IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 12, 2017, accepted October 4, 2017, date of publication October 17, 2017, date of current version March 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2017.2763624

Towards Optimization of Metaheuristic Algorithms for IoT Enabled Smart Homes Targeting Balanced Demand and Supply of Energy

SAQIB KAZMI[1], NADEEM JAVAID[1], (Senior Member, IEEE), MUHAMMAD JUNAID MUGHAL[1], MARIAM AKBAR[1], (Member, IEEE), SYED HASSAN AHMED[2], Member, IEEE), AND NABIL ALRAJEH[3]

[1]COMSATS Institute of Information Technology, Islamabad 44000, Pakistan
[2]School of Computer Science and Engineering, Kyungpook National University, Daegu, 41566, South Korea
[3]College of Applied Medical Sciences, King Saud University, Riyadh 11633, Saudi Arabia

Corresponding author: Nadeem Javaid (nadeemjavaidqau@gmail.com)

This work was supported by the Deanship of Scientific Research, King Saud University, under Grant RG-1435-0037.

ABSTRACT Internet of Things enabled smart grid (SG) is one of the most advanced technologies, which plays a key role in maintaining a balance between demand and supply by implementing demand response (DR) program. In SG, the main focus of the researchers is on home energy management (HEM) system, which is called demand side management. Appliance scheduling is an integral part of HEM system as it manages energy demand according to supply, by automatically controlling the appliances and shifting the load from peak to off peak hours. In this paper, the comparative performance of HEM controller embedded with heuristic algorithms, such as harmony search algorithm, enhanced differential evolution, and harmony search differential evolution, is evaluated. The integration of renewable energy source (RES) in SG makes the performance of HEM system more efficient. The electricity consumption in peak hours usually creates peaks and increases the cost but integration of RES makes the electricity consumer able to use the appliances in the peak hours. We formulate our problem using multiple knapsack theory that the maximum capacity of the consumer of electricity must be in the range, which is bearable for consumer with respect to electricity bill. Feasible regions are computed to validate the formulated problem. Finally, simulation of the proposed techniques is conducted in MATLAB to validate the performance of proposed scheduling algorithms in terms of cost, peak-to-average ratio, and waiting time minimization.

INDEX TERMS Smart grid, knapsack, enhanced differential evolution, harmony search algorithm, home energy management system, demand side management.

NOMENCLATURE

Variables and Subscripts	Description
t	Time interval
U	Energy consumed by fixed appliances
V	Energy consumed by flexible appliances
W	Energy consumed by un-interruptible appliances
ρ	Power ratings of appliances
F_{ap}	Set of fixed appliances
S_{ap}	Set of shift-able. appliances
UI_{ap}	Set of un-interruptible appliances
γ	ON/OFF status of appliances
$P(t)$	Total power consumption of shift-able., fixed and un-interruptible appliances
$C(t)$	Total electricity bill
λ	Pricing signal (RTP)
E_{PV}	Energy generated from RES
η	Efficiency of solar inverter
I_r	Solar irradiance
A_{PV}	Area of solar panel

T_a	Outdoor temperature
C	Maximum allowed power consumption
x_{ij}	Initial population
x_l	Lowest value in population matrix
x_u	Highest value in population matrix
U_j	Trial vector
V_j	Mutant vector
F	Mutant factor
CR	Crossover rate
x_{rl}	Target vector of EDE
τ_{sch}	Operation start time of appliances
τ_{ot}	Operation end time of appliances
H_{ij}	Harmony memory
H_l	Lowest value in HM
H_u	Upper limit of values in HM
x_i'	New harmony vector
V_{r1}	Target vector of HSDE
H_{ji}	Trial vector of HSDE
NI	Maximum no. of iteration

I. INTRODUCTION

Energy demand around the world is increasing day by day. To fulfil this demand the existing generation is facing a lot of challenges. It is estimated that total energy demand at the end of 2020 will increase by 75% as compared to energy demand in 2000 [1]. This increase may force utilities to reshape electricity generation and distribution in order to avoid demanding energy challenges. In order to fulfil energy demand, different means of electricity generation like renewable and sustainable energy resources (RSER) are introduced in the power system. The integration of renewable energy sources (RESs) in the existing traditional grid increases system complexities and dynamics [2]. Smart grid (SG) is another advancement in the field of power system. In SG, advanced information and communication technologies (ICTs) are introduced in traditional grids which provide customers the ability to interact with utility [3]. Advanced metering infrastructure (AMI) equips each home with smart meter that gathers energy demand information from customer and uploads to the utility server. SG allows integration of renewable and distributed energy generation to diminish the effects of CO_2 on environment and to optimize energy consumption. On the other hand demand side management (DSM) is a very important aspect of SG that efficiently manages the energy demand of end users by enabling the exchange of information between utility and consumers. The EDE parameters are summarized in Table 2. These programs aim at improving grids stability by reducing peak formation [4]. So, utilities and customers can manage the energy generation and consumption through the implementation of DSM programs by providing incentives or encouraging the customers to participate in energy management programs. The two-way flow of information and energy in SG keeps the electricity consumers informed about the pricing rates, load on utility, load shedding schedules and any type of equipment failure due to any natural or crew cause. It enables the utility company to monitor and analyze the real time information of consumers so that responsive actions may be taken according to utility/end-users demand. End users can take economic benefits by shifting peak load to off-peak hours using different optimization techniques.

In a traditional power system, utility companies manually shed the selected load of consumers during peak hours to make their operations safe. On the other hand, load shifting in SG is accomplished in peak hours to avoid peak formation. This not only benefits the users but also the utility company. This strategy in turn increases the reliability of the grid. Although shifting the load from high peak to low peak hours reduces the peak load and electricity cost, but it disturbs user comfort. So, there is a trade-off between user comfort and cost saving, which cannot be achieved at the same time. Thus, peak to average ratio (PAR), energy price signals, daily energy consumption and user comfort are the constraints needed to be considered. Beside considering end users desires and needs, utility companies also provide incentives to motivate consumers to reschedule their load to mitigate high peaks. Such challenges have motivated the need for intelligent energy management algorithms that can handle all types of loads and responds to price variations.

To address the aforementioned challenges, this paper presents energy management algorithms to schedule household appliances while meeting the constraints. The algorithms used in this paper are harmony search algorithm (HSA), enhanced differential evolution (EDE) algorithm and our proposed hybrid technique; harmony search differential evolution (HSDE) algorithm. The behavior of the system embedded with these algorithms is smart and user satisfactory with respect to billing, PAR, energy consumption and the waiting time.

The rest of the paper is organized as follows: Section II discusses the related work. Section III elaborates proposed system model and problem formulation is provided in Section IV. Proposed schemes are discussed in Section V. Feasible regions are briefly discussed in Section VI. In Section VII performance evaluation through simulation of proposed algorithms is elaborated in detail. Section VIII concludes this paper.

II. LITERATURE REVIEW

Researchers around the world work to optimally schedule the appliances to benefit the consumers. Most of the electric utility companies are investigating and implementing SG to make the existing power system advanced, reliable, self-healing and economical. The use of sensors, communication and computational ability and controlling characteristics in SG enhance the overall operation of electric power transmission system [5]. PAR, daily energy consumption, electricity cost and the hourly energy consumption of shift-able. and throttle-able appliances of the consumers are the constraints and the objective function in [6], all of which are to be minimized. This is accomplished by shifting the high energy consuming loads to off peak hours which helps to minimize the energy consumption in the peak hours. The authors formulate the initial optimization problem, to minimize the energy cost of the consumers by determining of the optimal usage of the power and operational time of throttle-able and shift-able. appliances. The authors use the distributed algorithms, which find the near-optimal schedule with minimal information exchange between the residential scheduler and consumers. The smart appliances present in smart homes work in automated fashion that provide consumers high comfort at less expense. In order to make home energy consumption more efficient and to control the power supply and demand numerous researches are presented.

