located between home area network and utility which forwards aggregated load demand to utility via smart meter. Then based on load data, utility calculates and provides pricing signal (i.e., ToU, RTP) which later on is used for load scheduling.

C. USER CATEGORIZATION

In this work, a new approach is proposed that autonomously generates energy consumption pattern for each appliance based on the electricity price tariff. First, we categorized the energy consumers into three categories; traditional users, smart users and smart prosumers. *Traditional users*- this class of users is non-price sensitive, thus have no HEM architecture in their homes. *Smart users*- this class of users has HEM architecture but have no on-site energy generation system. *Smart Prosumers*- this type of users not only consume the grid energy but also produce some energy from the RES system and have HEM architecture and RES generation along with storage system in their homes.

D. RENEWABLE ENERGY GENERATION MODEL

Due to recent energy crises and environmental concerns, much attentions are given to the integration of renewable energy resources. Among all renewable energy sources, solar energy is most abundant and easily accessible. However, its unpredictable nature poses many questions (i.e., availability, capacity, usage) to energy retailers and prosumers. A study conducted in [42] shows that Earth receives 174,000 terawatts solar radiations and approximately 30% are reflected back to atmosphere. While, the rest are absorbed by clouds, oceans, and land masses. Then based on solar radiations, the total energy (kW) obtained from solar panels can be calculated as [43]:

$$E_t^{PV} = \eta^{PV} \times A^{PV} \times I_{r,t}(1 - 0.005(T_t^a - 25)). \tag{1}$$

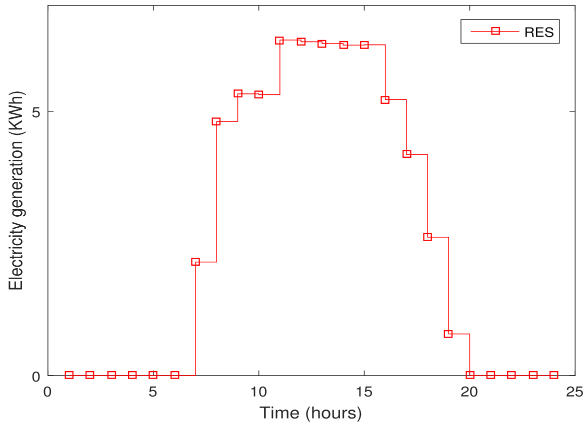

FIGURE 2. Renewable energy generation from solar panels.

This formulation addresses the recent trends in renewable energy integration into a smart home to lower electricity bill alongwith grid stability. Fig. 2 shows the amount of solar energy produced from renewable source. From $h_7 - h_{19}$, solar energy can be used for storage or to run residential load. However, from $h_1 - h_7$ and $h_{20} - h_{24}$, solar energy is not available and in this situation, optimization algorithm should be designed in such a way that it can handle residential loads even during peak hours. Keeping these tradeoffs in mind, this work utilises battery storage system to save extra energy during underload conditions. This, however, significantly reduces end user cost and flattens the peaks on grid side.

E. ENERGY MANAGEMENT MODEL

A demand side HEM model based on ToU pricing scheme for a household that is connected to the utility grid and an on-site RES is presented. The Smart Scheduler (SS) receives the differential price signal from the smart grid via smart meter and adjusts the hourly load level of the user accordingly. Firstly, the SS schedules the electrical appliances by shifting the maximum allowable load from high peak hours to low peak hours. Secondly, the SS checks the hourly energy cost and switches the load from the smart grid to the RES storage where the load costs maximum.

When SS is not included in HEM system then power (energy) is allocated to the appliances following first come first serve policy. When the SS is available, an optimal power pattern is allocated to a set of appliances that minimizes the total cost by solving the objective function.

The objective of the proposed model is to maximize the economic benefit, minimize high power imported from the grid during high peak hours and high peak demand, reduce the peak cost and exploit the use of RES.

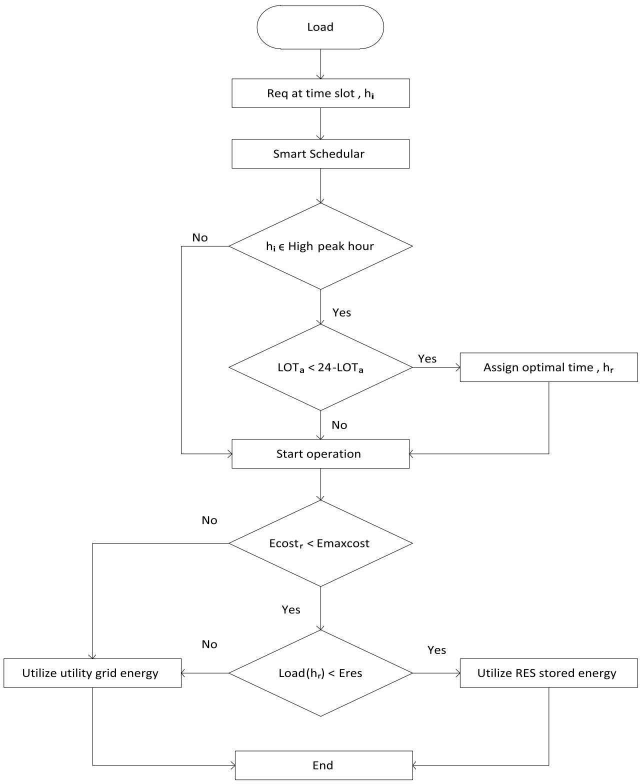

FIGURE 3. Proposed energy efficient model.

