Evolutionary Techniques-Based Optimized Load Management System for Smart Homes

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***Abstract*—Demand Side Management (DSM) programs play a key role in the future smart grid through intelligently managing the loads. These programs are implemented via residential load management systems for smart cities. In which the power consumption pattern of the household appliances is scheduled to deliver desired benefits i.e. optimizing the ON-OFF cycles of appliances while minimizing end-user electricity costs, reducing the Peak to Average Ratio (PAR), and increasing user comfort. In this study, for fulfilling the previous features, optimized DSMs based on evolutionary techniques, that are genetic algorithm and binary particle swarm, have been proposed for scheduling residential users' appliances. The effectiveness of the suggested DSMs has been verified utilizing MATLAB simulator. According to the obtained results, the introduced methodologies optimally schedule the appliances, resulting in lower electricity bills and PAR.**

Keywords—Demand-side management; Smart home; Energy management system; Appliance scheduling; Binary particle swarm optimization; Genetic algorithm; Electricity pricing; Smart grid;

I. INTRODUCTION

In traditional power grids, the demand and supply sides of the electricity are essentially separated, where the grid monitoring data should be handled only by the operations side. For achieving the purpose of power networks to be stable, they must be able to meet electrical demand on a consistent basis, which necessitates planning and communication on the generation and consumption subsystems. The smart grid aims to ensure transferring of the future networks into intelligent ones through the promotion of bi-directional information and active participation from whole inter-connected subsystems. The concept of demand management systems is used to accomplish this transformation. The Demand Side Management (DSM) strategies can be implemented for improving the utilization of renewable sources, increasing the economic profit, and reducing the feed grid power or minimizing the lower peak demand [1]]. The DSM system takes the objective load curve as an input and requests that the control action be made for satisfying the target consumption. The algorithm may be unaffected by such criteria of generating the objective load curve. DSM schedules the connection times of specific interruptible and uninterruptible devices. The interruptible appliances are those devices that can be delayed as well as interrupted during the operating time, such as washing machines and clothes dryers, while the uninterruptible appliances are those appliances that can be delayed but is not acceptable to be interrupted during the operating time, such as ovens or the fans. DSM technique must be developed to manage complexities, such as operation time intervals of more than one hour for electrical appliances and the ability to processing many controlled electrical devices with varying features, such as varied power consumption features. Furthermore, DSM system aims to obtain the final load curve as close to the objective load curve as possible [[2]].

In last decade, the researchers try to develop applicable pricing mechanisms for energy management in smart grids. Time-of-use (ToU) pricing, day-ahead pricing (DAP), critical peak pricing (CPP), and real-time pricing (RTP) are some of the dynamic pricing schemes of energy [[3]]. ToU pricing refers to the price rate variation according to the time of day, whether it's peak, off-peak, or shoulder. Day-ahead pricing is based on deals supplied by utilities in order to establish supply and demand equilibrium in hourly intervals. RTP may be defined as the rate of actual electric power delivery, which varies from hour to hour. Demand management strategies are employed from wholesale market prices to control and manage pricing. Demand Response and DSM are considered as the two main economic factors concerning the demand management of the smart grids. Customers are encouraged to reduce the consumption in such a reaction of changing the energy cost concerning the grid's economic usage. Demand Response programs fall into the category of load control programs. Demand Response programs assist utilities in reducing energy consumption, conserving energy, redistributing energy consumption, improving system dependability, lowering energy prices, and increasing economic efficiency [[4]].

Smart homes give users with a comfortable, completely managed, and secure lifestyle. Furthermore, smart homes may ensure saving the energy and cash by offering green energy into the grid and earning from it. On the other hand, many governments are encouraged to sponsor new smart-home technologies due to the likely reduction in total household energy loads. The European Standard EN 15232 [[5]] encourages the incorporation of smart-home devices in residential areas to reduce power demand. Smart-home loads may be categorized based on how they operate: schedulable and non-schedulable loads. Non-schedulable loads, for instance, printers, and hairdryers, are operated on an as-needed basis without any predictable operating patterns, whereas schedulable loads, for instance washing machines and air conditioners, have a predictable operating pattern as they may

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be through Smart Homes Energy Management Systems (HEMS). According to [[6]], manageable appliances can be categorized to interruptible and uninterruptible load in accordance with the impact of supply interruption on tasks.