Khosla [7] present a review of different research works on a wide range of energy management controllers for smart homes which reduce energy consumption, PAR and energy wastage. Various HEM schemes, pricing schemes, such as real time pricing (RTP), critical peak pricing (CPP), time of use (TOU) and day ahead pricing (DAP) and energy consumption are discussed in detail. Bao *et al.* [8] propose a hybrid approach (WDO-DE) from two existing techniques, i.e., wind driven optimization (WDO) and differential evolution (DE) algorithms. Fifteen benchmark functions are tested which contain unimodal, multi-modal, low dimensional and high dimensional to check the performance of proposed algorithm. The experimental results show that the proposed algorithm can be feasible in both low-dimensional and high-dimensional cases. The simulation results show that the performance of WDO-DE algorithm is better than genetic algorithm (GA), binary particle swarm optimization (BPSO), WDO, DE, and PSO to reach the optimal solution. The application of heuristic algorithms is not confined to scheduling of energy consumption of appliances, these algorithms are used in vast number of applications in many other fields such as image segmentation, cloud resource allocation, multi-level thresholding etc. as in [9] the authors propose a new quantum wind driven optimization (QWDO) for path planning of unnamed combat air vehicle (UCAV) in the battlefield considering the different threats and constraints. Two test instances are chosen in order to evaluate the performance of the proposed algorithm. The experimental results depict that the QWDO algorithm is an appropriate and reliable technique to solve the UCAV path planning problem and when compared with other algorithms it shows a better search performance. The combined pricing schemes of TOU and inclined block rate (IBR) is used for bill calculation in [10]. In this paper, the authors present an efficient DSM model for residential energy management system in order to avoid peak formation while decreasing electricity bill and preserving user comfort level within acceptable limit. For this purpose, three heuristic algorithms (GA, BPSO, and ACO) are used to evaluate the objective function. They suggest that the GA based EMC is better in term of electricity bill reduction and PAR minimization and maximization of user satisfaction than BPSO and ACO. However the computational time of the algorithm is higher. Arafa *et al.* [11] reduce the computational time by introducing evolutionary algorithm in an enhanced way, that improves the performance (convergence rate and accuracy) of DE called EDE for load scheduling in homes. It has less number of parameters to control. The algorithm is tested on 47 benchmark functions. All the steps are followed as in DE only the number of trial vectors is increased to minimize the chance of repetition of selection reduces. Many research works are still in progress to improve the performance of the algorithm in order to make them more compatible with increasing demands.

Moon and Lee [12] study a society based load scheduling problem with different classes of appliances in the grid. While designing the optimization algorithm the overall society′s satisfaction is kept under consideration. They design the smart grid with various constraints such as minimize energy consumption, alter peak formation and limit the budget. The overall society electricity usage pattern is observed keenly and sum of net consumption of all homes and their electricity cost are compared which give near-optimal scheduling. On the base of collected data the lower and upper bounds of the objective function are formulated. The simulation results show that the algorithm is effective in treating heterogeneous residences.

In [13], the negligence of user comfort in the previous papers is given consideration along with electricity cost saving and PAR reduction. They propose GA based algorithm for DSM. Five types of appliances are taken for scheduling and their mathematical models are formulated by considering thermal and comfort constraints. The pricing scheme used in this paper is RTP. When there are peak hours they integrate micro grid with the traditional grid so that the bill can be reduced and also user comfort can be increased.

The algorithms enable the consumers to pursue the best consumption benefits within consumption range. To improve the financial benefits of the electricity consumers, a novel concept of cost efficient load scheduling framework is introduced in [14]. The authors merge the two pricing techniques RTP and DAP by using fractional programming approach. They have explained the effect of simple power shifting of specific appliances on the consumption cost, to show the direct relationship between consumption load pattern and cost. Further proposed algorithm allows the consumers to fully utilize the electricity with remarkable savings of bill. Another contribution of the paper for the cost saving and minimization of CO_2 emission in environment is integration of RES into the grid. This RES along with the fractional programming reduce the electricity cost efficiently. However, the PAR minimization and user comfort are not discussed in the paper. Ahmad *et al.* [15] propose an optimized HEM system (OHEMS) to minimize the electricity bill in response to dynamic pricing by scheduling the household appliances using four heuristic algorithms; GA, BPSO, WDO and bacteria foraging optimization (BFO) algorithm. Moreover they offer a new hybrid GA-PSO (HGPO) algorithm which incorporates the positive features of GA and PSO algorithms in a single algorithm. RES and ESS are integrated to encourage the consumers to take part in DSM.

TABLE 1. Categories and parameters of appliances.

Load type	Appliances	Power rating (kW)	Daily usage (hours)
Fixed	AC Refrigerator Oven	5 1.5 3	16 19 14
shift-able	Water pump Water heater Vacuum cleaner Fan	3.5 2.5 0.8 0.7	13 17 14 16
Un-interruptible	Dish washer Washing machine Cloth dryer Light	1.5 1.5 3.4 0.8	10 5 4 20

A new meta-heuristic, population based algorithm mimicking the improvisation process by musicians was developed by Geem *et al.* [16] in 2001. It is simple concept based, less parameterized and easily implementable algorithm. It has been applied to various engineering and non engineering optimization problems successfully. Unlike GA, HSA generates a new optimal vectors considering all the available vectors in the search space, whereas, in GA only two parent vectors are selected to produce one better offspring. Therefore the flexibility and accuracy of HSA is better than other algorithms. We have further enhanced its performance by hybridizing it with EDE in this paper.

The fixed value of pitch adjustment ratio (PAR) and arbitrary distance bandwidth (bw) in improvisation step of the traditional HSA cause poor performance and increase the number of iterations needed to find the optimum solution. Mahdavi *et al.* [17] introduce a variable PAdR and bw values in the improvisation step to overcome the drawback. Moreover to check the effectiveness of improved HS, they apply this to different constrained and unconstrained benchmark functions. In [18], unit commitment problem is solved using HSA. The total production cost is minimized by optimizing the controllable parameters within the limits. The HSA has fast convergence time and is economical than conventional and improved GA. Fesanghary and Ardehali [19] present a novel meta-heuristic approach based on HSA to solve economic dispatch (ED) problem to minimize the total power generation cost. They formulate two approaches; swarm intelligence concept and hybrid harmony search quadratic programming (HSQP) to improve the quality and convergence rate of HSA. Karthigeyan *et al.* [20], the authors compare the performance of HS, bio-geography based optimization (BBO) algorithm and improved harmony search (IHS) algorithms for solving constraint economic dispatch power in power system. Twenty generating units are tested through these algorithms with ramp rate limits and valve point loading constraint. The improved HSA gives minimum fuel cost and good convergence characteristics as compared to HSA and BBO. The integration of RES in SG, its economical benefits in term of cost reduction and challenges while integration is discussed in [21]. Different types of RESs are available for integration

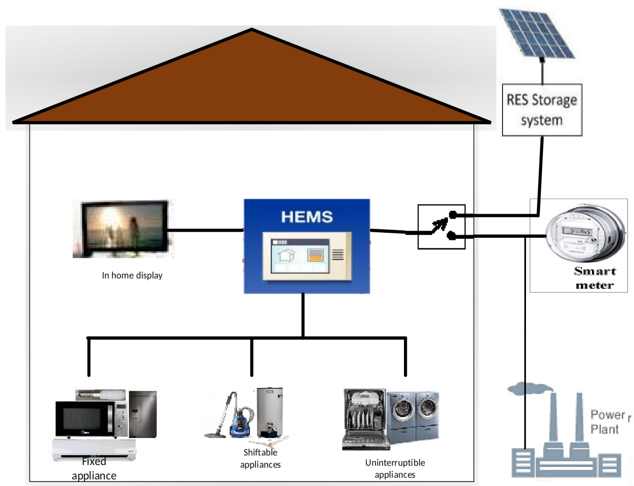

FIGURE 1. Proposed system model.

with SG in market nowadays. Phuangpornpitak and Tia [22] discuss in detail, the various sources of renewable energy, their utilization and trends of technological advancement in RES integration with SG. The security issues and impact of RES on environment are also elaborated.

III. PROPOSED SYSTEM MODEL

DSM in a smart grid makes operation of the grid more reliable and stable. In smart home it manages and controls the energy usage by scheduling the appliances according to the scheduler embedded in the HEM system [23]. The smart meter allows two way flow of information between consumer and utility, i.e., pricing signal and load demand. The information is sent to the EMC by smart meter and EMC accordingly schedules the appliances in the smart home based on pricing signal, load demand and user preferences. Simple architecture of HEM system is shown in Fig. 1.

A. LOAD CATEGORIZATION

We classify appliances into three categories; fixed, shiftable. and uninterruptible appliances according to consumer usage behavior. The power rating of appliances and time of operation in a day is summarized in Table 1. Details of these categories are given below.