F. HOUSEHOLD ORIENTED HEMS

EMS is deployed in a home to schedule the electrical appliances in order to consume the grid and RES stored energy optimally. The HEM system is comprised of different devices; Home Grid (HG), electrical appliances and an in home display device. The home has an intelligent appliance scheduling and decision making device, i.e., SS which is embedded in HEM architecture and coordinate with the appliances. The HEM architecture is demonstrated in Fig. 1.

Three types of users are taken into account. We model daily energy consumption of a single home that acts as consumer and as a producer of electrical energy, called Prosumer. The home is equipped with an on-site RES system for local energy generation. A smart meter which provides energy price signals and a set of electrical appliances that consume energy. We divide each day into 24 equal interval of time slots. The SS optimally computes the ON-OFF schedules of household appliances.

Consider a house which contains a set $\aleph = \{a_1, a_2, \ldots, a_N\}$ of appliances; $|\aleph| \in N$. Let the observation period be H and the loads be of two types: *interruptible loads* (**I**) and *base loads* (**B**). The set **I** includes a washing machine, a cloth dryer, an electric vehicle and an electric water heater. Similarly, the set **B** contains a refrigerator and a lighting source. Once activated, the interruptible appliances are deferrable at any time. For a scheduling problem, the number of shiftable appliances is greater than zero (i.e., $A > 0$). The end user objective is achieved by optimized control actions over shiftable loads.

TABLE 2. Different appliances with their attributes.

Load types	Appliances	OT	kW
I	Washing machine	1-2am,1-3pm	1
	Cloth dryer	1-5am, 9-11am, 7-9pm	4
	Electric vehicle	5-7am, 9-10am, 8-12pm	3
	Water heater	1-2am, 4-5am, 7-9am, 5-10pm	4.5
B	Refrigerator	12am-12am	1
	Lights	12am-12am	1.5

Lets $\alpha_{a_i,h}$ denotes a set of shiftable appliances at time slot h and base load is assumed to be unscheduled.

This assumption is made since the end user is not willing to re-schedule those loads. Each appliance has fixed LOT, i.e., the number of time slots each appliance needs to be run and each appliance completes its task within 24 hours. As the SS works on the principle of load shifting, so, each appliance can bear a certain amount of delay ζ_{a_i} given as follows:

$$\zeta_{a_i} = 24 - \beta_{a_i}, \tag{2}$$

where β_{a_i} denotes the LOT of a_ith appliance. The upper and the lower limits of ζ_{a_i} are given by the following equation:

$$\psi_1 \leq \zeta_{a_i} \leq \psi_2, \tag{3}$$

where $\psi_1 = 24 - \beta_{max}$ and $\psi_2 = 24 - \beta_{min}$. If $E_{(h,a_i)}$ is the energy consumption of appliance a_i at time slot h then the total demand of a household E_T is computed as follows:

$$E_T = \sum_{i=1}^{N} \sum_{h=1}^{24} E_{h,a_i}. \tag{4}$$

Furthermore, we assume that the household generates 40% of its total demand via RES. Thus, the user must be connected to the main utility. Considering that the hourly energy production of one photovoltaic module in kWh is $E_{RES,h}$ $\forall$ h $\epsilon\{1, 2, \ldots, 24\}$, the daily generation is given by the following equation:

$$E_{RES} = \sum_{h=1}^{24} E_{RES,h} \tag{5}$$

IV. PROBLEM FORMULATION FOR APPLIANCE SCHEDULING

Given the set $A = \{a_1, a_2, \ldots, a_N\}$, where each appliance consumes different amount of energy as shown in table 2. These appliances are connected to the HEMS' SS. Our objective is to minimize the electricity bill which is formulated as follows:

$$min \left(\sum_{h=1}^{24} \sum_{i=1}^{N} E_{cost_{a_i},h} \right), \tag{6}$$

$$s.t: \sum_{i=1}^{N} \sum_{h=1}^{24} E_{h,a_i} = E_{grid}, \quad \forall \mathbf{B}, \tag{6a}$$

$$\sum_{i=1}^{N} \sum_{h=1}^{24} E_{T,h} = E_{grid,h} + E_{RES,h}, \quad \forall \mathbf{I}, \tag{6b}$$

$$\zeta_{max,a_i} \leq 24 - \beta_{a_i}, \tag{6c}$$

$$\sigma_{h,a_i} \ \epsilon \ \{0,\ 1\}. \tag{6d}$$

Eq. (6) is the cost minimization objective function and Eq. (6a) denotes energy demand and balance in case of **B**. The energy demand of **I** is always fulfilled by grid and renewable sources (eq. 6b). Eq. (6c) shows maximum waiting time that any appliance can bear. In eq. (6d), a boolean variable is given to determine weather the appliance is ON or OFF.