DSM programs shift the operation of demand responsive appliances for residential customers from peak to low price periods to meet the goals of lowering electricity consumption costs and lowering the Peak-to-Average Ratio (PAR). Residential customers can assist to enhance the energy efficiency of the distribution network and smart grid with participating in the DSM program, which helps to minimize blackouts, dependability, and stability issues. This research concentrates on a price-based DR technique for scheduling electrical devices that uses electricity price data from smart meters. Several authors are conducted their research to solve the difficult challenge of efficient appliance scheduling [[7]]. The primary purpose of the home energy management scheduling problem is to keep supply and demand balanced while lowering the electricity consumption cost (ECC). Researchers have proposed a variety of solutions to achieve the goals of lowering electric energy consumption costs, increasing consumer comfort, and lowering PAR. For this purpose, metaheuristic algorithms can be applied for evaluating the objective function solution methods, such as Genetic Algorithm (GA), Binary Particle Swarm Optimization (BPSO), Ant colony optimization (ACO), and others [[7]]. Authors concluded that the GA based EMC methodologies are better than other methods considering the terms of electricity bill saving and minimizing and maximizing of PAR for users' satisfaction. However, the computational time of the algorithm is higher. Arafa et al. [[8]] introduced an enhanced version of the deferential evaluation algorithm to reduce the computational time for load scheduling in smart homes. Several classical and metaheuristic solution methods are reported for solving demand responsive appliances (DRAs) scheduling problem, including mixed-integer programming, rolling optimization, particle swarm optimization (PSO), grey wolf optimization, genetic algorithm (GA), and bat algorithm. Several classical and metaheuristic solution methods have been offered in other literature [[9]-[11]]. In [[12]], a mixed-integer nonlinear programming-based energy scheduling method was proposed to minimize ECC of residential consumers when energy prices were set at time-of-use. In [[13]], a mixed-integer linear programming methodology in order to optimally scheduling DRAs for minimizing ECC was presented. After DRAs scheduling, the power supply demand balance had been established. A dynamic programming solution for DRAs scheduling with predetermined time intervals and smart appliance preferences was proposed in [[14]]. The goal was to reduce ECC by transferring DRAs from high to low energy price times based on predetermined preferences. It can be summarized from the above-discussed literature that the optimization problem of HEMS can be optimized by applying algorithms of mixed-integer linear and non-linear, and integer linear programming and electron drifting. Moreover, techniques such as convex and dynamic programming have been applied with acceptable accuracy. Furthermore, GA, PSO, cuckoo search, score-based, and Dijkstra techniques have been applied for solving the addressed problem of HEMS. However, it is noted that these applied algorithms may culminate in several problems such as poor convergence characteristics, difficulties to find the global finest, or the weak ability to transact with the changeful nature of various DRAs.

In this study, cost-effective appliance scheduling systems for residential users have been presented. The model uses the BPSO and GA algorithms to build optimum schedules and has been simulated in a ToU pricing tariff. The findings reveal that the proposed technique works with an acceptable performance for scheduling household electrical equipment and saves consumers money by lowering their electricity bills.

The highlights of this paper can be written as the following:

- To solve the DSM difficulties, an effective load management framework has been designed using the smart grid's two-way communication infrastructure under utility and Renewable Energy Sources (RESs).
- The designed load management system has a Smart scheduler that schedules smart home loads using our suggested BPSO and GA techniques.
- A price-based demand response program is introduced, which sends out ToU pricing signals to consumers, encouraging them to join the DSM and achieve peak clipping through load shifting.
- An objective function is mathematically developed with the goal of minimizing high grid power imports during high peak hours and high peak demand, lowering peak costs, increasing the usage of renewable energy sources, and maximizing the economic gain.
- A BPSO and GA optimization techniques has been presented for solving the DSM problem through the optimal scheduling of residential loads
- Simulation results prove that the presented algorithm considerably decreases the electricity costs, reduces PAR and reduces consumer's discomfort.

The paper can be arranged as the following. The studied system model has been designed and briefly described in Section II. Section III deals with the problem formulation of the appliance scheduling. Section IV discusses simulation settings and results. Section V concludes the main outcomes of the paper.

II. Modeling of the Proposed HEMS

In a smart grid, DSM improves the grid's reliability and stability. It regulates energy consumption in the smart home through scheduling appliances in accordance with a scheduler built in the HEMS [[15]]. The smart meter enables two-way communication among the consumer and the utility; the first way can be named by the pricing signal while the other is called the load demand. The data has been forwarded to the HEMs using the smart meter, and the smart scheduler is used to schedule the smart home appliances using the price signal, load demand, and user preferences. Figure 1 shows the HEMS model. The smart scheduler collects tariff signal information as well as power flow, which are input into optimization algorithms to find the best scheduling to meet peak demand reduction goals. Considering the defined price of the electricity price at certain hours, the demand is directly met through utilizing grid energy, and direct renewable energy. However, for distributing energy to residential loads, the on-site renewable energy source acts as a first option. The load management system decreases the amount of energy gained from the utility in this way. Furthermore, integrating on-site renewable energy with the HEMS model helps to decrease high peaks on the grid during times of high energy demand.

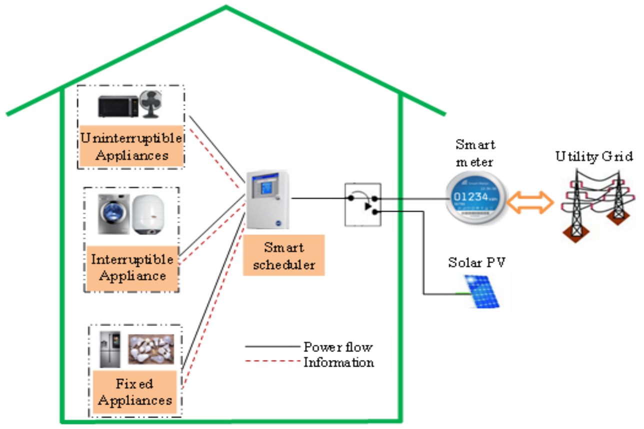

Figure 1: Proposed model of HEMS

A. *Smart Residential Appliances Modeling*

Home appliances have been classified to the following groups considering their types and functions. These categories include fixed load appliances, interruptible appliance or elastic appliances and uninterruptible deferrable appliances. All home appliances have been scheduled in the period of N-hours duration as stated by specified user preferences and N has been assumed 24 in this paper. The N-hours time duration set can be represented by, $t \in \tau = \{1, 2, \ldots \ldots \ldots, N\}$. Considering a house that has a set of $A = \{a1, a2, \ldots \ldots \ldots, an\}$ of appliances $|A| \in n$. The consumed energy of appliances has been presented in TABLE I. The household energy consumption of electric appliances without the presented HEMS is shown in Figure 2.