Literature review

Techniques	Objective	Domain and Features	Limitations
Quadratic programming (QP) [6]	PAR reduction	DSM for shift-able. and throttle-able appliances	User comfort is not discussed
HEM scheme, RTP, CPP, TOU, DAP [7]	Energy consumption, PAR and energy wastage discussed	EMC in smart home	No technical contribution, no simulation
WDO-DE [8]	To increase accurate and convergence rate of traditional WDO and DE	Test fifteen benchmark function	Increased convergence speed cause some local optimum information lost
Quantum QWDO [9]	Path planning of unnamed combat air vehicle (UCAV)	Air force training centre	Not defined
GA, BPSO and ACO [10]	PAR and bill reduction preserving user comfort	Residential energy management	Computational time is higher due to complexity in algorithms
EDE [11]	Optimization of power consumption to reduce bill	HEM system	Performance fluctuates if number of appliances or consumers increase
EDE [12]	PAR and electricity bill reduction	Society based load scheduling	User comfort was ignored
CPCT+GA [13]	User comfort maximization, PAR and cost minimization	HEM system in Smart home	GA become more complex and convergence rate become slow
Fractional programming (FP) [14]	Cost minimization	Integration of DER in smart home	PAR is not minimized
GA, BPSO, WDO, HGPO [15]	Cost and par minization	OHEMS by integrating RES and ESS	User comfort is not considered
HSA Algorithm [16]	Introduction of new technique	Heuristic algorithm	Complex technique compare to EDE
IHS [18]	Convergence rate of HSA	Five constrained and two Unconstrained functions	Slow convergence rate
HSA, HSQP [19]	Total generation cost minimization	Economic dispatch problem	Complexity increase due to quadratic programming merging into HSA
HSA, IHS, BBO [20]	Convergence rate and cost	Economic dispatch problem	Need to consider more constraints
RES integration with SG [21]	To explore different sources of RE so that CO_2 emission could be minimized	SG integration benefits the society and the users of electricity	Challenges and complexities while integration are not discussed

1) FIXED APPLIANCES

These are called fixed appliances because their operation length cannot be modified. The scheduler has to schedule these appliances between user defined time-slots. These appliances are light, AC, refrigerator and oven. We represent set of fixed appliances as F_{ap} and its power consumption as U. $f_a \epsilon F_{ap}$ has power rating of ρf_a, then total power consumed by fixed appliances in each timeslot is calculated using the following equation,

$$U(t) = \sum_{t=1}^{T} \left(\sum_{f_a \epsilon F_{ap}} \rho f_a \times \gamma f_a(t) \right), \tag{1}$$

where, $a = \{1, 2, \ldots, n\}$, $T = 24$ for one day, $\gamma f_a(t)$ is ON/OFF state of the appliance in the respective time-slot.

2) SHIFT-ABLE APPLIANCES

These appliances are those which can be shifted to any time-slot and when required can be interrupted during operation. These appliances include vacuum cleaner, water pump, water heater, and fans. As the AC and fans are both used for cooling purpose, the scheduler will schedule them accordingly so that user can get maximum comfort. We represent shift-able. appliances as S_{ap} and its power consumption by V. $s_a \epsilon S_{ap}$ has power rating of ρs_a, then the total power consumed by shift-able. appliances in each time-slot is calculated in the following equation,

$$V(t) = \sum_{t=1}^{T} \left(\sum_{s_a \epsilon S_{ap}} \rho s_a \times \gamma s_a(t) \right), \tag{2}$$

where, $\gamma s_a(t)$ is the ON/OFF state of the appliance in that hour. Our focus is to minimize the per hour cost of each appliance, as a result, the overall cost will be reduced.

3) UN-INTERRUPTIBLE APPLIANCES

These appliances can be delayed or schedule earlier but once started operation cannot be interrupted until the operation completes. Washing machine, cloth dryer and dishwasher are included in this category. UI_{ap} is the set of un-interruptible appliances such that $ui_a \epsilon UI_{ap}$ and ρui_a is the power rating of each appliance. The total power consumption W of this category appliances can be calculated as,

$$W(t) = \sum_{t=1}^{T} \Bigg(\sum_{ui_a \epsilon UI_{ap}} \rho ui_a \times \gamma ui_a(t) \Bigg). \tag{3}$$

B. INTEGRATION OF RES

The roof of smart home is fitted with rooftop photovoltaic (PV) energy source. The smart home is not fulfilled whole of its electricity demand by the PV source rather only when the utility is providing electricity with peak pricing, the PV source operates. The EMC integrates the PV source with the utility grid when required. In each time-slot the power generated by PV source is $E_{PV}(t)$.

The PV source provides the energy for the time-slots $t_\alpha - t_\beta$, so the total energy generated each day by the PV source can be calculated as,

$$E_{PV} = \sum_{t=t_\alpha}^{t_\beta} E_{PV}(t), \tag{4}$$

The PV source can be integrated only if it is meeting a minimum capacity defined below,

$$E_{PV} \geq E_{PV}^{min}. \tag{5}$$

In the smart home forecasting device of the expected PV generation is installed according to which the scheduler schedules the appliances. The forecasted output power of PV source is affected by many factors like solar irradiance I_r, area of the solar panel A_{PV}, the outdoor temperature at that time $T_a(t)$ and inverter efficiency η. The generated output power of the PV source can be calculated by, [24].

$$E_{PV} = \eta_{PV} \times A_{PV} \times I_r(1 - 0.005(T_a(t) - 25)), \tag{6}$$

C. ENERGY CONSUMPTION MODEL

The total energy consumption of all the appliances in each hour can be calculated using the following equations,

$$P_T(t) = W(t) + V(t) + U(t), \tag{7}$$

$$\begin{aligned} P_T(t) = &\sum_{f_a \epsilon F_{ap}} \Bigg(\sum_{t=1}^{24} \rho f_a \times \gamma f_a(t) \Bigg), \\ &+ \sum_{s_a \epsilon S_{ap}} \Bigg(\sum_{t=1}^{24} \rho s_a \times \gamma s_a(t) \Bigg), \\ &+ \sum_{ui_a \epsilon UI_{ap}} \Bigg(\sum_{t=1}^{24} \rho ui_a \times \gamma ui_a(t) \Bigg). \end{aligned} \tag{8}$$

To calculate the total energy consumed (demand of consumer) in a day, the per hour energy consumption is calculated and added.

D. ENERGY COST MODEL

The electricity cost is calculated by multiplying pricing signal with energy consumed by appliances.

$$C_T = \sum_{t=1}^{T} (P(t) \times \lambda(t)), \tag{9}$$

where, λ is pricing signal used in our work. We have taken RTP scheme which has per hour changing behavior w.r.t price and remains unchanged in that hour. The price or rate at which electrical energy is supplied to consumers is called tariff. Numerous electrical tariffs are available to define the energy pricing over a day such as ToU, DAP, RTP, CPP etc.

IV. PROBLEM FORMULATION

Formulation of objective function is a key step in optimization problem. In this paper, the objective function is defined as electricity consumption cost minimization to achieve maximum user comfort. The smart home is equipped with smart meter which sends the consumer's energy demand and preferences to the utility company. The utility accordingly offers DR signal which contain necessary load scheduling and optimization. The smart meter can directly communicate with EMC and grid. The EMC defines operating schedule of household appliances and communicates with appliances using communication technologies. Home appliances are categorized based on operating time and energy consumption requirement for efficient management of energy. We formulate our problem as knapsack that the total electricity consumption must not exceed the maximum capacity defined, i.e.,

$$\max \sum p_i \times x_i, \tag{10}$$

$$s.t., \sum_{i=1}^{n} w_i \times x_i \leq C, \tag{11}$$

where, p_i shows the profit of each item, w_i represents weight of each item and x_i represents the binary number 1 and 0 means ON/OFF state of each appliance. (11) shows that the collective weight after considering maximum profit must not exceed the capacity C of the knapsack. We consider appliances as items and weight as power ratings of appliances. The operational cost of an appliance is taken as its profit. Our objective is to minimize the electricity cost by getting maximum profit,

$$\min \sum_{t=1}^{T} \sum_{i=1}^{m} P_T \times \gamma_i(t), \tag{12}$$

$$s.t., \sum_{t=1}^{T} \sum_{i=1}^{m} P_T \times \gamma_i(t) \times \lambda(t) < C, \tag{13}$$

and,

$$\tau_{sch} = \tau_{ot}, \tag{14}$$

where, $\gamma_i(t)$ is the ON/OFF state of the appliance at the time-slot t, τ_{sch}, τ_{ot} represent the operation start and ending times

TABLE 2. Parameters of EDE.

Parameters	Values
Population size	300
x_l	50
x_u	100
Mutation factor (F)	0.5
Crossover rate (CR)	0.3, 0.6, 0.9
Max. iteration	300

of the appliance and C is the maximum allowable power to be consumed. Violation of this constraint may lead to peak formation and system stability issues. For this purpose, the scheduling algorithms must follow the knapsack constraint. When the amount of consumed power exceeds the maximum limit, the EMC computes new optimal allocation using an algorithm and sends control message to the appliances. Once the power consumption constraint is satisfied the scheduler gives a consumption pattern, now accordingly we formulate our energy consumption cost.

V. PROPOSED SCHEMES

The appliance scheduling problem formulated in section IV is evaluated using three heuristic algorithms (HSA, EDE and our proposed technique HSDE). Contrary to classical optimization techniques like linear programming (LP) [25], integer linear programming (ILP) [26], and mixed integer linear programming (MILP) [27], heuristic algorithms poses fast convergence rate and simple steps to reach the optimum solution. The proposed algorithms are discussed in detail below.

A. EDE

The EDE algorithm is advanced form of differential evolution algorithm introduced by Storn and Price [28] in 1995. It has now become one of the most common technique to solve the scheduling problem. This algorithm has only three parameters; mutation, crossover, and selection. The tuning control parameters are size of the population, scaling factor of mutation, and crossover rate. Like all other algorithms the first step is the random population generation. The generation of population in EDE algorithm is simple given as,

$$x_{ij} = x_l + rand(1) \times (x_u - x_l), \tag{15}$$

where, x_{ij} is the initial population and x_l and x_u are lower and upper limits of the values in the population. This population is in the form of real numbers between the upper and lower limits which is given in the parameters defined. Once the population is generated it is converted to binary number by any function like sigmoid function. The three operations of EDE are briefly discussed below.

