

Application Of Gaze Cues Learning-Based Flow Direction Algorithm For Energy Management In Smart Homes

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Abstract:

There is no end to the expansion of automated home appliances driven by the proliferation of cutting-edge technology. To ensure the safety of home installations, it is essential to determine how to regulate our electrical usage. In this regard, Demand Side Management (DSM) is a proposed solution that has been crucial in the development of microgrids and Smart Grids. Through the DSM program, customers can interact with the grid operator, allowing them to participate in decision-making and helping utilities reduce peak power demand. Achieving this goal is possible with careful load management and consistent client satisfaction. Nowadays, several DSM programs have been proposed in the literature, with almost all of them focusing on domestic sector energy management systems. This article proposes an enhanced Flow Direction Algorithm (FDA) that utilizes the gaze cues learning strategy to improve its performance. Gaze cues learning enhances the adaptability of the algorithm, promoting better exploration of potential solutions and improving overall convergence towards the optimal flow direction. The performance of the proposed Gaze Cues Learning Flow Direction Algorithm (GFDA) is evaluated using 14 standard benchmark functions, as well as energy scheduling in smart homes. The proposed model used in this experiment is based on two different electricity pricing schemes: Critical Peak Price and Real-Time Price. Simulation results demonstrate that the proposed model optimally schedules appliances, leading to reduced electricity costs and peak reductions without compromising user comfort. Hence, the results confirm the superiority of the GFDA algorithm over other optimization techniques.

Keywords: Gaze Cues Learning, Demand Side Management, Flow Direction Algorithm, Energy Scheduling, Home Energy Management.

Introduction:

This is further increasing the gap between supply and demand of energy, as the domestic electrical consumption is rising at a faster rate compared to the increasingly growing capacity of electricity-generating devices [1]. In a bid to resolve this matter, the public services within a traditional grid approach fill this gap by increasing power production. However, these temporary solutions, or half-solutions, may negatively affect the security of the electrical system and lead to severe problems, such as the problem of maximum load-ability at peak hours. And due to the additional costs, which are charged as a result of the tariff, and which are charged at on-peak hours, the total expense of power increases too.

In order to solve such a scenario, utilities propose that their consumers save on electricity bills by not using the maximum consumption during the on-peak hours; evolve optimal planning and management operations of both electric companies, which is patterned at encouraging the end-users to reduce their level of consumption and model of energy consumption. Nevertheless, the ignorance of users concerning the methods of forecasting on-peak hours, along with time-varying prices, compels the utilities to address such issues. It is obtained via a suggestion of a beneficial and automatic home power utilization routine that fulfills the criteria of minimizing the overall power expenses as well as the travel time of each gadget utilizing it. This method is referred to

as DSM [2]. DSMI is one of the major components of the Smart Grid (SG) that ensures balance between the supply and the demand sides. DSM programs can be utilized to decrease the electric bill that consumers are required to pay and to assist utility companies in maintaining a reliable electric supply so that users can feel comfortable [3 and 4]; this can be done in a clever way by only reducing the load demand during peak hours.

Home Energy Management System (HEMS) to schedule smart appliances within the framework of the smart grid consists of several parameters: Smart Meter, Smart Appliance, Electricity Storage System (ESS), and RES. HEMS is an intelligent technology that is able to serve autonomous direction, as instructed by the source of energy, in order to maximize the load consumption of electric appliances during peak hours. When crediting the previous study to the HEMS, the authors divided the types of energy management in the study into real-time and presumptive-based management. The earlier plan of getting an optimal solution was to predict the energy consumed using the past data. They also used a presumptive approach to energy management as demonstrated in past studies [4], but the output was not precise; this is the reason why real-time optimization is applied to overcome the drawbacks of presuming. But their concepts were expensive and complicated, only applicable to large-scale regions. But, their presuming method of energy management was complicated and costly, which can only be applicable to scale regions [5].

Pricing tariffs are noted to schedule the optimum time of residential appliances, and the best examples are the Real Time Pricing (RTP), Time of Use (ToU), Critical Power Pricing (CPP), and so on. In [6], a Mixed-Integer Linear Programming (MILP) model is used to reduce the energy consumption, Peak Average Ratio (PAR), and consumption cost using RES to schedule the appliances of residential consumers. The findings indicate that the optimal cost and peak load reduction target was obtained with the provided scheme. To apply MILP in [7], they give an approach to cost saving to the consumers of energy generated by a Micro Grid (MG). The implications of temperature and heat, as well as energy demands, are discussed in detail. They included the Distributed Energy Resource (DER) patented as a Wind Turbine (WT) and Photovoltaic (PV) without Micro Turbine (MT). A MILP model was applied to implement the cost of total energy optimization in [8]. With the help of different kinds of DERs, they combined the production part of their system that comprises the MT, PV, WT, batteries, and diesel generators. Their formulation does not, however, take into account the costs of implementation, maintenance of their system, and the cost of generator fuel.