The fixed appliances are those appliances whose operating length could not be changed. The smart scheduler is applied to schedule the appliances among the described time slots. Light and refrigerator can be considered as an example of the controlled appliances. The total consumed power $E_{fa}(t)$ considering the fixed appliances in each time slot has been formulated as follows (1):

$$E_{fa}(t) = \sum_{h=1}^{N} \left(\sum_{Fa \in \boldsymbol{Fa}} P_{fa} \ \vartheta Fa(t) \right) \quad (1)$$

where Fa is a set of fixed appliances, Fa represents the power rating of P_{fa}, and $\vartheta Fa(t)$ represents the ON-OFF state of the fixed appliance in the corresponding time slot.

Cloth dryers, dish washers, water heaters are just a few of the interruptible appliance that can be found in a residential home. These appliances can be shifted to any time slot. When they are required, they can be interrupted during operation and can be called interruptible appliance or elastic appliances. The total power consumption related to those devices $E_{Ia}(t)$ can be calculated using the following formula.

$$E_{Ia}(t) = \sum_{h=1}^{N} \left(\sum_{Ia \in Ia} P_{Ia} \ \vartheta Ia(t) \right) \quad (2)$$

where Ia is a set of interruptible appliances, Ia has power rating of P_{Ia}, and $\vartheta Ia(t)$ is ON-OFF state of the interruptible appliance in the relevant time slot.

TABLE I. THE PARAMETERS OF HOUSEHOLD APPLIANCES

Load type	Appliances	Power rating (kw)	Daily usage (hrs)
fixed	Lights	1.5	24
	refrigerator	1	24
Interruptible or elastic	Washing machine	1	3
	Cloth dryer	4	8
	Water heater	4.5	8
Uninterruptible	Oven	3	14
	Fan	0.7	16

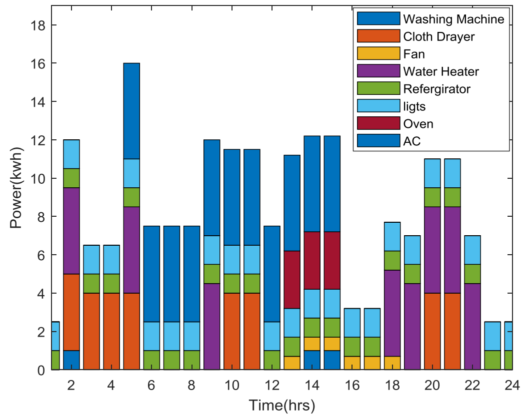

Figure 2: Appliances consumed energy without HEMS

The last type of these appliances is uninterruptible deferrable appliances. The ability of delaying or earlier scheduling of these appliances is available but after the starting the interruption is not available during their operation. The total energy used with these appliances $E_{Ua}(t)$ at time instant, t, is determined as the following (3).

$$E_{Ua}(t) = \sum_{h=1}^{N} \left(\sum_{Ua \in Ua} P_{Ua} \ \vartheta Ua(t) \right) \quad (3)$$

where P_{Ua} is the power rating and $\vartheta Ua(t)$ is ON-OFF state of the appliance in that time slot.

III. Problem Formulation for Appliance Scheduling

A. *Appliances Energy Utilization*

For calculating the total hourly consumed energy of all appliances, the equation (4) can be used:

$$E_T(t) = E_{Ba}(t) + E_{Ia}(t) + E_{Ua}(t) \quad (4)$$

where,

$$E_{Ba}(t) = \sum_{h=1}^{N}\left(\sum_{Fa\in Fa} P_{fa}\ \vartheta Fa(t)\right)$$

$$E_{Ia}(t) = \sum_{h=1}^{N}\left(\sum_{Ia\in Ia} P_{Ia}\ \vartheta Ia(t)\right)$$

$$E_{Ua}(t) = \sum_{h=1}^{N}\left(\sum_{Ua\in Ua} P_{Ua}\ \vartheta Ua(t)\right) \tag{5}$$

The cost of electricity is computed by multiplying the pricing signal by the amount of energy used by appliances.

$$E_{CT}(t) = E_T(t).\xi(t) \tag{6}$$

where pricing signal ξ which changes the price rate according to the time of day, whether it's peak, off-peak, or shoulder. As mentioned above, many electrical tariffs may be utilized to determine the daily energy pricing such as ToU, DAP, RTP, CPP, and others. In this study ToU has been considered for energy pricing. In this study ToU has been considered for energy pricing.

B. Energy Provision via Utility Grid Only

The major goals for the appliance scheduling problem are to reduce the cost of the consumed energy $E_{CT}(t)$ and to minimize the peak-to-average ratio. The suggested scheme's objective function for the household appliance scheduling problem using utility grid only can be expressed mathematically as:

$$\min\left(\sum_{i=1}^{N} E_{CT}(t)\right) \tag{7}$$

subject to:

$$\gamma(t) = \begin{cases} 0 & for\ appliance\ a_i\ is\ OFF \\ 1 & for\ appliance\ a_i\ is\ ON \end{cases} \tag{8}$$

$$E_{grid} = \sum_{i=1}^{N} E_{ET}(t) \tag{9}$$

$$\Gamma_{\max} = 24 - \mathrm{LOT} \tag{10}$$

where $E_{ET}(t)$ is the consumed energy by each appliance at time slot, E_{grid} is the total demand energy of a household from grid, Γ_{max} is the amount of time delay for the appliances, LOT is the load operating time, and $\gamma(t)$ represents the ON-OFF status of the appliances a_i during the day. The cost minimization objective function is in (7) and in (8) a one-digit binary variable is provided to specify whether the appliance is required to be energized or de-energized (ON or OFF). Energy demand and balance for appliances denoted by (9) and (10) gives the most waiting time for an appliance to respond.