1) MUTATION

It expands the search space of the problem. For mutation three vectors are selected randomly. One vector is taken as target vector and the difference of other two vectors are multiplied with mutation factor F and the result is added to target vector to get the mutant vector,

$$V_j = x_{r1} + F \times (x_{r2} - x_{r3}), \tag{16}$$

where, V_j is a mutant vector, X_{r1}, X_{r2} and X_{r3} are the target and other two randomly selected vectors to produce mutant vector.

2) CROSSOVER

It incorporates successful solution from the previous generation. Once the mutation step is completed, EDE algorithm performs crossover operation to produce trial vectors. The trial vector is generated from the variables of mutant vectors and variables of target vectors,

$$U_{j1} = \begin{cases} V_j, & \text{if } rand(b) \leq CR_1, \\ x_{r1}, & \text{if } rand(b) > CR_1, \end{cases} \tag{17}$$

where, U_{j1} is the trial vector, CR represents crossover rate. The variable to be selected for trial vector will be chosen from target and trial vector while keeping (15) in consideration. The difference between DE and enhanced DE (EDE) lies here that in DE only one trial vector is generated to replace the target vector selected from the population while in EDE five trial vectors are generated. Three of which are produced at different crossover rates as shown in the following equations,

$$U_{j2} = \begin{cases} V_j, & \text{if } rand(b) \leq CR_2, \\ x_{r1}, & \text{otherwise}, \end{cases} \tag{18}$$

$$U_{j3} = \begin{cases} V_j, & \text{if } rand(b) \leq CR_3, \\ x_{r1}, & \text{otherwise}. \end{cases} \tag{19}$$

The two trial vectors are generated below,

$$U_{j4} = rand(b) * x_{r1}, \tag{20}$$

$$U_{j5} = rand(b) * V_j + (1 - rand(b)) * x_{r1}. \tag{21}$$

3) SELECTION

The trial vectors and target vector are test by fitness function. Among six vectors; five trial vectors and one target vector, the one which is fittest will replace the target vector in the population,

$$x_{r1} = \begin{cases} U_{ji}, & \text{if } F(U_{ji}) > F(x_{r1}), \\ x_{r1}, & \text{otherwise}. \end{cases} \tag{22}$$

Once the mutation, crossover and selection is completed the algorithm will continue search for next fittest value until maximum iteration defined reaches.

B. HSA

HSA is introduced by Geem *et al.* [16]in 2001. It is formed from the concept of the improvisation process of a musician in which the musician always search for perfect state of harmony. The musician tries to find pleasing harmony just as optimization techniques search for global best solution. The musician makes various combination of pitches stored in the

TABLE 3. Parameters of HSA.

Parameters	Values
HM size	30
H_l	0
H_u	1
HMCR	0.9
Number of appliances	9
$PAdR_{min}$	0.4
$PAdR_{max}$	0.9
bw_{min}	0.0001
bw_{max}	1
Max. Iteration	200

harmony memory. If all the pitches make a good harmony one by one, those pitches are stored in the library/memory and the chance of producing better harmony in the next try increases. Same process happens in the engineering optimization where each decision variable chooses initial values from the search space and makes single solution vector. If this solution vector is fitter than the previous one, then search for more better solution (global best) continues until stopping criteria reaches. The parameters used in HSA are defined in Table 3.

The HS algorithm requires less mathematics and no initial value setting of the decision variables. The main steps of HS algorithm are

1) Harmony memory generation
2) Improvisation of new harmony from HM
    a) Harmony memory consideration rate (HMCR) adjustment
    b) PAdR adjustment
    c) Random selection
3) Update HM
4) Repeat step 2 and 3 until stopping criteria reaches.

1) HARMONY MEMORY GENERATION

Initial HM is generated randomly,

$$H_{ij} = H_l + rand(b) * (H_u - H_l), \tag{23}$$

where, H_{ij} represents the set of random values in the HM, H_l and H_u are the lower and upper limit of values in the HM.

2) IMPROVISATION OF NEW HM

A new harmony vector x' is produced from HM considering HMCR, PAR and random selection. Each value in a new harmony vector is taken by comparing with HMCR and PAdR values. The value of x' can be chosen from x'_1, x'_2, x'_3, ..., x'_n with probability of HMCR and 1-HMCR, these values can be taken from the entire feasible region x_{ij}.

$$x' = \begin{cases} x'_i \in [x'_1, x'_2, x'_3 \cdots, x'_n], & \text{with prob } HMCR, \\ x \in H_{ij} & \text{with prob } 1 - HMCR. \end{cases} \tag{24}$$

Each value in the new harmony vector x' is checked whether it should be pitch adjusted or not.

$$pitch\ adj\ for\ x'_i = \begin{cases} yes, & \text{with prob } PAdR, \\ no, & \text{with prob } 1 - PAdR. \end{cases} \tag{25}$$

The value of probability (1-PAdR) shows that no adjustment is required for the variable but if the pitch adjustment check is satisfied, then the variable x'_i is adjusted below,

$$x'_i = x'_i + rand(b) * bw, \tag{26}$$

where, bw is the arbitrary distance bandwidth.

3) UPDATE THE HM

The new generated harmony vector $x' = [x'_1, x'_2, \cdots, x'_n]$ is compared with the worst harmony vector in HM using objective function, in our case minimum cost is fittest one. If the new vector is better than worst one then new one will take place of the worst one in the memory.

4) STOPPING CRITERIA

Once the maximum number of iterations are completed, the algorithm stops its execution.

C. HYBRID HSDE ALGORITHM

The hybrid HSDE has the common features of both EDE and HSA in it. The random selection step of HS algorithm is replaced by the fitness check steps of EDE which provides a good result in terms of user comfort and PAR reduction. The steps of HSDE are same as HS algorithm except the improvisation of harmony the random selection is replaced by fitness evaluation of the new harmony vector and randomly selected target vector. The fittest vector is stored in the harmony memory and then search for the next fittest vector starts until some stopping criterion is reached. The working principle of HSDE algorithm is summarized in Algorithm 1. The parameters used in HSDE are defined in Table 4.

The target vector for evaluation of fitness is selected in the following equation,

$$H_{r1} = V_{r1} + F \times (V_{r2} - V_{r3}), \tag{27}$$

where, H_{r1} is mutant vector, V_{r1} is target vector, F is mutant factor, V_{r2} and V_{r3} are other two randomly selected vectors from HM. After mutation, crossover step is followed same as in EDE. Here only three trial vectors are generated for evaluation so the computational time is reduced,

$$H_{j1} = \begin{cases} H_{r1}, & \text{if } rand(b) \le CR_1, \\ V_{r1}, & \text{otherwise}, \end{cases} \tag{28}$$

$$H_{j2} = \begin{cases} H_{r1}, & \text{if } rand(b) \le CR_2, \\ V_{r1}, & \text{otherwise}, \end{cases} \tag{29}$$

$$H_{j3} = \begin{cases} H_{r1}, & \text{if } rand(b) \le CR_3, \\ V_{r1}, & \text{otherwise}. \end{cases} \tag{30}$$

TABLE 4. Parameters of HSDE.

Parameters	Values	Parameters	Values
HM size	300	H_u	1
H_l	0	$PAdR_{max}$	0.9
$PAdR_{min}$	0.4	Crossover rate (CR)	0.3, 0.6, 0.9
Mutation factor (F)	0.5	Max. Iteration	200
HMCR	0.9	Bw_{max}	1
Bw_{min}	0.0001		

The selection of trail vector in HSDE will be same as in EDE that the fittest value among the trial vectors, target vector and new generated harmony vector will be saved in the memory.

$$H_{ij} = \begin{cases} x', & \text{if } F(H_j) < F(x') > F(V_{r1}), \\ H_j, & \text{if } F(V_{r1}) < F(H_j) > F(V_{r1}), \\ V_{r1}, & \text{if } F(H_j) < F(V_{r1}) > F(V_{x'}). \end{cases} \quad (31)$$

VI. FEASIBLE REGIONS

The feasible region contains the set of possible solutions which satisfy all the constraints of a system. In this work the feasible regions for cost vs waiting time termed as user comfort and cost vs load are defined. The scheduler ensures that the power consumption should be done in such a way that the cost does not exceed the range defined in feasible region. The feasible region for waiting time and cost have trade-off behavior as shown in Fig. 2. When the delay is maximum, the electricity bill lies in the range between $28.05 - 57.54$ cents for minimum and maximum loads as shown by P_2 and P_3 respectively. While the electricity cost is maximum when the waiting time is zero with maximum and minimum power consumption as shown by points P_5 and P_1 respectively.