Conversely, in [9], the fundamental plan of action in using an Integer Linear Programming (ILP) model of residential areas is introduced, which is a balance between energy needs and requests. Their suggested methodology is effective in calculating the optimum operation time and optimum load of time-shiftable and load-shiftable residential appliances on an individual basis. The outcome of tests shows that their suggested system successfully attained the promised goals. A Genetic Algorithm (GA) is used in [10] to suggest an optimum solution to a problem of minimizing the costs of electricity consumption and balancing the load between electricity demand and supply. The cost and PAR reducing scheduling techniques used by authors in [11] are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). They applied three cost tariff indicators, which are RTP, CPP, and ToU, and calculated energy costs using Multiple Knapsack Problems (MKP). These findings indicate the efficiency of their approach, and GA is more efficient than alternative algorithms. Curtailed electricity price in Smart Grid was understood in [12], they incorporate RES and storage mechanisms, such as a battery, using the GA scheme. During periods when the demand for energy and the cost are high,

they resolve this problem by utilizing storage devices. The author added the charging boundaries and discharging boundaries of the batteries, and it can also install a controller to control the battery in case it gets any damage. Nevertheless, the author does not attach importance to the cost of installation and maintenance of RES. In [13], the author applied DSM to the GA scheme where they compute DSM with GA and DSM without GA for energy consumption, and compare findings of their data sets. According to the simulation results, the GA-DSM had an optimal reduction in energy consumption, which would lead to a 21.91% decrease in peak-hour energy consumption. Nevertheless, they overlook PAR and user comfort. In [14], they have employed Distribution Requirements Planning (DRP) in DSM to plan the best for how residential appliances should run in the optimization of HEMS. They used a PSO method with an in-built 2PEM (Two-Point Estimation Method) to optimize the operating load. They compare the outcome of gradient-based 2PEM-PSO and Latin Hypercube sampling (LHS), GA with PSO (GAPSO). Nevertheless, their findings explain that the provided scheme seems to be far superior and more effective than LHS-GAPSO. They fail to mention the cost of energy and PAR, which cannot be trusted by electricity consumers. A MINLP resulting in Electricity Tariff (ET) ToU is developed in [15], to be used in home appliance consumption, the cost-reduction scenario. They, however, disregard PAR in their work. The other cost-cutting scheme is introduced in [16] that allows applying game theory to interact with consumers to produce more energy, as well as allocate the operating point of residential appliances to the different time intervals by applying Dynamic Programming (DP). The author talks about the case of residents who use RES to produce electricity to power their appliances, and also sell the excess energy to another consumer in the same neighbourhood or to a commercial utility provider. They did not consider the cost of deployment and maintenance of RES.

The main contributions of this paper can be summed up as follows: a novel, refined algorithm on the energy optimization problem, i.e., Gaze Cues Learning Flow Direction Algorithm (GFDA), is studied and examined. Moreover, to test the nature-inspired technique proposed, we validated it in one home with two time periods affecting the operation time (OTI) of 1 hour duration. The remainder of the paper is structured as follows: Section 2 includes the description of the problem, objectives, and mathematical formulation. Section 3 suggested a methodology and was described in detail. Section 6 will provide the Graphical results of the paper, including the section on detailed discussions and Conclusions.

Problem Formulation:

The core aims of Smart Grid (SG) are minimization of the electricity bills, PAR-reduction, User-Comfort-maximization, and optimal management of loads. The above literature lacks an inclusive discussion on the advantages of SG, where the interest of certain researchers is to reduce the electricity bill and PAR-reduction, whereas other researchers are interested in the maximization of user comfort and optimal load management. Overall, the mutual goal is to reduce the electricity bills with a maximum level of satisfaction of the user comfort. However, what matters even more is how to keep the electricity bill down allowing the persons using it not to be uncomfortable (maximal satisfaction of users' comfort), or lowering the PAR value.

Objective-function

The primary purpose of our scheduling method is to reduce both the total cost of energy for the consumer, with the potential to improve the average ratio to their peaks, and to

prevent discomfort of users through minimal waiting time so that they are not frustrated. The objective function may be formulated as: To minimize the household appliances scheduling in every time interval with the aim of minimizing the payment of electricity by the end-users. Each appliance has a single status, as it can be ON/OFF. A mathematical optimization model can be defined as follows: Eq. 01.

$$\min \sum_{t=1}^T \left(\sum_{a=1}^{App} \varphi_{app} \times X(t) \times E_{a,t}^{Price} \right) \quad \dots$$

(01)

Subjected to

$$L(t) = E_{interru}(t) + E_{shiftable}(t) + E_{fixed}(t) \quad \dots$$

(02)

$$L(t) \leq \lambda_{th} \quad \dots$$

(03)

$$L_{total}^{Sched} = L_{total}^{Unsched} \quad \dots (04)$$

$$C_{total}^{Sched} = C_{total}^{Unsched} \quad \dots (05)$$

$$t_{\alpha} < t < t_{\beta} \quad \dots$$

(06)

$$X(t) \in [0, 1] \quad \dots$$

(07)

where φ_{app} is Power rating of () appliance, $E_{a,t}^{Price}$ Electricity-price at any time interval t , $E_{interru}$ is Energy consumed by interruptible appliances, $E_{shiftable}$ is Energy consumed by non-interruptible appliances, E_{fixed} Energy consumed by fixed appliances, L_{total}^{Sched} is Total-load scheduled per 24-h, $L_{total}^{Unsched}$ is Total-load unscheduled during 24-h, C_{total}^{Sched} is Total-cost scheduled per 24h, $C_{total}^{Unsched}$ is Total-cost unscheduled during 24h, t_{α} is Start time of appliance and t_{β} is End time of appliance, $X(t)$ Status of appliances OFF\ON.