C. Energy Trading

HEMS imports energy from main grid in case of local energy depletion and exports energy to main grid in case of local excess energy availability. The overall energy transaction with main grid at time t is computed using the following equations.

$$E_R = RES * \mho \tag{11}$$

$$\partial(t) = \min(E_R, E_{ET}(t)) \tag{12}$$

$$\Delta(t) = abs(\partial(t) - E_{ET}(t)) \tag{13}$$

$$E_{grid} = \sum_{i=1}^{N} \Delta(t) \tag{14}$$

where RES is renewable energy generation from solar panels shown in Figure 3 and $\mho$ is a matrix that represents ON-Off status for all appliances. The proposed objective function for the household appliance scheduling optimization problem utilizing the utility grid and solar energy resource can be expressed as:

Objective function

$$min\left(\sum_{i=1}^{N} \Delta(t) * \xi(t)\right) \tag{15}$$

Subject to:

$$RES = \sum_{i=1}^{N} E_{RES}(t) \tag{16}$$

$$\sum_{i=1}^{N} E_{Total}(t) = \sum_{i=1}^{N} E_{Tgrid}(t) + \sum_{i=1}^{N} E_{Tsolar}(t) \tag{17}$$

where (15) expresses the objective function of in case using solar energy, (16) is the total daily solar energy consumption, and (17) is the total consumed energy which equals the summation of the energy provided by the utility grid and that provided by the RES.

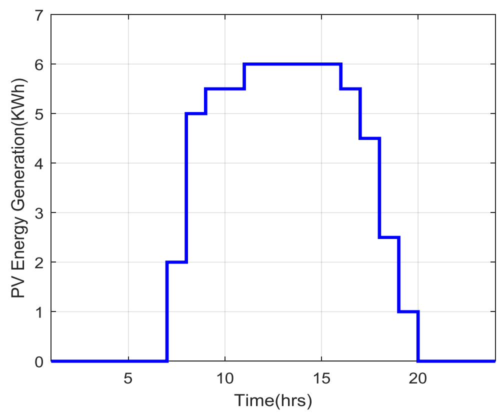

Figure 3: Solar energy

D. Peak-to-Average Ratio

The peak-to-average ratio (PAR) is defined as the ratio between the highest energy demanded by a consumer and the average energy usage over a specific time period, i.e.,

$$PAR = \frac{\max(E_T(t))}{2*mean(\sum_1^N E_T(t))} \tag{18}$$

where $E_T(t) = \{E_T(1), E_T(2), E_T(3), \ldots\ldots, E_T(N)\}$

The PAR expresses the energy consumption behavior even for the utility and consumers. Accordingly, the utility tends to generate extra power at the time of peak demand. Therefore, it is essential for utility grid as well as the consumers to minimize their PARs.

IV. Optimization of the Scheduling Process

A. BPSO-Based Optimization

Optimization can be defined as getting the perfect solution to a given problem under some constraints. Particle swarm optimization is the second population-based approach influenced by animals [[16]]. This simulation was used to solve an optimization problem for continuous nonlinear functions, simulating bird flocking and fish schooling foraging patterns. The BPSO technique is based on two fundamental concepts: velocity and positions for each particle. In a solution space, each particle has an initial position and velocity is generated randomly by (19).

$$X_{ij} = l_j + rand.(U_j - l_j) \tag{19}$$

Let j is the particles (variables) number, m is a vector with elements ranging from 1 to j i.e. $m = (1,2,3,4, \ldots, j), k$ is population size or candidate of BPSO, and n is a vector with elements ranging from 1 to k i.e. $n = (1,2,3,4, \ldots, k)$. The particles converge toward the optimal solution positions as the program advances.

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,j} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ X_{k,1} & X_{k,2} & \cdots & X_{k,j} \end{bmatrix}$$

$$V = \begin{bmatrix} V_{1,1} & V_{1,2} & \cdots & V_{1,j} \\ V_{2,1} & V_{2,2} & \cdots & V_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ V_{k,1} & V_{k,2} & \cdots & V_{k,j} \end{bmatrix} \tag{20}$$

Each particle tests the best particle in its neighborhood (local best particle). Accordingly, the position of the best considered particle is $P_{lb} = [P_{lb,1}\, P_{lb,2}\, P_{lb,3} \ldots . P_{lb,j}]$, whereas the global best position is $P_{gb} = [P_{gb,1}\, P_{gb,2}\, P_{gb,3} \ldots . P_{gb,j}]$. During iteration t the velocity and position of a particle j is updated as follows:

$$V_{ij}^{t+1} = wV_{ij}^{t} + c_1.rand_1\left(P_{lb,i}^{t}(j) - X_{ij}^{t}\right)$$

$$+c_2.rand_2(P_{gb}^{t} - X_{ij}^{t}) \tag{21}$$

$$X_{ij}^{t+1} = X_{ij}^{t} + V_{ij}^{t+1} \tag{22}$$

where V_{ij}^{t+1} is the element of the velocity vector of j^{th} particle at $t+1$ iteration, X_{ij}^{t+1} indicates the element position of j^{th}particle at $t+1$ iteration, and $rand_1$ and $rand_2$ are two variables with random values ranging from 0 to 1. Where c_1 and c_2 are two constants for pulling the particle position towards the local and the global best positions, respectively, andw is the weight of the momentum of the particle which can be expressed by (23):

$$w = w_i + \frac{(w_f - w_i)\cdot t}{t_{max}} \tag{23}$$

where w_i is the initial weight and w_f is the final weight, and t_{max} is the maximum number of iterations. During t_{max} iterations, the global best solution P_{gb} is chosen as an optimal solution by a smart scheduler. Thus, the status of the appliances which are represented as bits vector is determined. In current sampling period, the smart scheduler calculates the objective function cost against the pattern and transmits this pattern to a sample where cost of the objective function is minimum. The flow chart of the algorithm is given in Figure 4.