$$\sigma_{h,a_i} = \begin{cases} 1 & \text{if appliance } a_i \text{ is ON} \\ 0 & \text{if appliance } a_i \text{ is OFF.} \end{cases} \tag{7}$$

1) BPSO BASED OPTIMIZATION

BPSO is a heuristic population-based search technique that locates the solution to an optimization problem. Each Particle is composed of N elements. An optimal solution is found by moving the particle in the solution space. Each particle is considered as a position and each element of a particle position can take the binary value 0 (not included) or 1 (included).

Suppose a swarm consists of M particles, and each particle's (ith particle's) initial position vector S_i and velocity vector V_i are randomly initialized, respectively. Each particle checks the best particle in its neighbourhood (local best particle). Position of the best searched particle is therefore, $P_{lbest} = \{p_{lbest_1}, p_{lbest_2}, \ldots, p_{lbest_M}\}$. The best particle among all the particles is said to be global best and its position is, $P_{gbest} = \{p_{gbest_1}, p_{gbest_2}, \ldots, p_{gbest_M}\}$. Both P_{lbest} and P_{gbest} are determined by evaluating the objective function. There are two main differences between P_{gbest} and P_{lbest} with respect to their convergence characteristics. Due to larger particle inter connectivity, the P_{gbest} converges faster than the P_{lbest} but P_{lbest} is less susceptible of being trapped in local optima. Each particle updates its velocity vector using the following equation:

$$V_i^{t+1}(j) = \big(wV_i^t(j) + c_1 r_1(\ P^h_{lbest,i}(j) - S_i^h\left(j)\right) + c_2 r_2(P^h_{gbest,i}(j) - S_i^h(j)\big) \tag{8}$$

where $V_i^{h+1}(j)$ is the jth element of the velocity vector of $i$the particle in $t+1$th iteration, $S_i^h(j)$ is the position of the jth element of ith particle in tth iteration and r_1 and r_2 are random variables between 0 and 1. The constants c_1 and c_2 are the pulls for the local and the global best positions, respectively. The w is the weight of the particle's momentum and it is calculated as:

$$w = w_{initial} + (w_{final} - w_{initial}) \times \frac{t}{t_{max}} \tag{9}$$

where, both $w_{initial}$ and w_{final} are the initial weight and final weight of the particle's momentum, respectively; t is the current iteration number and t_{max} is the maximum number of iterations. Also,

$$S_i^{t+1}(j) = \begin{cases} 1, & if\, sig\ (V_i^{t+1}(j)) > r_{ij} \\ 0, & otherwise. \end{cases} \tag{10}$$

where,

$$sig\left(V_i^{t+1}(j)\right) = \frac{1}{\left(1 + \exp(-V_i^{t+1}(j))\right)}. \tag{11}$$

In BPSO, velocity of a particle coordinate is mapped to a probability using a sigmoid function and the resulting probability determines whether the coordinate takes a value of 1 or 0. The velocity of particle ranges between $-V_{max}$ and V_{max}. The cost, i.e., fitness against each particle is calculated using objective function (6). All the particles are thus ranked according to their fitness values.

After t_{max} iterations, a particle P_{gbest} is selected as an optimal solution by the SS. The P_{gbest} is the pattern of bits representing statuses of the appliances. The SS anticipates cost against this pattern for each hour and shifts this pattern to that hour where it costs the minimum. The SS shifts the adjustable load from grid to RES stored energy where grid energy costs the maximum to the residential user. The pseudo code and flow chart of the algorithm are given in Algorithm 1 and Fig. 3, respectively.

2) GA BASED OPTIMIZATION

GA is used to perform search in the solution space to find an optimal solution (pattern) to the objective function (cost minimization) subject to its defined constraints. For a population of M number of randomly initialized chromosomes (chromosomes represent the solutions to the problem), each one is constructed as an array of bits, the length of the chromosomes is directly related with the number of household electrical appliances. Once the population is created, the objective function is evaluated in terms of fitness. A fitness function is chosen such that the algorithm achieves a final load curve as close to the objective load curve as possible. The fitness function is given as follows:

$$Fitness = \sum_{i=1}^{M} \sum_{h=1}^{24} (E_{h,a_i} \times EP_h) \quad \forall\, h \in \{1, \ldots, 24\} \tag{12}$$

Selection allocates more copies of those solutions with higher fitness values (i.e., $min(Fitness)$ values) and thus imposes the survival of the fittest mechanism on the candidate solutions. Many selection procedures namely roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection are used. In this work, binary tournament is used in which two individuals are randomly chosen with a chance. The probability of each individual is calculated and individuals having probability greater than 0.5 but less than 1 are selected for further reproduction to produce new fitter offsprings.