Energy consumption:

The mathematical form to compute energy consumption is by the following equation:

$$Energy^{Consumption} = \sum_{t=1}^T \left(\sum_{a=1}^{App} \varphi_{app} \times X(t) \right) \quad \dots$$

(08)

Load balancing:

A grid stability is required in order to guarantee continuity of service as well as maintain customer loyalty. A decrease in the value of PAR is to maintain the load balancing, to aid in the reduction of the cost of electricity. it is mathematically determined by the equation (08).

$$PAR = \frac{\max(L_{oad}^{Sched})}{\text{avg}(L_{oad}^{Sched})} \quad \dots$$

(09)

Flow Direction Algorithm (FDA):

The FDA [44] is based on the D8 method, which determines the flow direction in a drainage basin after converting rainfall into runoff.

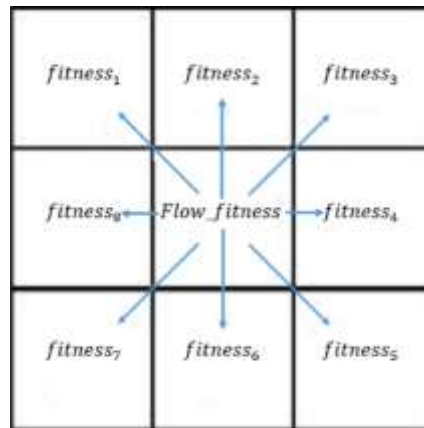


Figure 1: Flow and the eight positions around it [44].

Initially, this method considers population size α , neighbors β , and neighborhood radius Δ ; the calculation of flow direction for the FDA method uses the following equation:

$$\text{FlowX}(i) = \text{lb} + \text{rand} \times (\text{ub} - \text{lb}) \quad \dots \quad (10)$$

where, $\text{FlowX}(i)$ represents the position of the i^{th} flow, while lb and ub denote the lower and upper bounds of the decision variables, respectively, rand refers to a random value between $[0, 1]$; additionally, the presumption is that every flow has β neighbouring points, with their positions determined by the following equation:

$$\text{NeighborX}(j) = \text{FlowX}(i) + \text{randn} \times \Delta \quad \dots \quad (11)$$

where, 'NeighborX' represents the position of the j^{th} neighbor. Smaller values of Δ lead to searching within a range, with bigger numbers enabling a more extensive search. A larger search range increases the diversity of solutions, elevating the probability of discovering optimum (globally) solutions; the algorithm converges towards the global optimum. A smaller search range improves precision in finding the global optimum solution (local) solutions, emphasizing the need to balance both search strategies. Therefore, to balance both search methods, the study uses a formula that linearly changes Δ from a big to a small value, encouraging broader exploration at first and narrowing the search as the algorithm progresses towards optimal solutions.

$$\Delta = (\text{rand} \times \text{Xrand} - \text{rand} \times \text{FlowX}(i)) \times \|\text{BestX} - \text{FlowX}\| \times W \quad \dots \quad (12)$$

where, Xrand is a random position created using equation (10). W is a nonlinear weight, represented by a random value between 0 and infinity. The first term in this equation indicates that $\text{FlowX}(i)$ moves toward a random position Xrand . In the second term, as the iterations increase, $\text{FlowX}(i)$ gets closer to BestX and the Euclidean distance between BestX and $\text{FlowX}(i)$ gradually approaches zero, reducing the local search. The weight W in the third term is calculated as follows:

$$W = \left(\left(1 - \frac{\text{iter}}{\text{MaxIter}} \right)^{(2 \times \text{randn})} \right) \times \left(\overline{\text{rand}} \times \frac{\text{iter}}{\text{MaxIter}} \right) \times \overline{\text{rand}} \quad \dots \quad (13)$$

Figure 5 illustrates the variation of W as the iterations increase. It is clear that W exhibits significant changes throughout the iterations, which helps ensure the algorithm can escape from local optima.

The flow direction changes with velocity V to reach the neighbor flow that has the lowest objective function. The flow's velocity toward the neighbours is directly influenced by its slope. Therefore, the following equation is used to compute the flow velocity vector:

$$V = \text{randn} \times S_0 \quad \dots$$

(14)

where, S_0 is the slope vector between the flow current position and its neighbor. The random number randn helps generate diverse solutions, thereby enhancing the global solution.