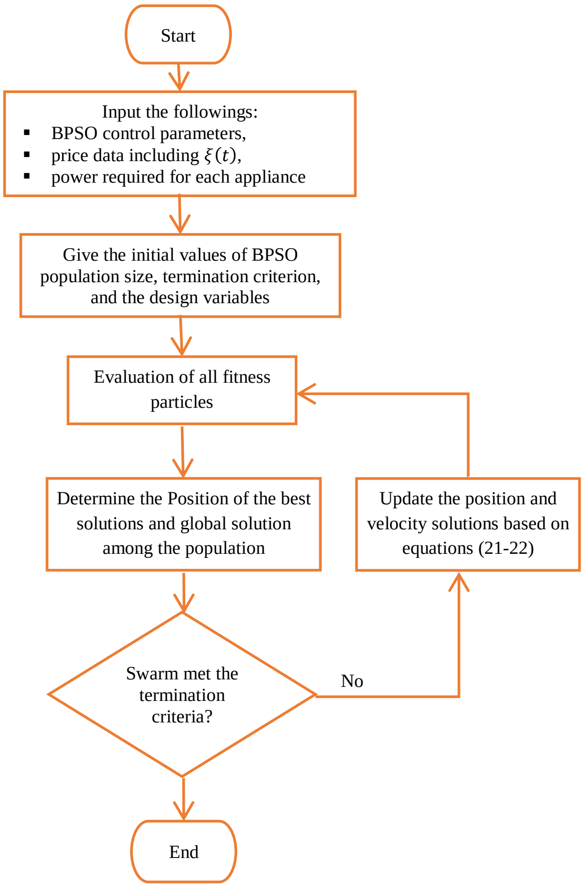

Figure 4: Flow Chart for BPSO

B. GA-Based Optimization

Genetic algorithms (GA) are a type of stochastic search optimization approach that solely uses function values in the search process to proceed toward a solution, regardless of how the functions are evaluated. In GA, a population of chromosomes is initialized, and each chromosome represents a solution where the size of population depends on complexity of problem. Qualification of each individual among the population is estimated by fitness function, the best chromosomes are chosen to transmit information to the following generation and genetic procedures such as mutation, selection and crossover are performed upon the selected ones. Fitness of individuals increases as the number of generations increases. This process continues until it converges to the best set of chromosomes according to a given criterion [[18]-[19]]. The flow chart for GA is shown in Figure 5.

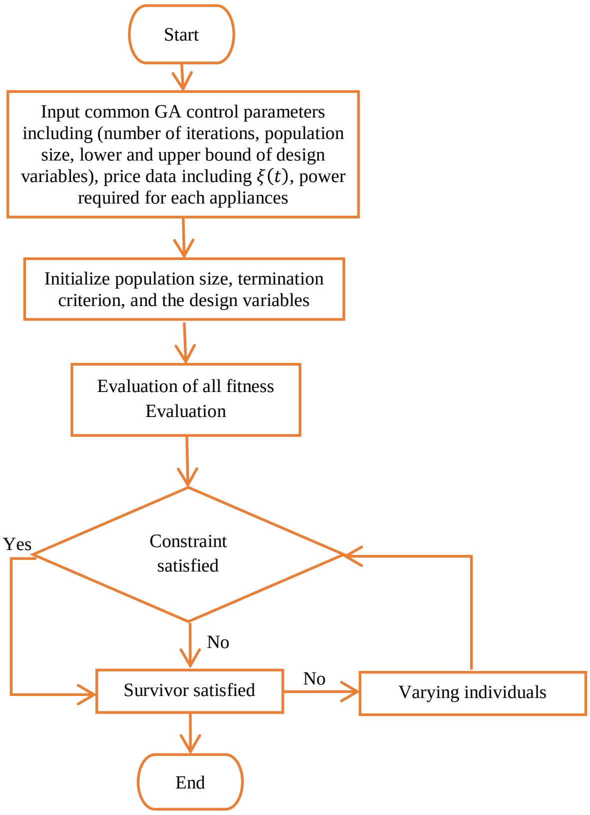

Figure 5: Flow Chart for GA

The smart scheduler examines the pattern of the consumed energy with the best-chosen individuals and generates control signal to manage the appliances operation i.e., energized, or de-energized. These individuals are utilized by the smart scheduler through a complete day (24-hour time horizon) and schedule the load to a time slot wherever it has a minimal cost.