Fig. 3 shows feasible region for electricity cost and electricity consumption with the help of P_1, P_2, P_3, P_4 and P_5 forming a trapezoidal shape. Point P_1 represents the electricity bill when minimum possible energy consumption (minimum load) is scheduled with minimum price value in the RTP signal. Point P_2 shows the electricity bill when minimum load is scheduled with maximum price value in the RTP signal. Similarly points P_4 and P_5 represent the electricity bills when maximum load (all operating appliances) are scheduled with minimum and maximum price values in the RTP signal. As the pricing signal is always set by the utility company and the consumer can never change or modify it, the consumer can only schedule their appliances accordingly so that maximum saving could be achieved. We have put a constraint that the scheduler must always schedule the appliances of the smart home in such manner that the cost at any time-slot must not exceed 350.6 cents. The point P_3 is the point of constraint given to the scheduler.

VII. SIMULATION RESULTS

In this section, we discuss the simulation results and analyze the performance of the scheduling algorithms in term of electricity cost savings, user comfort and PAR. We take eleven different appliances with different energy demands and different operation times normally used in the homes. RTP pricing signal has been used for billing purpose. The simulation is performed for the time period of 24 hours.

Algorithm 1 HSDE Algorithm

Initialize algorithm parameters (HMCR, HMS, CR, PAdR, bw, F, I)
Generate the harmony memory

for *{p=1:NI}* **do**
  Find $f(x^{worst})$
  Generate a new harmony vector (x_i')
  for x_i' = *1:HMS* **do**
    if *rand (1)< HMCR* **then**
      $x' = \text{HM[i][j]}$ where $i \in (1, 2, \ldots, \text{HMS})$ **if** *rand(1) < PAdR* **then**
        $x_i' = x_i' * \text{rand}(1) * \text{bw}$
      end if
    end if
    else
      Select three harmony vectors to generate mutant and trial vectors
      Mutation
      $V_j = x_{r1} + F \times (x_{r2} - x_{r3})$
      Crossover
      $U_{j1} \begin{cases} V_j & \text{if } rand(b) \leq CR_1 \\ x_{r1} & Otherwise \end{cases}$
      Check for the fittset one among trial vector
      if $f(V_j) < f(x')$ **then**
        Replace x^{worst} with trial vector Else
        Replace x^{worst} with x'
      end if
    end if
  end for
  Update the harmony for next iteration
end for
Continue until termination criteria reaches

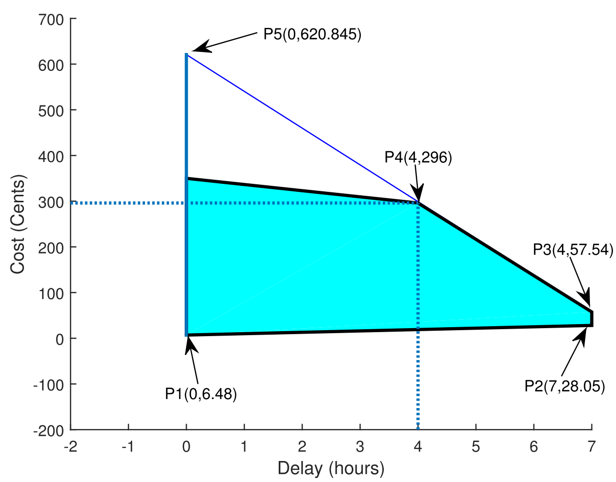

FIGURE 2. Feasible region cost vs waiting time.

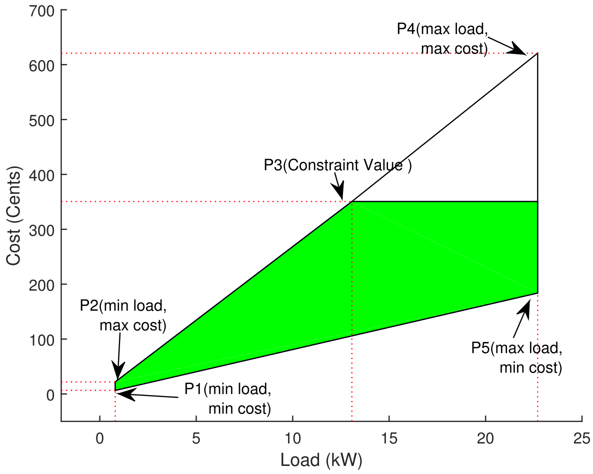

FIGURE 3. Feasible region cost vs load.

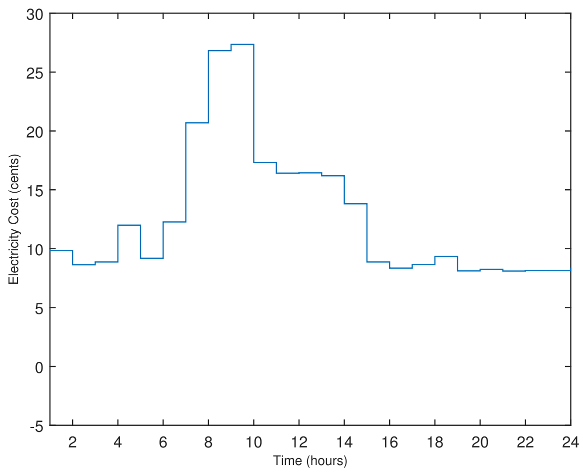

FIGURE 4. RTP.

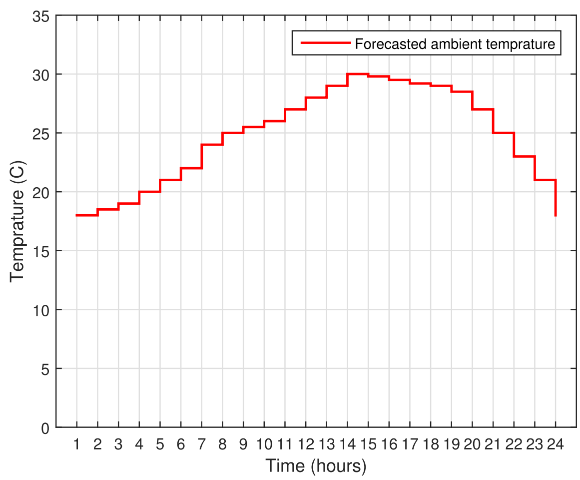

FIGURE 5. Forecasted daily temperature.

Fig. 4 and Fig. 5 are forecasted input pricing and temperature signals given to the HEM system from utility company and METEONORM 6.1 for Islamabad region of Pakistan. The forecasted outdoor temperature is formulated to inform

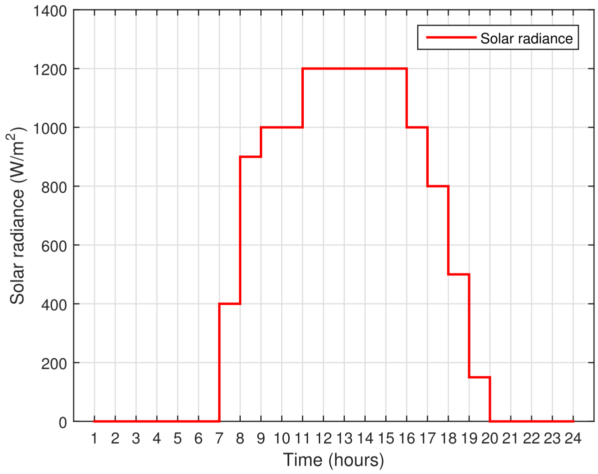

FIGURE 6. Solar irradiance.

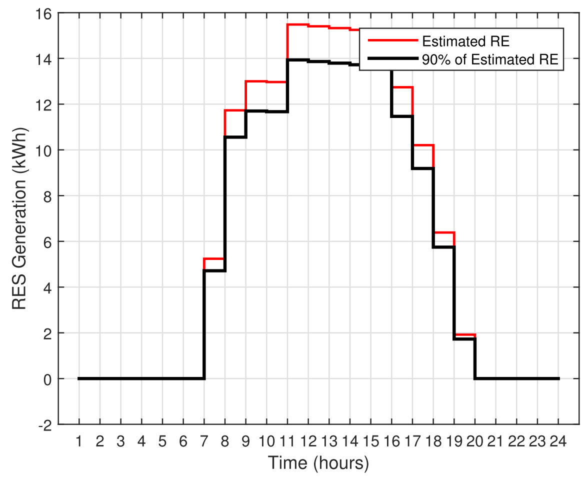

FIGURE 7. PV system generation.

the scheduler how much generation is possible for that day. The RTP signal is made by utility on the average consumption behavior of the consumers for the last three months. The price in each hour is changing and from 7 : 00 a.m to 3 : 00 p.m it is comparatively high and expensive. Similarly temperature forecasted for 24 hours is high at noon.

The conversion efficiency of generator, area of generator, solar irradiance and outdoor temperature are the factors effecting the generation of PV system as modeled in (6). The 90% of estimated power generated by PV system is utilized by the consumers at day time to reduce their electricity bill and the remaining 10% is utilized by system to facilitate integration complexities. Fig. 6 and Fig. 7 present the solar irradiance and the estimated electricity generation from PV system.