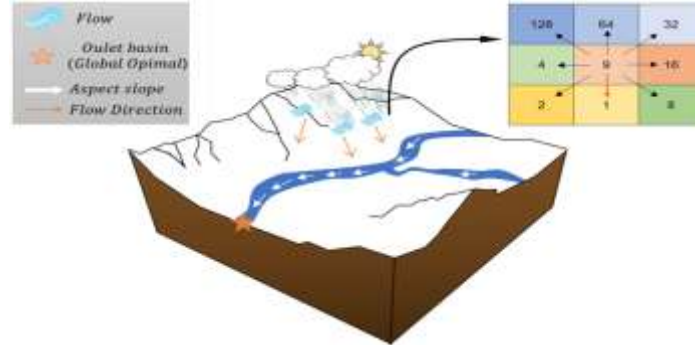


Figure 2: Schematic scheme of moving flow to outlet of basin and D8 method.

The slope vector for flow i^{th} relative to neighbor j^{th} is also calculated using the following equation:

$$S_0(i,j,d) = \frac{\text{FlowFitness}(i) - \text{NeighborFitness}(j)}{\|\text{FlowX}(i,d) - \text{NeighborX}(j,d)\|} \quad \dots$$

(15)

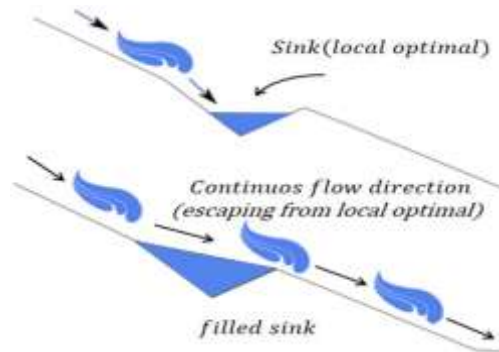


Figure 3: Position of a sink before and after filling.

where, $\text{FlowFitness}(i)$ and $\text{NeighborFitness}(j)$ refer to the objective values for flow i and neighbor j , respectively. The parameter d represents the dimensions of the problem. The following equation is used to calculate the new position of the flow:

$$\text{FlowNew}(i) = \text{FlowX}(i) - V \times \frac{\text{FlowX}(i) - \text{NeighborX}(j)}{\|\text{FlowX}(i) - \text{NeighborX}(j)\|} \quad \dots (21)$$

where, $\text{FlowNew}(i)$ represents the new position of flow i .

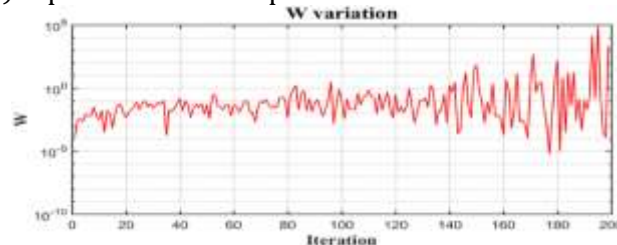


Figure 4: The variation of W.

The FDA method randomly selects another flow; if its objective function is lower than that of the current flow, it moves in the same direction. Otherwise, the flow moves in the direction of the dominant slope; the mathematical expression as follows:

$$\begin{cases} \text{if FlowFitness}(r) < \text{FlowFitness}(i) \\ \text{FlowNewX}(i) = \text{FlowX}(i) + \text{randn} \times (\text{FlowX}(r) - \text{FlowX}(i)) \\ \text{else} \\ \text{FlowNewX}(i) = \text{FlowX}(i) + 2\text{randn} \times (\text{BestX} - \text{FlowX}(i)) \end{cases} \quad \dots$$

(16)

Gaze cues Learning-based Flow Direction Algorithm (GFDA)

The G-FDA consists of three different search strategies i.e. original FDA, Neighbour Gaze-Cues Learning (NGCL), and Random Gaze-Cues Learning (RGCL). The NGCL improves the ability of exploitation and decreases the possibility of trapping in local optima, and RGCL is to maintain the diversity and strike a balance between exploration and exploitation.