As the algorithm progresses, new populations of chromosomes are produced from the existing ones which have possibly better fitness than the previous population. This operation is called crossover. There is a chance that the chromosomes of the two parents randomly crossover to form new fittest offsprings. In this work, one point crossover is used which is shown in Fig. 4.

Algorithm 1 Appliance Scheduling Algorithm Based on BPSO

Require: number of particles, swarm size, t_{max}, electricity price, LOT and appliance power consumption rating
Randomly generate the particles' positions and velocities
$P_{gbest} \leftarrow \infty$
for $t = 1$ **to** *swarmsize* **do**
  initialize (swarmsize,tbits)
  $P_{vel} \leftarrow randomvelocity()$
  $P_{pos} \leftarrow randomposition(swarmsize)$
  $P_{lbest} \leftarrow P_{pos}$
end for
for h $= 1$ **to** 24 **do**
  Validate Constraints
  for $i = 1$ **to** M **do**
    if $f(\sigma_i) < f(p_{lbest,i})$ **then**
      $p_{lbest,i} \leftarrow \sigma_i$
    end if
    if $f(P_{lbest,i}) < f(P_{gbest,i})$ **then**
      $P_{gbest,i} \leftarrow P_{lbest,i}$
    else
      $P_{gbest,i} \leftarrow P_{gbest,i}$
    end if
    Decrement one from the TOT of the working appliance
    if $E_{cost} > E_{maxcost}$ **then**
      if $E_{Tot_{RES}} > E_{load_h}$ **then**
        Switch the load to RES storage system
      else
        Consume the grid energy
      end if
    end if
    Return $P_{gbest,i}$
    Update the velocity vector using Equation 8
    Update the inertia weight factor using Equation 9
    Update the position vector using Equation 10
  end for
end for

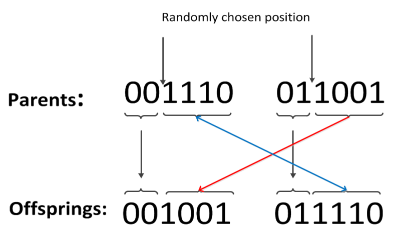

FIGURE 4. **Single point crossover.**

Where two parents produce two offsprings. Parental combination at random points may lead to the creation of possibly new and better solutions. A large crossover rate ensures faster convergence of the solution. Through extensive simulations, we have found the best *Crossover Rate* $(P_c) = 0.9$ subject to the objective function (6). In order to avoid repetition of the same chromosomes in the population genetics, randomness is needed so that a chance is provided to randomly change the gene of a child (refer to Fig. 5). Thus, mutation locally but randomly modifies a solution. Again, through extensive simulations, we have found a relation for the best mutation rate given as follows:

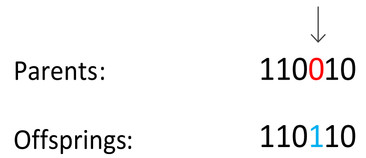

FIGURE 5. **Mutation operator.**

$$Mutation\ Rate\ (P_m) = \frac{1 - P_c}{10}. \tag{13}$$

In order to preserve elitism, both parent and offspring populations are combined. The resulted population is evaluated using the fitness function and sorted based on their fitness values. Eventually, the fittest individuals are chosen for next generation and the best chromosome among the M fittest individuals is selected as an optimal solution during that generation.

The SS checks the energy consumption pattern against the selected fittest individuals and sends control signal to the appliances either to operate or not. The SS uses this fittest individual and checks the 24 hours time horizon and shifts load to a time slot where it costs the minimum. Moreover, SS shifts the acceptable load from utility grid to RES stored energy where grid energy costs the maximum to the residential user.

It is worth mentioning here that the user provides information about the operation time and the power rating of each newly added appliance or an appliance changed with an existing one in the HEM system; in-home display is used for this purpose. Once the information is provided, the algorithm adaptively adjusts all the parameters accordingly to generate new solutions.

3) CUCKOO SEARCH BASED OPTIMIZATION

Cuckoo search belongs to an evolutionary algorithm category which can be used to find optimal solution of any problem. This algorithm works on the breading behavior of cuckoo species. Some Cuckoos dump their eggs in other birds nests, called "host nests". Host birds discover the eggs that are laid by other Cuckoos for reproduction. The number of host nests are fixed and the discovering probability of the host is $Pa = [0, 1]$. Cuckoo search algorithm finds the optimal solutions on the basis of following rules.

- Every Cuckoo dump only one egg in the randomly selected nest.
- For reproducing next generation, the nests having superior quality eggs (or solutions) among others are migrated.