V. Results and Discussions

The simulated results of the proposed load management system are presented in this section. BPSO and GA optimization algorithms have been implemented to provide smart homes energy management systems. Numerical simulations have been conducted using MATLAB software to evaluate the effectiveness of the proposed scheduling schemes i.e., electricity cost savings, user comfort and PAR. the simulations depend on TOU electricity pricing scheme [[20]] for a residential area as presented in Figure 6. A model for a smart home has been introduced including eight smart appliances. Parametric values that are used in the simulation is shown in the TABLE I. Three different operating cases have been configured to test performances of the proposed BPSO and GA optimization schemes compared with the traditional operating case. The simulation has been conducted for complete one day i.e., 24-hour time period.

Simulations have been performed for the following three cases: i) traditional user without HEMS, ii) Smart HEMS depending on the utility grid only as the energy source, iii) Smart HEMS depending on the utility grid and RES as energy sources. Maximum saving should be obtained by adjusting the load by changing the requests of the interruptible and uninterruptible appliances by turning them on and off in an optimized manner.

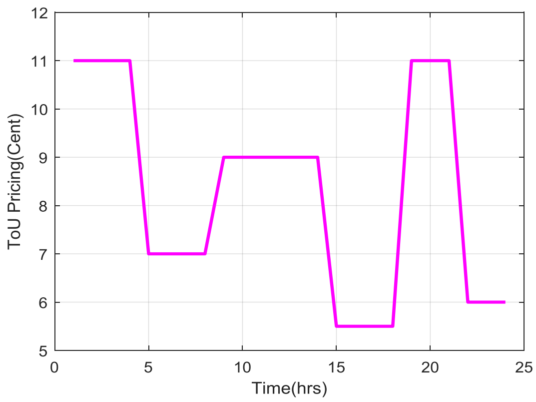

Figure 6: ToU pricing scheme.

A. *Traditional Use without HEMS: Case I*

Because the traditional use without HEMS architecture, the customer must depend on grid energy as the unique source of energy when it is needed. Figure 7 depicts the energy that got from the utility and consumed by appliances throughout various time slots. Figure 8 shows the cost of consumed energy for unscheduled loads and utilizing the ToU pricing tariff.

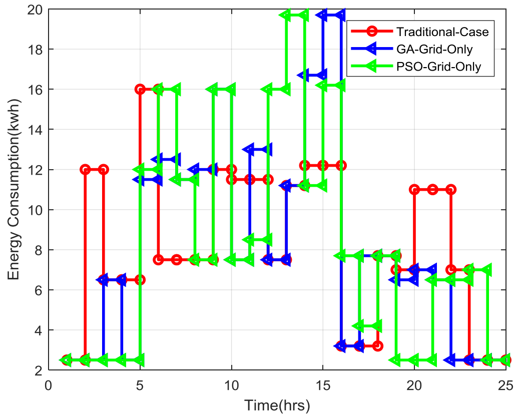

Figure 7: Consumed Energy for operating Case I

B. *HEMS with Utility Grid Only: Case II*

Two optimization schemes have been proposed for smart HEMS, i.e., BPSO-based and GA-based smart HEMSs. Both of those architectures try to avoid appliances operation during peak hours. Figure 7 shows the optimal scheduling for the under-study HEMS loads for a complete one day (over 24-hour time horizon) utilizing BPSO-based and GA-based architectures, the figure illustrates the hourly energy consumption with no integration of the solar source to the smart home. It is clear from Figure 7 that, the unscheduled scenario produces peaks whereas the two BPSO and GA algorithms have optimized the consumed energy by handing out the load over the scheduling horizon with regard to cost minimization. Both algorithms have transferred high loads from peak cost slots to the middle and low-cost slots. In case of using BPSO, peaks that are produced in the unscheduled scenario in the time slots 2, 5, 10, 11, 20 and 21 reaching 12, 16, 11.5, 11.5, 11 and 11 kwh, have been reduced to 2.5,12,7.5, 8.5, 2.5 and 6.5 kwh, respectively. BPSO shows moderate behavior throughout middle and low cost for the scheduled loads. BPSO shows some peaks in the time-slots 6, 7, 9, 12, 13 and 15 hours and it has maximum electricity consumption of 16, 11.5, 16, 16, 19.7, 16.2 kWh as shown in Figure 7.

The smart HEMS architecture based on GA optimization scheduling distributes the consumed energy optimally through transferring the loads during peak hours to off peak hours considering user preferences and constraints. The performance of load against the consumed energy is shown in Figure 7. Load has been reduced in peak from 12 to 2.5 kwh in time slot 2, from 6.5 to 2.5 kwh in time slot 4, from 16 to 11.5 kwh in time slot 5, from 11 to 6.5 kwh in time slot 19, and from 11 to 7 kwh in time slot 20 as shown in the figure.

Load distribution has been modified from high peak hours (1-5 and 19-21) to low and middle peak (6-18) hours. Accordingly, the electricity cost and high peaks have been minimized as indicated by Figure 8. The total consumed energy with the proposed optimization techniques in the under study smart home against the traditional unscheduled use of energy is tabulated in TABLE II.

TABLE II. SUMMARY OF RESULTS.

Optimization Technique	Energy consumption from grid	Total cost	Reduction from unscheduled case	Saving %	PAR
Traditional case	199.2	1700.75	0	0	3.8554
GA with grid only	199.2	1609.25	91.5	5.37	2.5
BPSO with grid only	199.2	1568.5	132.25	7.77	2.3
GA with RES	60.5	600	1100.75	64.72	2.1583
BPSO with RES	51.5	433.75	1267	74.49	1.7

Figure 8 clarify the hourly pricing of consumed energy in case of unscheduled and scheduled load. The obtained results indicate that the bills of GA-based and BPSO-based scheduling schemes are considered convenient solutions. The two proposed techniques (GA and BPSO) have minimized the electricity cost remarkably. The total electricity bill 1700.75 cent in traditional case, 1568.5 cent in case of BPSO with grid only, and 1609.25 cent in GA with grid only, indicating that HEMS that depends on BPSO and GA optimization algorithms minimize the electricity bill by 7.77% and 5.37% respectively. Figure 9 shows the peak to average ratio of Case II, it clear from the figure that PAR is feasibly minimized when utilizing smart HEMSs with BPSO and GA optimization than the PAR in case of unscheduled scenario. Figure 10 and Figure 11 show distribution of consumed energy of the household appliances over 24-hour time horizon after optimization implementing GA and BPSO optimization schemes, respectively.