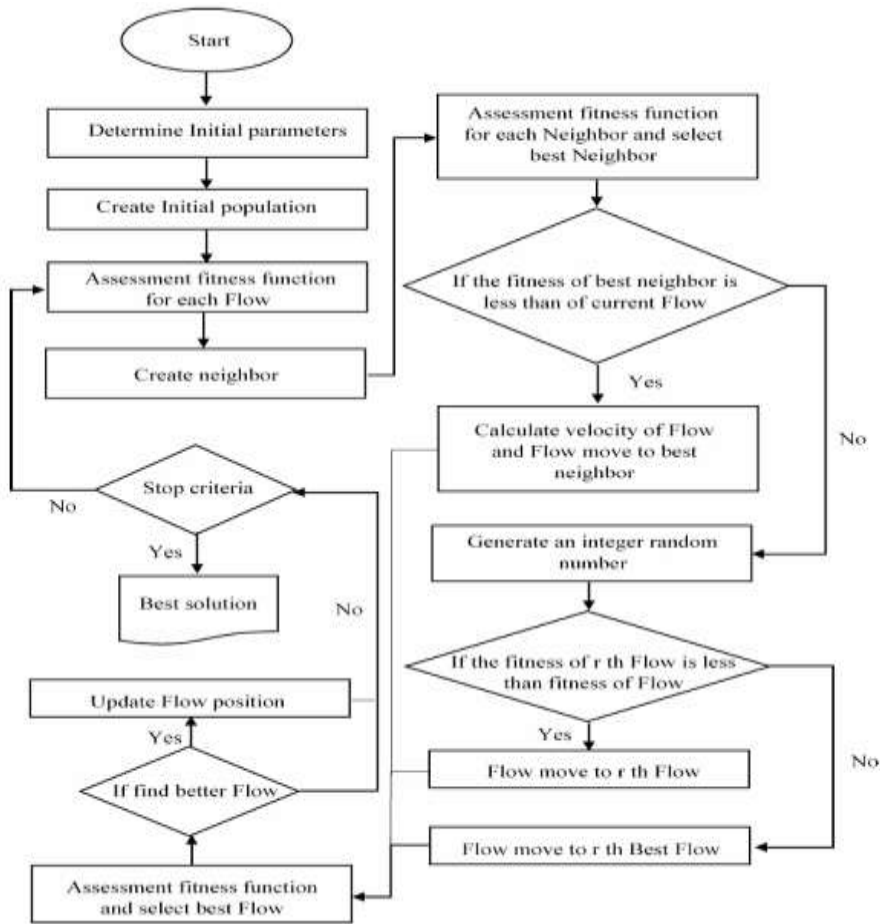


Figure 5: shows the flowchart of the FDA algorithm.

Neighbour Gaze cues Learning (NGCL) Search Strategy:

In NGCL, a candidate position X_{i-NGCL} is generated for flow X_i such that each dimension d is learned by gaze cueing the immediate neighbours of X_i . The immediate neighbours of X_i are a set denoted by N_i , including four elements such that two flow before X_i and two flow after it are selected from the population sorted in a fitness-ascending order. The neighbour gaze cues learning (NGCL) is done by Eq. (17), in which $X_{b,d}$, $N_{i,d}$ and $X_{i,d}$

are the D^{th} dimension of the flow, a random element of N_i and X_i , respectively. Also, F_i is a random number generated by Cauchy distribution as follow: for each wolf X_i , a scale factor F [39] is determined by $F_i = \text{randc}_i(\mu_f, \sigma)$ in which $\sigma=0.5$ and μ_f is the improved scale factors' mean value initiated by 0.5.

$$X_{i\text{-NGCL},d}(t+1) = X_{\alpha,d}(t) + F_i \times (N_{i,d}(t) - X_{i,d}(t)) \quad \dots (17)$$

The F_i value must be between (0, 1), then if $F_i \leq 0$, it will be calculated again, and if $F_i > 1$, it is assumed to be 1. If there is no flow with an enhanced fitness, the scale factor F remains unchanged, but if there is any improved flow in the population, then the weighted Lehmer mean is used to calculate μ_f by Eq. (18).

$$\mu_f = \frac{\sum_{f_i \in S_f} w_{f_i} \times f_i^2}{\sum_{f_i \in S_f} w_{f_i} \times f_i} \quad \dots (18)$$

Where S_f is the set of all scale factors of X_i that $f(X_i(t)) - f(X_i(t+1))$ the weight w_{f_i} is calculated by Eq. (19), where $\Delta f_i = f(X_i(t)) - f(X_i(t+1))$

$$w_{f_i} = \frac{\Delta f_i}{\sum_{f_i \in S_f} \Delta f_i} \quad \dots (19)$$

Random gaze cues learning (RGCL) Search Strategy:

In RGCL, the flow X_i is learned by gaze cueing two random flows X_{r_1} and X_{r_2} , and each dimension of the candidate position $X_{i\text{-RGCL}}$ is generated by Eq. (20).

$$X_{i\text{-RGCL}}(t+1) = X_{i,d}(t) + F_i \times X_{r_1,d}(t) - X_{r_2,d}(t) \quad \dots (20)$$

Where $X_{i,d}$, $X_{r_1,d}$, and $X_{r_2,d}$ are the D^{th} dimension of the i^{th} flow and two random flows selected from the population, and F_i is the same as used in the NGCL search strategy. It is expected that using RGCL can maintain diversity and enhance the exploration because of learning from two random flows X_{r_1} and X_{r_2} .

Results and Discussions

The suggested GFDA was tested on fourteen benchmark functions and Scheduling of smart home appliances for optimal energy management in smart grid to prove effectiveness and robustness. This article has taken the mean value and standard deviation of fourteen functions with 500 maximum iterations, 50 population sizes, and 30 independent runs for a fair comparison.

Benchmark Function:

To further assess the proposed method, 14 benchmark functions are selected to evaluate the performance of GFDA. A detailed description of these functions can be found in Table 1 and Table 2. These 14 benchmark functions are categorized into single-peak and multi-peak dimensional functions. Single-peak functions have a single global optimal solution across the entire space, making them suitable for testing the exploitation performance of the proposed method. On the other hand, multi-peak functions contain multiple local optima, and as the dimensionality increases, the frequency of local optima may rise. Consequently, GFDA is tested on these benchmark functions to evaluate its exploration and exploitation capabilities fairly. A fair comparison is ensured by testing all methods under identical conditions, avoiding bias towards a particular method.