Fig. 8a shows the hourly electricity consumption without RES and ESS integration. Peaks are formed in unscheduled scenario and the three algorithms have optimized the consumption by uniformly distributing the load over the scheduling horizon. Though EDE and HSA has shifted maximum

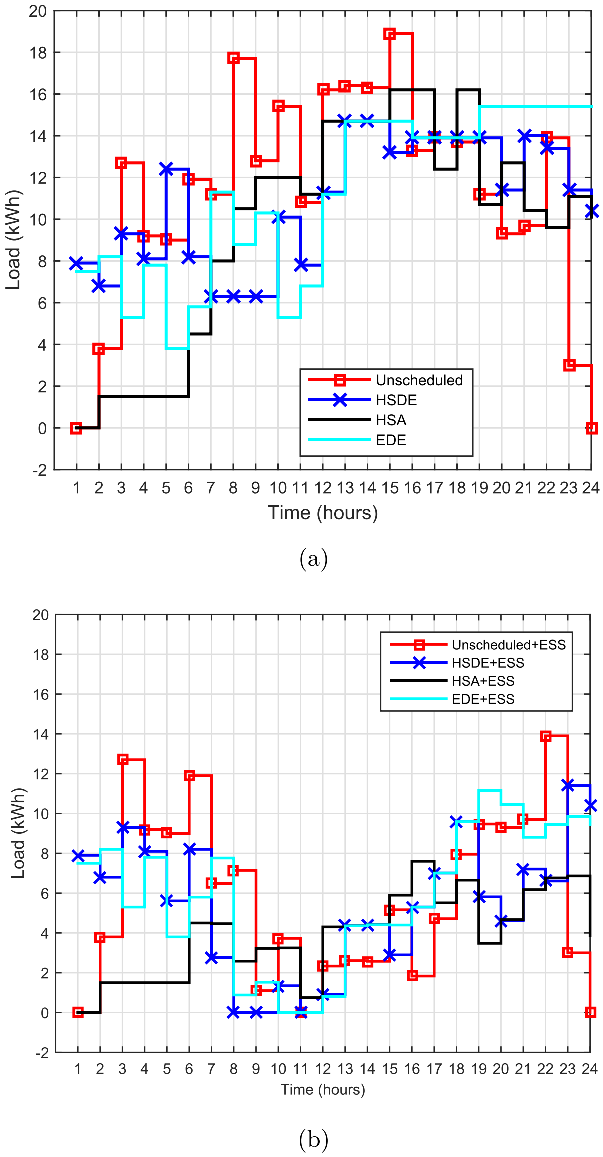

FIGURE 8. Energy consumption per hour. (a) Energy consumption per hour without RES. (b) Energy consumption per hour with RES.

load to the ending time-slots, however, their peaks are still lower than peaks of unscheduled pattern. Peaks are formed in unscheduled scenario in the time-slots 8 and 15 touching 17.8, and 18.9 kWh, respectively. The hybrid technique, i.e., HSDE shows moderate behavior throughout the scheduling horizon. HSA shows some peaks in the ending time-slots 15, 16 and 18, it has maximum electricity consumption of 16.2 kWh. It has shown minimum and negligible consumption in the starting hours, i.e., $1-6$. EDE based scheduling technique reduces the peaks and provides moderate consumption pattern. It has minimum electricity consumption in time-slot 1 and 3, i.e., 4.6 and 5.1 kWh, respectively, and maximum value of consumption in any time-slot is 15.6 kWh in the time-slots $19-24$.

The hourly energy consumption patterns of unscheduled and scheduled load along with RES and ESS integration are presented in Fig. 8b. The unscheduled load pattern has a peaks of 12.9, 11.95 and 14 kWh in time-slots 3, 6 and 22, respectively. It has minimum consumption in time-slot 9 and zero consumption from utility in time-slots 1, 11 and 24. Rest of the time-slots are showing the moderate consumption. Using HSA technique with RES and ESS, the peaks in unscheduled pattern are reduced up to 7.5 kWh in time-slot 16. As compared to unscheduled energy consumption pattern, the per hour energy consumption in HSA is optimum. The consumption is maximum, i.e., 7.5 kWh in time-slot 16 and minimum in time-slots $2-6$, and 8, i.e., 1.7 and 2.7 kWh respectively. In time-slots 1 and 24 there is zero energy consumption. Rest of the time-slots have average consumption pattern. EDE based scheduling shows some peaks in the starting and ending hours but the overall electricity consumption pattern is moderate. The consumption pattern of EDE shows peaks in time-slots 8 and $17-24$. The minimum consumptions is in time-slots 9, 13 and 14 are 1.5, 2.4 and 2.4 kWh, respectively, and in time-slots 8 and 11 negligible amount of electricity is consumed from the utility. Our proposed hybrid technique, i.e., HSDE also has peaks at the starting and ending time-slots but when RES and ESS are integrated the consumption pattern shows minimum and negligible behavior in time-slots $7-17$. The maximum electricity consumption of 11.5 kWh is shown in time-slot 23 which are followed by other peaks in time-slots 3, 6, 18 and 24. The energy consumption in these time-slots is 9, 9, 9.8 and 10.9 kWh, respectively.

The hourly electricity bill of unscheduled and scheduled load without RES and ESS is shown in Fig. 9a. Results show that the bill of heuristic algorithms (HSA, EDE and HSDE) based scheduling remains within the feasible region. From the figure it can be seen that unscheduled scenario results in maximum bill. In time-slot 8, the electricity cost is 475 cents which is maximum among all. The three proposed techniques (HSA, EDE and HSDE) have reduced this electricity cost considerably. In the same time-slot the maximum cost of each algorithm falls which is 28.84%, 38.72% and 49.89% less than unscheduled cost. In the starting time-slots $1-7$, the electricity cost is comparatively lower than last time-slots. The electricity bill of scheduled load is less than unscheduled load.

The hourly electricity bill of unscheduled and scheduled loads with RES and ESS is shown in Fig. 9b. This shows that the electricity bills of scheduling algorithms (HSA, EDE and HSDE) is less as compared to unscheduled cost. The overall cost in all the time-slots is also less than that in Fig. 9a. The energy consumption pattern of unscheduled scenario is most expensive in the graph e.g. in time-slot 9 the cost of unscheduled pattern is 195 cents. This expensive peak is reduced by all the three algorithms up to 45, 40 and 60%. HSDE has maximum cost in 6^{th} hour of a day, i.e., 116.3 cents that is 43% less than the peak of unscheduled cost. HSA has maximum cost in $7th$ hour of a day, i.e., 90 cents that is 55% less than unscheduled maximum cost and EDE has maximum cost of 100 cents in 4^{th} hour of a day

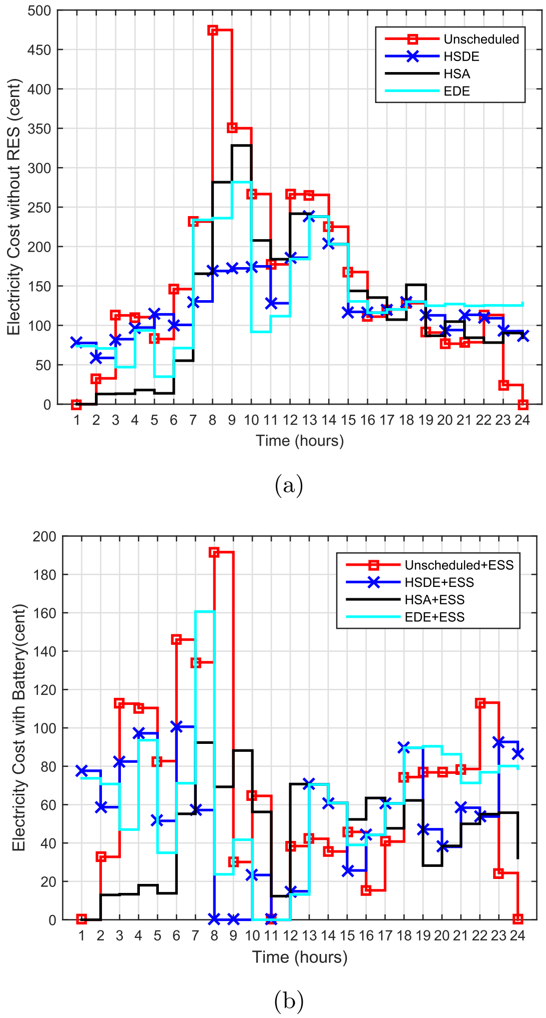

FIGURE 9. Electricity cost per hour. (a) Bill per hour without RES. (b) Bill per hour with RES.