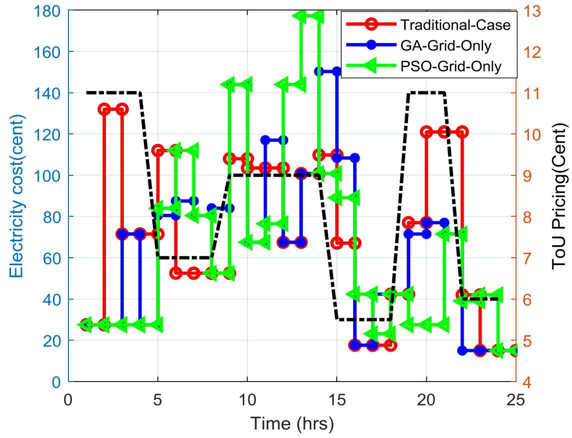

Figure 8: Bill per hour without RES.

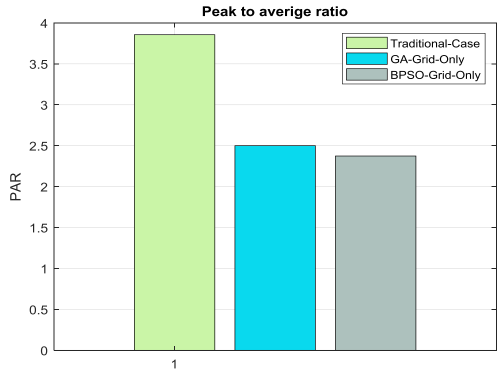

Figure 9: PAR without RES.

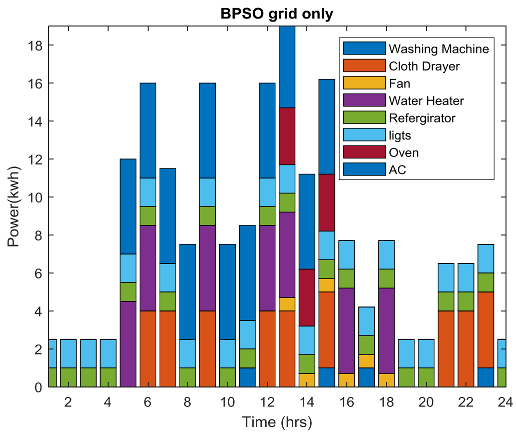

Figure 10: Appliances consumed energy with GA-based HEMS

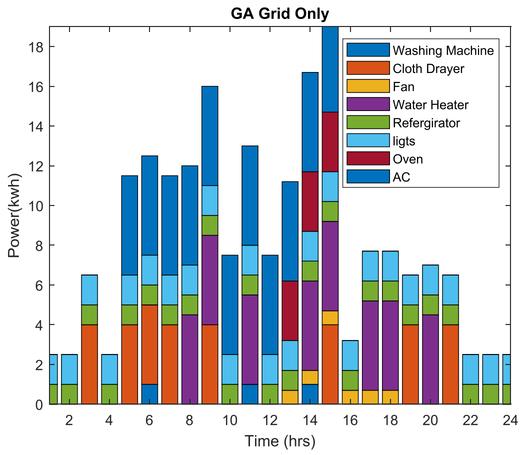

Figure 11: Appliances consumed energy with BPSO-based HEMS

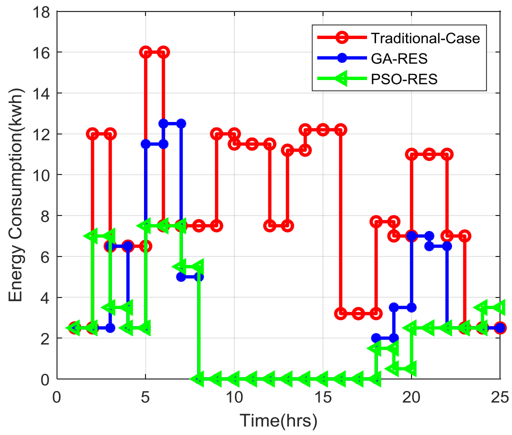

Figure 12: Energy consumption from grid per hour with RES.

C. HEMS with RES: Case III

Commonly RES such as solar energy sources are integrated into smart home network, so that the third scenario is conducted considering RES shown in Figure 3. The smart scheduler utilizes the RES energy where grid energy costs maximum and shifts the load to be fed from RES energy instead of the utility grid and thus reduces the electricity bill significantly. The performance of the proposed HEMSs is shown in Figure 12. Figure 3 shows that depending on solar irradiance during the day hours, solar energy is obtainable during specific time slots but with variable amount.