The performance of the proposed algorithm is primarily assessed based on two key components of the simulation results: the average result (Avg) and the standard deviation (Std). The experimental outcomes for GFDA are highlighted in bold in the table.

All experiments are carried out under the same conditions, utilizing 30 search agents and 500 evaluations as described in the paper. It is essential to independently run each function 30 times to minimize the effects of randomness. A non-parametric statistical test with a significance level of 0.05, incorporating the Wilcoxon signed-rank test, Friedman rank test, and success rate at a specific threshold, is used to determine whether GFDA's performance is significantly better than other methods. The following simulation experiments are performed on a PC with a 3.11GHz processor running Windows 11, and all comparative tests are executed using MATLAB R2018b.

Table 1: Description of unimodal benchmark functions.

Functions	Dim	Range	F _{min}
$F_1(x) = \sum_{i=1}^n x_i^2$	30	[-100, 100]	0
$F_2(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	30	[-10, 10]	0
$F_3(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$	30	[-100, 100]	0
$F_4(x) = \max_i \{ x_i , 1 \leq i \leq n \}$	30	[-100, 100]	0
$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30, 30]	0
$F_6(x) = \sum_{i=1}^n ([x_i + 0.5])^2$	30	[-100, 100]	0
$F_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}(0,1)$	30	[-1.28, 1.28]	0

Table 2: Description of multimodal benchmark functions.

Functions	Dim	Range	F _{min}
$F_8(x) = \sum_{i=1}^n x_i \sin(x_i) + 0.1x_i $	30	[-100, 100]	0
$F_9(x) = \sum_{i=1}^n [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[-5.12, 5.12]	0
$F_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^n x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^n \cos(2\pi x_i) + 20 + e\right)$	30	[-100, 100]	0
$F_{11}(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{1}}\right) + 1$	30	[-100, 100]	0
$F_{12}(x) = \sum_{i=1}^n x_i^2 + \left(\frac{1}{2} \sum_{i=1}^n ix_i\right)^2 + \left(\frac{1}{2} \sum_{i=1}^n ix_i\right)^4$	30	[-5, 10]	0
$F_{13}(x) = \sum_{i=1}^{D/4} [(x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} - x_{4i})^2 + (x_{4i-2} - 2x_{4i-1})^4 + 10(x_{4i-3} - 10x_{4i})^4]$	30	[-4, 5]	0
$F_{14}(x) = 10n + \sum_{i=1}^n [x_i^2 - 10\cos(2\pi x_i)]$	30	[-5.12, 5.12]	0

The comprehensive experimental results are provided in Table 3, where the (Average) and (Std. Dev) values for each of the involved procedures are shown based on 30 independent runs. The results for GFDA are specifically highlighted in bold for clarity and emphasis. Upon reviewing the table, it is evident that GFDA consistently outperforms the other methods, securing the highest rank overall, as reflected in the ranking section at the bottom of Table 3. This ranking confirms that GFDA is the most effective method across the 14 benchmark functions tested, making it the superior choice compared to the other algorithms.

Table 3: Average and Standard Deviation values of all algorithms.