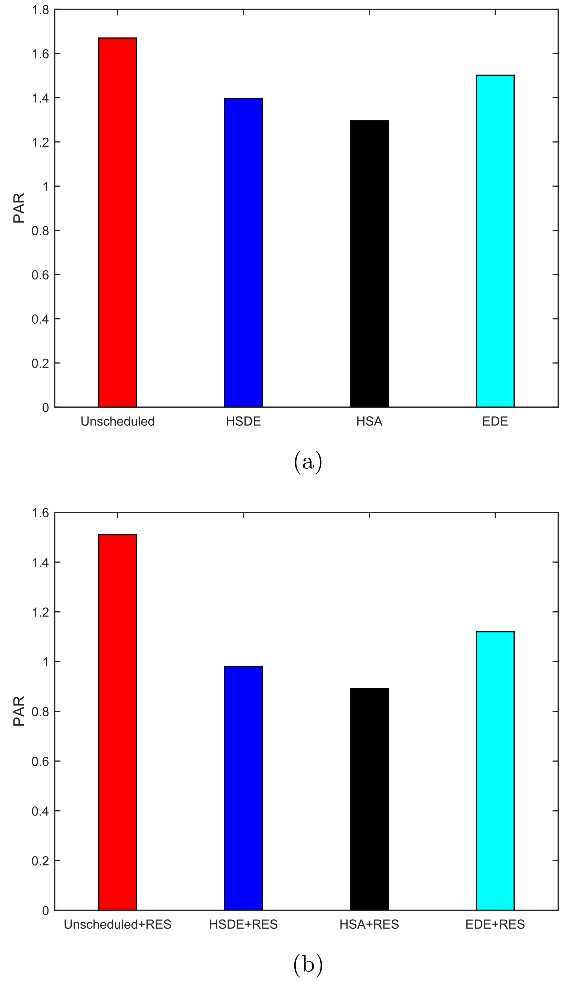

FIGURE 10. PAR. (a) PAR without RES. (b) PAR after RES.

that is 49.5% reduced than unscheduled cost. HSDE has zero cost in 8^{th} and $9th$ time-slots which means in these hours the total energy is consumed from RES and ESS. Similarly, EDE has zero consumption in time-slots 8 and 11.

Peak formation is a major drawback in traditional electric power system as it causes customer to pay high electricity bill as well as challenges the stability of grid. Performance of all the designed models (HSA-EMC, EDE-EMC and HSDE-EMC) with respect to PAR reduction is shown in Fig. 10a. It shows that PAR is significantly reduced by HSA-EMC, EDE-EMC and HSDE-EMC than the unscheduled case because these are designed to avoid peak formation.

When RES and ESS are integrated the load pattern becomes smooth and the peaks are reduced. The smart user does not fully rely on the utility grid, instead prefer the use of RES and ESS when available. By doing this both cost and PAR are reduced resulting in grid stability. In Fig. 10b the PAR values after integration of RES and ESS are shown which are lower than Fig. 10a.

TABLE 5. Performance trade-off comparison.

Technique	Value	value
HSA	4.7	3000.02
EDE	4.1	3223.6
HSDE	4.3	3163.39

The comparison of overall daily electricity bill of the unscheduled and scheduled load without RES and ESS is shown in Fig. 11a. The daily electricity cost in unscheduled, and in scheduled load scenarios using HSDE, HSA, and EDE algorithms are 3652.63, 3163.39, 3000.02, and 3227.61 cents respectively. The comparison of total electricity cost shows that HSDE, HSA, and EDE algorithms based HEM system reduces the electricity bill by 13.2%, 17.86%, and 11.5% respectively. In Fig. 11b, daily electricity costs after integration of RES and ESS are shown. Compare to Fig. 11a the electricity bill bars of Fig. 11b are shorter. HSA along with RES and ESS gives minimum cost than others.

A. TRADE-OFF BETWEEN PARAMETERS

The trade-off behavior explained in Section VI is summarized in Table 5 as shown in Figs. 11 and 12. HSA has maximum

TABLE 6. The overall comparison of the algorithms.

Technique	Electricity cost (cents)	Reduction	% saving	PAR	Waiting Time (s)
Unscheduled	3652.6	0	0	1.67	0
HSDE	3163.39	488.7	13.2 %	1.3972	4.3
HSA	3000.02	662.58	17.84%	1.2953	4.7
EDE	3227.6	425	11.12 %	1.5017	4.1
Unscheduled + RES	2049.9	1602.8	43.459 %	1.51	0
HSDE+RES	1575.8	1448.1	47.8 %	0.98	4.3
HSA+RES	1426.3	1602.8	52.919 %	0.89	4.7
EDE+RES	1740.5	1483.1	46.075 %	1.12	4.1

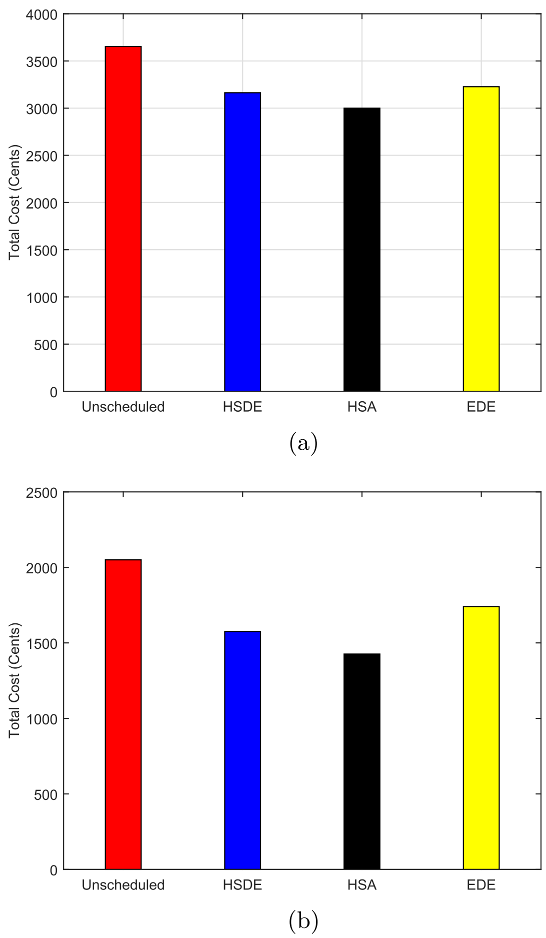

FIGURE 11. Daily cost. (a) Daily cost without RES. (b) Daily cost with RES.

waiting time (less user comfort) which has minimum cost among the three algorithms, i.e., 3000.02 cents in Fig. 11 while EDE entertains the user with maximum comfort giving less saving in electricity bill, i.e., 425 cents. Our proposed HSDE algorithm presents less waiting time than HSA. The electricity bill offered by this algorithm is also expensive then HSA. Results reveal that integration of RES and ESS minimizes the electricity bill up to 52% daily. Peaks in the electricity consumption pattern are smoothen and the per hour consumption of all three algorithms is invulnerable to utility and consumer. HSDE shows balanced load pattern than HSA and EDE which increases the power system stability.

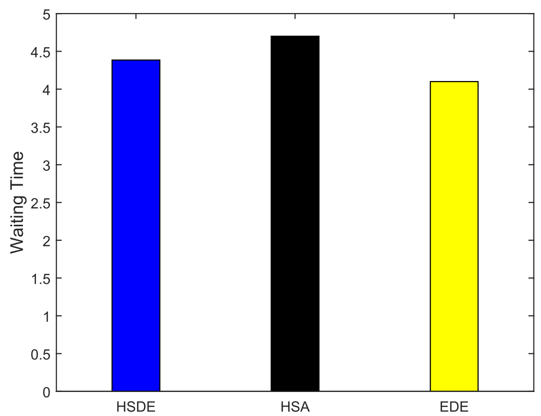

FIGURE 12. Waiting time.

Reduction in PAR by HSDE, HSA and EDE is 17.247%, 32.871% and 16.586% respectively. Furthermore our simulation verify the feasible regions which is provided before the simulation for optimal solution. On the other hand, there exists a trade-off between electricity cost and user waiting time which is depicted in our work.

The overall performances of the algorithms before and after RES integration is shown in Table 6.

VIII. CONCLUSION

Due to lack of energy sources and aging of existing power systems, demand for smarter and efficient power system has increased. The concept of SG has been introduced for this reason in which the appliances are made smart in such a way that they can coordinate through EMC and even control the power consumption of smart home. The integration of RES and ESS into SG maximizes the user comfort by economically consuming electricity in the peak hours. In this paper a new hybrid algorithm HSDE is proposed by hybridizing two existing heuristic algorithms (HSA and EDE). Their performance on the bases of PAR, electricity cost, user comfort and energy consumption is evaluated. To tackle the intermittent behavior of RES and implementing RES with future work is another direction of our work.