Algorithm 2 Appliance Scheduling Algorithm Based on GA

Require: popsize, maxgen, tbits
Generate initial population
initgeneration(popsize,tbits)
for $h = 1$ **to** 24 **do**
  Evaluate the population and record current Fittest chromosome
  $[best]$ = Evaluatefitnessfunction(cost,popnew,popsize)
  if $best_{a_i} == 1$ **then**
    $LOT_{a_i} = LOT_{a_i} - 1$;
  end if
  Search for chromosome optimal position in the entire search space
  for $t = 1$ **to** m **do**
    $h = find_minimum_cost(best, f(best), t)$
    Shift to that hour the current best chromosome
  end for
  if $E_{cost}(h) < E_{max}$ **then**
    if $E_{Tot.RES} > load_h$ **then**
      Switch the load to RES storage system
    else
      Consume the grid energy
    end if
  end if
  Generate new population
  for $j = 1$ **to** $popsize$ **do**
    Select crossover pair
    Select(a,b)
    if $p_c > rand$ **then**
      crossover(a, b)
    end if
    if $p_m > rand$ **then**
      mutation(c,insite)
    end if
    New population generated
    popnew(popsize,tbits)
  end for
  $Validate - constraints(popnew)$
end for

- The number of host nests are fixed and the eggs discovering probability is 0 or 1. Accordingly, the host birds threw the egg for next generation or leave for producing new nest.

Lévy flight is performed for generating new solutions: (i) for a Cuckoo "i", (ii) animals search diet in random way naturally. Normally, the foraging method of an animal depends on random walk because the next step is based on the basic status and transition probability to the next state. A Lévy flight is a random walk in which step lengths are distributed by probability distribution. After maximum number of steps, the distance from the beginning of the random walk tends to a stable distribution.

Algorithm 3 Appliance Scheduling Algorithm Based on Cuckoo Search

Require: host nests, P.a, max. iterations,
Objective function f(x), x = 1 to n
n = no. of host nests
for $h = 1$ **to** 24 **do**
  no. of host nests are fixed, $n = 1, 2, 3, \ldots n$
  while $i \leq maxgen(n)$ **do**
    get a solution through random walk (levy flight)
    consider local best
    for $c = 1$ **to** d **do**
      compare $lbest$ with $nextbest$
      if $nextbest >$ lbest **then**
        $gbest = nextbest$
      else
        $gbest = lbest$
      end if
      if $best_c == 1$ **then**
        $LOT_c = LOT_c - 1$
      end if
    end for
    if $E_{cost}(h) < E_{max}$ **then**
      if $E_{RRS}(h) > load(h)$ **then**
        use RES
      else
        use grid energy
      end if
    end if
  end while
end for

V. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed appliance scheduling schemes, we simulate daily energy use of a set of household appliances. The attributes; number of appliances, Operation Time (OT) and the power rating of the appliances are shown in table 1. Simulations are performed for three main cases: i) Traditional homes (without HEMS), ii) Smart homes, iii) Smart homes with RES system. Peak shaving was realized by load adjustment of devices with soft schedules. Shiftable appliances requests were altered by systematically switching them off and on.

A. ELECTRICITY TARIFF

The ToU pricing policy is used for billing of the energy users. ToU pricing establishes a variable price structure for high peak, shoulder peak, low peak and off peak hours. These prices are typically established well in advance by the utility grid. The ToU pricing provides financial benefits to the users who take part in DR program for shifting their load from high peak to off peak hours. In ToU pricing scheme, the cost of electricity is charged at different rates during different time horizons. Fig. 6 shows the ToU signal sent by utility to the end users.

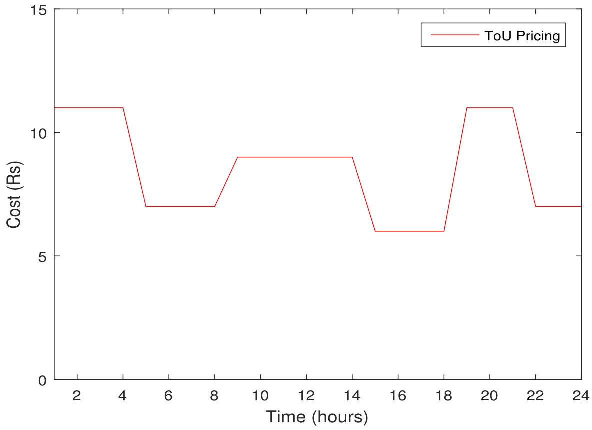

FIGURE 6. ToU pricing scheme.

TABLE 3. Control parameters for BPSO method.

Swarm size	Particle size (bits)	Maximum iteration	Velocity Range
100	6	600	[-4 4]

TABLE 4. Control parameters for the GA method.

Populations size	Maximum Generation	Crossover	Mutation
100	200	90%	10%

Simulation Performance parameters are:

i) Energy consumption: Electrical Energy consumption(kWh) is the amount of power consumed by the household appliances during any time slot *h*.

ii) cost: It is defined as the cost paid by the user to the utility corresponding to the energy consumed by the different appliances at time slot *h*. The Electricity cost is calculated in Pakistani Rupees (Rs).