Function		BA	SCA	AOA	FDA	OFDA	MFDA	GFDA
F1	Average	2.72E+04	2.91E+00	2.03E-37	1.01E-04	9.03E-70	1.52E-181	0.00E+00
	Std. Dev	9.85E+03	7.10E+00	1.11E-36	6.78E-05	4.95E-69	0.00E+00	0.00E+00
F2	Average	1.63E+06	8.86E-03	0.00E+00	4.59E-04	3.92E-16	5.04E-143	0.00E+00
	Std. Dev	5.88E+06	1.76E-02	0.00E+00	2.96E-04	2.01E-15	1.76E-142	0.00E+00
F3	Average	7.69E+04	7.18E+03	1.40E-03	1.99E+01	1.18E-06	3.02E-176	0.00E+00
	Std. Dev	3.02E+04	5.50E+03	3.58E-03	9.44E+00	5.78E-06	0.00E+00	0.00E+00
F4	Average	6.40E+01	3.06E+01	2.06E-02	1.50E+01	1.46E+01	1.36E-100	0.00E+00
	Std. Dev	8.65E+00	1.37E+01	2.07E-02	2.57E+00	2.92E+00	6.46E-100	0.00E+00
F5	Average	2.61E+07	1.06E+04	2.82E+01	5.20E+01	2.08E+01	2.42E+01	2.90E+01
	Std. Dev	2.52E+07	2.67E+04	3.92E-01	4.33E+01	7.06E+00	8.67E-01	4.15E-02
F6	Average	2.95E+04	9.66E+00	2.85E+00	9.20E-05	0.00E+00	6.30E-06	6.58E+00
	Std. Dev	1.01E+04	1.17E+01	3.30E-01	1.22E-04	0.00E+00	5.92E-06	4.57E-01
F7	Average	7.40E+00	7.20E-02	3.37E-05	7.09E-02	5.54E-04	1.66E-04	8.62E-05
	Std. Dev	2.21E+00	6.67E-02	2.79E-05	2.83E-02	5.33E-04	1.29E-04	1.00E-04
F8	Average	1.38E+02	2.58E+01	2.70E-54	2.32E-01	1.29E-04	2.33E-87	0.00E+00
	Std. Dev	5.02E+01	2.91E+01	1.46E-53	4.30E-01	4.05E-04	1.27E-86	0.00E+00
F9	Average	1.39E+02	3.26E+01	0.00E+00	5.15E+01	1.72E+01	0.00E+00	0.00E+00
	Std. Dev	4.87E+01	3.48E+01	0.00E+00	1.13E+01	2.52E+01	0.00E+00	0.00E+00
F10	Average	1.77E+01	1.41E+01	8.88E-16	3.27E+00	4.20E-15	3.14E-15	8.88E-16
	Std. Dev	1.00E+00	8.90E+00	0.00E+00	9.95E-01	1.60E-15	1.74E-15	0.00E+00
F11	Average	3.06E+02	8.09E-01	1.14E-01	3.65E-02	0.00E+00	0.00E+00	0.00E+00
	Std. Dev	7.83E+01	3.35E-01	8.59E-02	3.92E-02	0.00E+00	0.00E+00	0.00E+00
F12	Average	1.12E+03	2.13E+01	2.11E+02	7.10E-02	8.59E-05	0.00E+00	0.00E+00
	Std. Dev	1.46E+03	1.50E+01	6.19E+01	3.43E-02	4.32E-04	0.00E+00	0.00E+00
F13	Average	5.95E+01	6.47E+00	9.93E-02	1.02E-02	9.02E-04	0.00E+00	0.00E+00
	Std. Dev	1.22E+02	8.57E+00	2.96E-01	6.78E-03	1.77E-03	0.00E+00	0.00E+00
F14	Average	1.59E+02	3.10E+01	0.00E+00	5.56E+01	8.42E+00	0.00E+00	0.00E+00

Std. Dev	5.01E+01	2.92E+01	0.00E+00	1.48E+01	1.43E+01	0.00E+00	0.00E+00
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Looking at the individual functions, for F5, OFDA achieves the lowest (Average) value, indicating a better overall mean performance for this specific function. However, it is GFDA that delivers the lowest (Std. Dev) for the same function, suggesting superior stability in its results. In the context of optimization, a smaller (Std. Dev) typically signifies greater reliability and consistency in the method's performance. For F6, OFDA surpasses GFDA, offering a better optimal solution. This suggests that in this particular case, OFDA is a more reliable choice for achieving the best possible result, demonstrating its competitive advantage over GFDA.

Table 4: Outcomes of the Wilcoxon Signed-Rank Test for all selected algorithms.

GFDA vs	BA	SCA	AOA	FDA	OFDA	MFDA
F1	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12
F2	1.21E-12	1.21E-12	0.00E+00	1.21E-12	1.21E-12	1.21E-12
F3	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12
F4	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12
F5	3.02E-11	3.02E-11	4.08E-11	1.00E+00	3.02E-11	3.02E-11
F6	3.02E-11	1.38E-02	3.02E-11	3.02E-11	1.21E-12	3.02E-11
F7	3.02E-11	3.02E-11	3.15E-02	3.02E-11	9.06E-08	3.56E-04
F8	1.21E-12	1.21E-12	1.21E-12	1.21E-12	2.21E-06	1.21E-12
F9	1.21E-12	1.21E-12	0.00E+00	1.21E-12	6.61E-05	0.00E+00
F10	1.21E-12	1.21E-12	0.00E+00	1.21E-12	3.34E-11	1.79E-07
F11	1.21E-12	1.21E-12	1.21E-12	1.21E-12	0.00E+00	0.00E+00
F12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	0.00E+00
F13	1.21E-12	1.21E-12	1.21E-12	1.21E-12	1.21E-12	0.00E+00
F14	1.21E-12	1.21E-12	0.00E+00	1.21E-12	1.46E-04	0.00E+00
+/-/-	14/0/0	14/0/0	10/0/4	13/1/0	13/0/1	9/0/5

Additionally, the results of the Friedman Test are summarized in Table 3, offering a detailed and comprehensive comparison of the performance of each algorithm tested. The table includes a ranking for each algorithm based on their performance across various test cases. At the conclusion of the table, the Average Ranking Value (ARV) for each algorithm is presented. The ARV represents the mean rank assigned to each algorithm across all test cases, providing a clear indication of its relative performance. Importantly, GFDA stands out by achieving the lowest mean ranking value, signalling that it outperforms all other algorithms in the tests. This superior ranking highlights GFDA's exceptional overall performance, making it the most effective algorithm among those tested.

Similarly, for F11, OFDA, MFDA, and GFDA all yield the same solution, further demonstrating that these methods are capable of finding the same optimal result for this function. In contrast, for functions F12 and F13, both MFDA and GFDA deliver identical solutions, reinforcing the strong performance of these two algorithms in those cases.