REFERENCES

[1] (2010). *Deploying a Smarter Grid Through Cable Solutions and Services*. Accessed: Jan. 31, 2016. [Online]. Available: http://www.nexans.com/Corporate/2010/WHITE-PAPER-SMART-GRIDS-(2010).pdf

[2] Y. Guo, M. Pan, and Y. Fang, "Optimal power management of residential customers in the smart grid," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 9, pp. 1593–1606, Sep. 2012.
[3] A. Agnetis, G. de Pascale, P. Detti, and A. Vicino, "Load scheduling for household energy consumption optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2364–2373, Dec. 2013.
[4] H. Nilsson, "The many faces of demand-side management," *Power Eng. J.*, vol. 8, no. 5, pp. 207–210, 1994.
[5] S. L. Nalbalwar, J. D. Ruikar, and S. R. Sakpal, "Smart grid: A modernization of existing power grid," *Int. J. Adv. Eng. Res. Stud.*, vol. 1, no. 2, pp. 295–298, 2012.
[6] Y. Liu, C. Yuen, S. Huang, N. Ul Hassan, X. Wang, and S. Xie, "Peak-to-average ratio constrained demand-side management with consumer's preference in residential smart grid," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 6, pp. 1084–1097, Dec. 2014.
[7] K. Patel and A. Khosla, "Home energy management systems in future smart grid networks: A systematic review," in *Proc. IEEE 1st Int. Conf. Next Generat. Comput. Technol. (NGCT)*, Sep. 2015, pp. 479–483.
[8] Z. Bao, Y. Zhou, L. Li, and M. Ma, "A hybrid global optimization algorithm based on wind driven optimization and differential evolution," *Math. Problems Eng.*, vol. 2015, Jul. 2015, Art. no. 389630.
[9] Y. Zhou, Z. Bao, R. Wang, S. Qiao, and Y. Zhou, "Quantum wind driven optimization for unmanned combat air vehicle path planning," *Appl. Sci.*, vol. 5, no. 4, pp. 1457–1483, 2015.
[10] S. Rahim *et al.*, "Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources," *Energy Buildings*, vol. 129, pp. 452–470, Oct. 2016.
[11] M. Arafa, E. A. Sallam, and M. M. Fahmy, "An enhanced differential evolution optimization algorithm," in *Proc. IEEE 4th Int. Conf. Digit. Inf. Commun. Technol. Appl. (DICTAP)*, May 2014, pp. 216–225.
[12] S. Moon and J.-W. Lee, "Multi-residential demand response scheduling with multi-class appliances in smart grid," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2518–2528, Jul. 2018
[13] M. B. Rasheed *et al.*, "Real time information based energy management using customer preferences and dynamic pricing in smart homes," *Energies*, vol. 9, no. 7, p. 542, 2016.
[14] J. Ma, H. H. Chen, L. Song, and Y. Li, "Residential load scheduling in smart grid: A cost efficiency perspective," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 771–784, Mar. 2016.
[15] A. Ahmad *et al.*, "An optimized home energy management system with integrated renewable energy and storage resources," *Energies*, vol. 10, no. 4, pp. 1–35, 2017.
[16] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: Harmony search," *J. Simul.*, vol. 76, no. 2, pp. 60–68, Feb. 2001.
[17] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Appl. Math. Comput.*, vol. 188, no. 2, pp. 1567–1579, May 2007.
[18] R. Effatnejad, H. Hosseini, and H. Ramezani, "Solving unit commitment problem in microgrids by harmony search algorithm in comparison with genetic algorithm and improved genetic algorithm," *Int. J. Tech. Phys. Problems Eng.*, vol. 6, no. 21, pp. 61–65, 2014.
[19] M. Fesanghary and M. M. Ardehali, "A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem," *Energy*, vol. 34, no. 6, pp. 757–766, 2009.
[20] P. Karthigeyan, M. S. Raja, R. Hariharan, S. Prakash, S. Delibabu, and R. Gnanaselvam, "Comparison of harmony search algorithm, improved harmony search algorithm with biogeography based optimization algorithm for solving constrained economic load dispatch problems," *Procedia Technol.*, vol. 21, pp. 611–618, Nov. 2015.
[21] M. A. Islam, M. Hasanuzzaman, N. A. Rahim, A. Nahar, and M. Hosenuzzaman, "Global renewable energy-based electricity generation and smart grid system for energy security," *Sci. World J.*, vol. 2014, Aug. 2014, Art. no. 197136.
[22] N. Phuangpornpitak and S. Tia, "Opportunities and challenges of integrating renewable energy in smart grid system," *Energy Procedia*, vol. 34, pp. 282–290, Jul. 2015.
[23] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, Sep. 2012.
[24] E. Shirazi and S. Jadid, "Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS," *Energy Buildings*, vol. 93, pp. 40–49, Apr. 2015.
[25] J. Y. Lee and S. G. Choi, "Linear programming based hourly peak load shaving method at home area," in *Proc. IEEE 16th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2014, pp. 310–313.
[26] T. Hubert and S. Grijalva, "Realizing smart grid benefits requires energy optimization algorithms at residential level," in *Proc. IEEE PES Innov. Smart Grid Technol. (ISGT)*, Jan. 2011, pp. 1–8.
[27] K. M. Tsui and S. C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1812–1821, Dec. 2012.
[28] R. Storn and K. Price, "Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces," *J. Global Optim.*, vol. 11, no. 4, pp. 341–359, 1997.

SAQIB KAZMI received the M.S. degree in electrical engineering from the Department of Electrical Engineering, COMSATS Institute of Electrical Engineering, Islamabad, Pakistan, under the supervision of Prof. J. Mughal and Dr. N. Javaid.

NADEEM JAVAID (S'08–M'11–SM'16) received the bachelor's degree in computer science from Gomal University, Dera Ismail Khan, in 1995, the master's degree in electronics from Quid-i-Azam University, Islamabad, Pakistan, in 1999, and the Ph.D. degree from the University of Paris-Est, France, in 2010. He is currently an Associate Professor and the Founding Director of Communications over Sensors Research Lab, Department of Computer Science, COMSATS University Islamabad, Islamabad. He has supervised 15 Ph.D. dissertations and 100 master's theses. He has authored over 700 articles in technical journals and international conferences. He is also an Associate Editor of the IEEE Access Journal and an Editor of the *International Journal of Space-Based and Situated Computing*. His research interests include energy optimization in block chain based smart grids and IoT enabled wireless sensor networks, and data analytics in smart grids/wireless sensor networks. He was a recipient of the Best University Teacher Award from the Higher Education Commission of Pakistan, in 2016, and the Research Productivity Award from the Pakistan Council for Science and Technology, in 2017.

MUHAMMAD JUNAID MUGHAL is currently the Chairman of the Department of Electrical Engineering, COMSATS Institute of Information Technology, Islamabad, Pakistan.

MARIAM AKBAR (S'13–M'16) received the M.Sc. and M.Phil. degrees from Quid-I-Azam University, Islamabad, and the Ph.D. degree in electrical engineering from the COMSATS Institute of Information Technology, Islamabad, under the supervision of N. Javaid. She is currently an Assistant Professor with the Department of Computer Science, COMSATS Institute of Information Technology. Her research interests include wireless networks and smart grids.

SYED HASSAN AHMED (S'13–M'17) received the B.S degree in computer science from the Kohat University of Science and Technology, Pakistan, and the master's and Ph.D. degrees from the School of Computer Science and Engineering (SCSE), Kyungpook National University (KNU), South Korea. In 2015, he was also a Visiting Researcher with the Georgia Institute of Technology, Atlanta, USA. He is currently a Post-Doctoral Research Fellow with SCSE, KNU, where he also teaches ''Design and Analysis of Computer Networks'' course at the Graduate School. He authored or co-authored over 90 International journal articles, conference proceedings, book chapters, and two Springer brief books. His research interests include sensor and ad hoc networks, cyber physical systems, vehicular communications and future Internet. He received the Research Contribution awards by SCSE at KNU, from 2014 to 2016, and the Qualcomm Innovation Award at KNU, in 2016.

Dr. Hassan is a member of ACM. He is serving as a TPC Member or Reviewer in more than 50 International Conferences and Workshops, including IEEE Globecom, IEEE ICC, IEEE CCNC, IEEE ICNC, IEEE VTC, IEEE INFOCOM, ACM CoNEXT, ACM SAC, and much more. He has been reviewing papers for more than 30 International Journals, including the IEEE WIRELESS COMMUNICATIONS MAGAZINE, the IEEE NETWORKS MAGAZINE, the IEEE COMMUNICATIONS MAGAZINE, the IEEE COMMUNICATIONS LETTERS, the IEEE SENSORS LETTERS, the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, *Vehicular Technologies*, *Intelligent Transportation Systems Big Data*, *Mobile Computing*, Elsevier *Computer Communications*, and *Computer Networks*.

NABIL ALRAJEH received the Ph.D. degree in biomedical informatics engineering from Vanderbilt University, USA. He was a Senior Advisor for the Ministry of Higher Education, and his role was in implementing development programs, including educational affairs, health information systems, strategic planning, and research and innovation. He is currently a Professor with the Health Informatics, Biomedical Technology Department, King Saud University. His research interests include E-health applications, hospital information systems, telemedicine, intelligent tutoring systems, energy management in smart grids, and wireless sensor networks.