The control parameters of BPSO are table 3:

i) Swarm: Swarm is the number of particles used to analyze the performance of the proposed BPSO technique.

ii) Velocity: The particles move in the search space and try to find the optimal solution. The particles move between two ranges of the velocities, i.e., V_{min} and V_{max}.

iii) Appliance status: It determines whether to operate the appliances.

The control parameters of BPSO and GA based HEM architecture are listed in tabl. 3.

The control parameters of the GA based HEM architecture are discussed as under (table 4):

i) Chromosome: Parameters of the solution, i.e., genes are concatenated to form a string known as a chromosome. The size of each chromosome is 6-bits.

ii) Population size: Population size is the set of chromosomes. Each chromosome represents a possible solution.

iii) Crossover operator: Crossover is a genetic operator used to vary the programming from one generation to the next generation. It forms new elements for the new population from the current population.

iv) Mutation operator: Mutation is sparingly applied to the genes randomly chosen for elimination. It randomly flips the bits within a single chromosome.

TABLE 5. Control parameters for the cuckoo search.

Number of Nests	Maximum Iteration	Discovery Rate
50	4000	0.25%

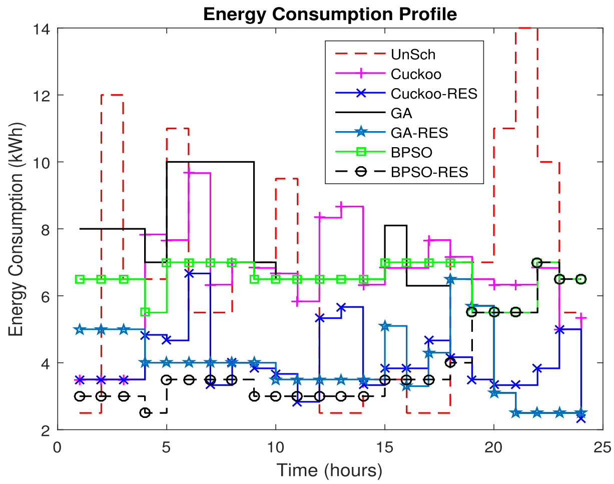

FIGURE 7. Energy consumption profile.

The control parameters of Cuckoo search algorithm are given as (table 5):

i) Cuckoos: The scheme is proposed on the basis of some special type of cuckoo species which provides different parameters for problem solution. We assume these parameters in the form of 0 and 1.

ii) Host Nests: The number of host nests represent number of possible solutions. From these solutions, we select the solution of high fitness value.

iii) Discovery Rate: This parameter shows the discovery rate of eggs (or solutions) discovered by the host bird. Its value ranges between 0.5 and 0.50. However, in our work, the value of discovery rate is fixed 0.25.

1) APPLIANCE SCHEDULING SCHEMES

In order to demonstrate the performance of the proposed model for appliance scheduling algorithms, the simulation result and evaluation of proposed schemes in three scenarios are analysed and discussed in this section.

a: CASE I (WITHOUT HEMS)

Traditional user has no HEM architecture and thus uses grid energy when required. The energy obtained from the grid and is consumed by appliances in different time slots is shown in Fig. 7.

The electricity cost for unscheduled load under the ToU pricing scheme is demonstrated in Fig. 8.

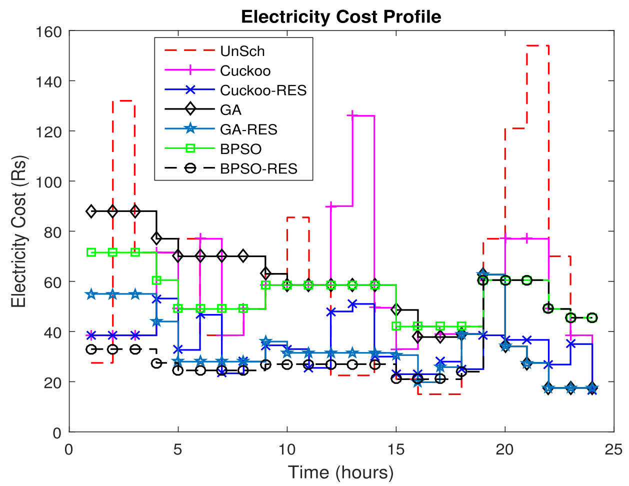

FIGURE 8. Energy cost profile.

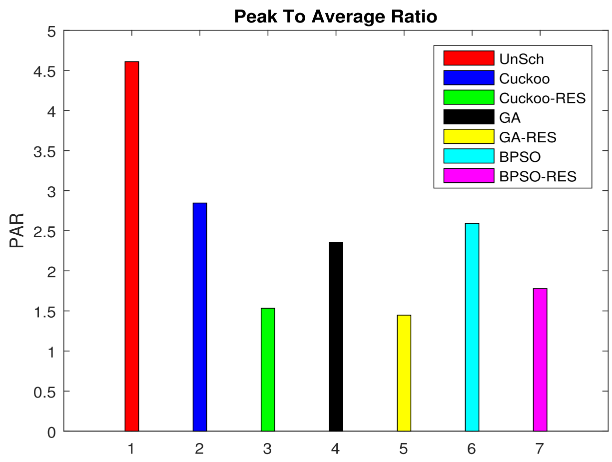

FIGURE 9. PAR.