The available solar energy can be used directly to cover the load demand. It is clear from Figure 12 that, with the integration of solar energy, high peaks have been reduced during off-peak hours. However, during on-peak hours (time slots from 1 to 5 and from 18 to22), the customer does not depend totally on the utility grid as the smart HEMSs transfer the loads to be fed from solar energy. Accordingly, electricity bill is so far minimized. Furthermore, the high peaks of the consumed energy and PAR are significantly minimized, resulting in enhancing the stability of the utility grid. The PAR values after integrating solar energy source to smart home grid is shown in Figure 13, it is clear from the figure that PARs when utilizing RES are lower than those at Figure 9.

Figure 14 illustrates the hourly pricing of the consumed energy in case of unscheduled and scheduled loads with RES integration. The daily electricity price in case of unscheduled, and scheduled load utilizing GA-based and BPSO-based smart HEMS are 1700.75, 600, 433.7 cents respectively, indicating that scheduling the loads using GA and BPSO schemes minimizes the daily electricity price by 64.72% and 74.49% respectively. Figure 15 and Figure 16 show distribution of the consumed energy of the household appliances over 24-hour time horizon after implementing GA and BPSO optimization schemes, respectively. It is obvious from the figures that, the scenario when utilizing BPSO-based HEMS with RES integration provide minimum cost comparing to others scenarios.

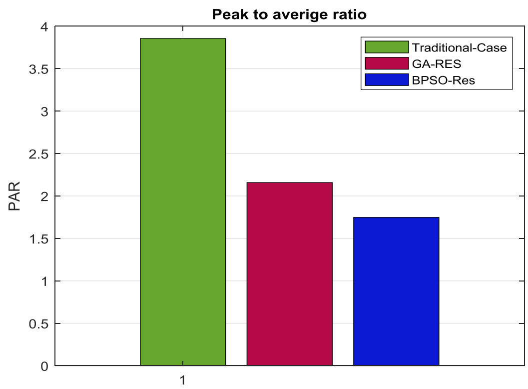

Figure 13: PAR with RES.

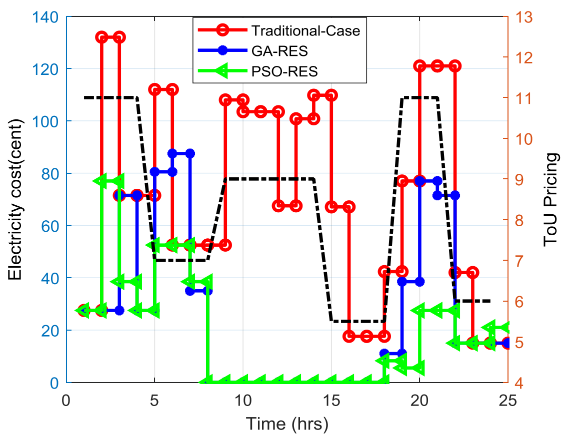

Figure 14: Energy consumption from grid per hour with RES.

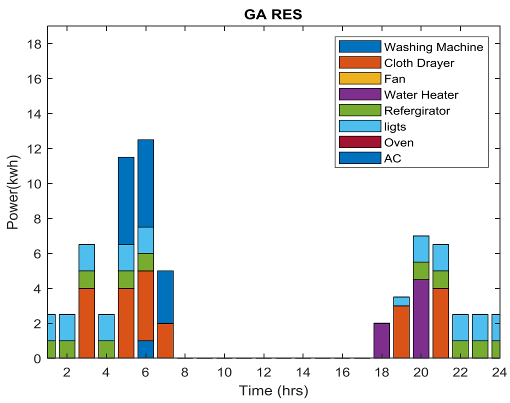

Figure 15: Appliances consumed energy with GA-based HEMS and RES

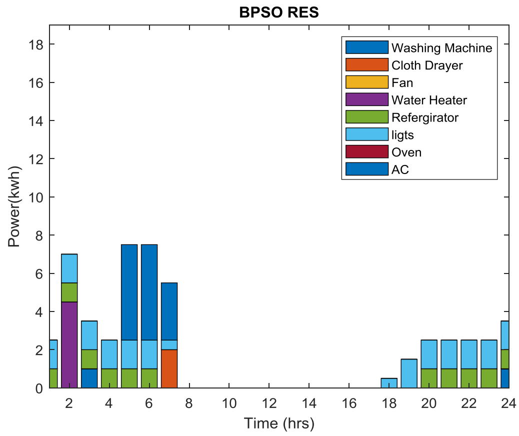

Figure 16: Appliances consumed energy with BPSO-based HEMS and RES

VI. Conclusion

This research proposes smart load management systems relying on optimization techniques to schedule the energy of a residential place in response to the ToU pricing with solar energy integration. A model has been introduced for the smart Homes Energy Management Systems (HEMS) where optimization techniques i.e., Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO) have been implemented to solve the scheduling problem for two different operating scenarios: without photovoltaic integration and with the photovoltaic system integration. This study aims to encourage the consumers to participate in RES generation and utilize smart HEMS to schedule the loads in order to solve the Demand Side Management (DSM) issues through coping with the gap between demand and generation. The aim of solving the DSM problem is to facilitate utility and end-users by minimizing electricity daily cost, the peak load demand, and emission of carbon dioxide via using clean energy sources. The obtained results show that, compared to operation without scheduling, the proposed GA-based HEM, and BPSO-based HEMS in case of using utility grid only as operating scenario, reduced electricity cost by 5.37%, and 7.77%; where it was reduced by 64.72and 74.49%; respectively, in case of integrating RES as operating scenario. In the future, the authors are willing to perform the scheduling process in real-time, in addition they will investigate other intelligent techniques for further reduction of the electricity bills at end uses.

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