TABLE 6. Summary of results obtained from simulations.

Optimization Technique	Case	HEM	RES	Total cost	Saving
BPSO	2	√	×	1307	5.35%
		×	×	1381	
	3	√	√	795	42.43%
		×	×	1381	
	1	√	√	795	39.17%
		√	×	1307	
GA	2	√	×	1310	5.03%
		×	×	1381	
	3	√	√	813	42.43%
		×	×	1381	
	1	√	√	813	37.93%
		√	×	1310	
Cuckoo	2	√	×	1285.2	6.93%
		×	×	1381	
	3	√	√	785.7	43.10%
		×	×	1381	
	1	√	√	785.7	38.86%
		√	×	1285.2	

b: CASE II (HOUSEHOLD ORIENTED HEM)

Two types of HEM architecture is presented for smart users. The HEM architecture based on BPSO avoids the appliances to operate during high peak hours. The performance of the BPSO based HEM architecture in making optimal schedules for the household appliances in 24 hours time horizon is shown in Fig. 7 and the cost paid to the utility against these consumption is demonstrated in Fig. 8. It is evident from the Fig. 7, the SS not only shifts the load from high peak hours to low peak hours, but it also checks and shifts the load to that hour where it costs minimum.

The smart user having HEM architecture based on GA consumes the energy optimally and benefices the household by shifting load during peak hours to off peak hours taking into account the different user preferences and constraints. The behaviour of load towards energy consumption after taking part in DR is shown in Fig. 7. Similarly, Figs. 7, 8 show the energy consumption and electricity cost of residential loads using Cuckoo search algorithm. Load has been shifted from on-peak hours (h_{1-5}) to off-peak (h_{6-10}) hours. This, however, reduces electricity cost and high peaks caused due to load shifting where users rely only on grid energy (Fig. 9). With this kind of benefits, many customers can be motivated to participate in efficient utilization of energy via scheduling their appliances. The daily savings of the residents having HEM architecture in their homes against the traditional users is tabulated in table.6

c: CASE III (PROSUMER ORIENTED HEM)

In this case, the user takes advantage of the differential pricing scheme as well as utilizes the stored RES energy optimally to minimize their electricity cost. The home taken into consideration in this scenario, is the amalgamation of HEM (BPSO, GA and Cuckoo) and RES generation along with storage system. The SS utilizes the RES stored energy where grid energy costs maximum and shifts the load from the grid to RES energy and thus minimizes the electricity cost by a very significant amount. The performance of all HEM architectures towards the optimal consumption of the grid energy as well as the stored RES energy is shown in Fig. 7. According to Fig. 2, solar energy is available during specific time slots depending upon solar irradiations and total area (eq. 1). So, this energy can directly be utilized during high demanding hours ($h_{1-5,18-22}$) or can be stored in batteries.

High peaks during off-peak hours have been eliminated by the utilization of RES stored energy. During on-peak hours ($h_{1-5,18-22}$), users do not fully rely on the utility grid and prefer to use RES stored energy. In this way, electricity cost and high peaks are significantly reduced. Furthermore, it will lead towards grid stability. The energy cost of the HEM with RES system against the energy consumption and peaks reduction are presented in Figs. 8, 9. At the end, tables 7 and 8 provide the comparisons of the proposed scheme with other schemes used in the literature. It is clear that the proposed system is more efficient towards residential load management. Furthermore, the integration of on-site RES enhances its feasibility for smart home.

TABLE 7. Trade-offs made by the proposed optimization techniques.

User	Appliances	Mechanism	Optimization Technique	Appliance operation	Achievement	Cost paid
Traditional	Unscheduled	N/A	N/A	Manual	Maximum comfort, no delay	High electricity bill
Smart	Scheduled	HEM	GA	Automatic	Lower electricity bill	Comfort level, delay
Smart Prosumer	Scheduled	HEM with RES	GA	Automatic	Lowest Electricity bill	Low comfort level, low delay

TABLE 8. Comparison of the proposed scheme with other schemes.

References	Technique	Pricing scheme	Cost saving	Load categorization	User categorization	RE integration	User comfort
[22]	PSO	N/G	✓	✗	✗	✗	✗
[23]	PSO	N/G	✓	✗	✗	✗	✗
[29]	GA	N/G	✓	✗	✗	✓	✗
[33]	Game Theory	RTP	✓	✓	✗	✗	✓
Proposed	GA, BPSO, Cuckoo	ToU	✓, Table VI	✓	✓	✓	✓

N/G=not given, RE=renewable energy.

Note: Selection of the best solution in the current generation is necessary for directing the EAs towards the global optimum. The tendency to select the best individual in the current generation is known as selective pressure; it plays an important in maintaining genetic diversity. High selective pressure has a negative impact on genetic diversity leading to premature convergence. On the other hand, low selective pressure prohibits the EAs to converge to an optimum solution in reasonable time. We have achieved the balance between convergence rate and pre-mature convergence using simulation based iterative mechanism.

VI. TRADE-OFFS MADE BY THE OPTIMIZATION SCHEMES

HEMS enables the user to optimally schedule the appliances and to shift the load from high peak hours to off peak hours. There exists a trade-off between electricity cost and delay that comes due to load shifting. HEM anticipates the optimal time for appliances, uses the grid energy optimally and allows the users to pay minimum electricity bills while satisfying the user comfort level. The HEM incites the users by reducing the electricity bill. On the other side, the SS shifts the load so the users bear some delay in the operations that need to be completed in high peak hours, thus a minimum sacrifice over some user comfort level are to be accepted.

Smart prosumers have both HEM and RES generation and storage system. This class of households has an intelligent HEM system and thus allows the user to optimally consume energy and reduce the electricity bill. Besides RES system, this class of users enables them to optimally use the grid energy as well as their own on-site RES generation energy. Thus, they get maximum advantage of the ToU pricing scheme and optimally consume the grid energy and RES stored energy. Finally, an overall comparison is done in table.6. Traditional user pays the maximum electricity bill for the same energy used by the smart user. The smart user has HEM architecture, thus get maximum benefits from the ToU pricing scheme.Although, the comfort level of traditional user is although maximum but he/she pays the maximum electricity bill to the utility so there exists a trade-off between user comfort and electricity bill. In the second case, the user pays minimum electricity bills as compared to traditional user, but compromises on some comfort level. In the third case, the user optimally uses the energy and pays for utility much low as compared to Smart users. Table 7 shows the trade-offs made by the proposed techniques.

The load shifting pattern of GA based HEM architecture is smooth, avoids load peaks during high peak hours, increases the life time of the in-home electrical circuitry. It is evident from the Fig. 7 that GA schedules the appliances in much sophisticated way and allows the appliances to complete the task with minimum delay. Whereas, the BPSO gets benefit from differential pricing scheme and shifts the load to off peak hours much efficiently. On the other hand, the user having BPSO based HEM architecture suffers high delay as compared to the user having HEM architecture based on GA, and also suffers high load peaks that may not be good for the stability of user in-home circuitry.

From Fig. 7, it is clear that the smart prosumer having BPSO based HEM architecture may not be able to use the RES stored energy optimally as compared to GA based HEM architecture due to the high peak loads. As the behaviour of BPSO towards load management is non uniform, i.e., it creates peaks and shifts all the load from high peak hours to low peak hours and this leads towards peak generation. The average delay using BPSO based HEM architecture is very high as compared to the GA based HEM architecture and the user has to wait enough to complete the task. On the other hand, GA based HEM architecture response to the RES stored energy is very well and utilize the RES energy where the grid energy costs maximum to the user. The GA algorithm shifts the load from high peak to low peak hours uniformly, as it may not shift the load completely from high peak to low peak hours but it shifts in a manner that cost is minimized and the peaks are also reduced.

The users having HEM architecture based on GA suffer less delay to operate their appliances and complete their daily routine tasks. The GA based algorithm benefices the users by paying minimized electricity cost, relatively affordable delay and optimal utilization of RES energy.

Regarding Cuckoo search algorithm, the simulation results show the supremacy of the proposed technique when compared with counter part techniques. It is evident from the results that Cuckoo search optimally schedules the smart appliances from on-peak hours to off-peak hours in order to reduce electricity cost and high peaks. Sometimes users desire to shift all load to low peak hours for reducing electricity cost. However, it may create high peaks on grid side. So, algorithms are designed in such a way that alongwith cost, high peaks are also reduced.

Therefore, it can be concluded from the simulation results that the GA based HEM architecture shows better performance to obtain minimum electricity cost and minimum delay. The GA based HEM algorithm efficiently uses heuristics to find the optimum appliance task completion. From table 6, it is clear that both the optimization algorithm reduce the electricity cost. Smart user having GA based HEM architecture gets more advantage over the smart user having BPSO based HEM architecture. Furthermore, the smart prosumer having GA based HEM architecture efficiently exploits the RES energy and benefices the end user by paying minimum electricity bill.

VII. CONCLUSION AND FUTURE WORK

This paper presented a new HEM model based on ToU pricing scheme with and without RESs. In order to optimally consume grid and RES energy, the proposed model used EAs; BPSO, GA and Cuckoo. The results obtained from the simulations revealed that cost saving is achieved in terms of minimized user electricity bill. By using BPSO, GA and Cuckoo algorithms, the proposed model significantly reduced the electricity bill and high peaks. From table 6, it can be concluded that with and without RES, Cuckoo search algorithm provides better results (6.93%, 43.10 %) in comparison to GA and BPSO.

In the future, we will investigate other optimization techniques for further reducing the electricity bills of end uses.

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