In the case of F7, AOA provides a slightly better optimal solution compared to GFDA. Despite this, GFDA's results still fall within a satisfactory range when considering the error margin, indicating that it remains a strong contender, even if not the absolute best. For functions F9 and F14, the results from AOA, MFDA, and GFDA are identical, showing that these three algorithms reach the same optimal solution for these particular functions. This suggests that, for these cases, all three methods perform equivalently well. Overall, the detailed results provide a comprehensive view of the performance of each algorithm across various test cases, highlighting the strengths and weaknesses of each and underscoring the relative advantages of GFDA in terms of both performance and stability.

Table 5: Friedman test results by all selected algorithms.

Function	BA	SCA	AOA	FDA	OFDA	MFDA	GFDA
F1	7.00	6.00	3.03	5.00	3.87	2.10	1.00
F2	7.00	5.93	1.50	5.07	4.00	3.00	1.50
F3	7.00	6.00	3.20	5.00	3.73	2.07	1.00
F4	6.97	5.80	3.00	4.63	4.60	2.00	1.00
F5	7.00	5.97	3.47	3.90	1.13	2.03	4.50
F6	7.00	5.30	4.00	3.00	1.00	2.00	5.70
F7	7.00	5.40	1.37	5.60	3.70	2.90	2.03
F8	6.97	6.00	2.87	5.03	2.92	3.00	1.22
F9	6.97	5.10	2.28	5.60	3.48	2.28	2.28
F10	6.33	6.37	1.75	5.30	3.50	3.00	1.75
F11	7.00	6.00	4.87	4.13	2.00	2.00	2.00
F12	6.63	5.10	6.17	4.10	3.00	1.50	1.50
F13	6.63	6.17	3.60	4.83	3.77	1.50	1.50
F14	7.00	4.97	2.30	5.80	3.33	2.30	2.30
Average	6.89	5.72	3.10	4.79	3.15	2.26	2.09

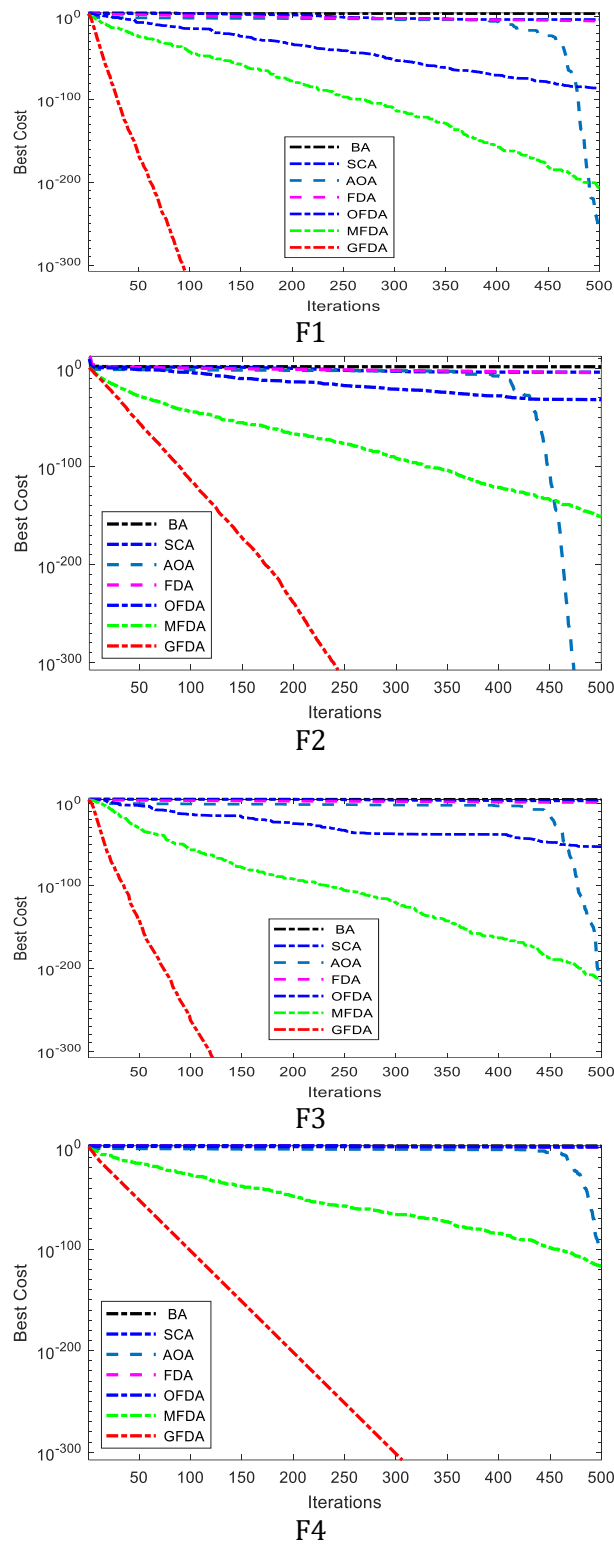
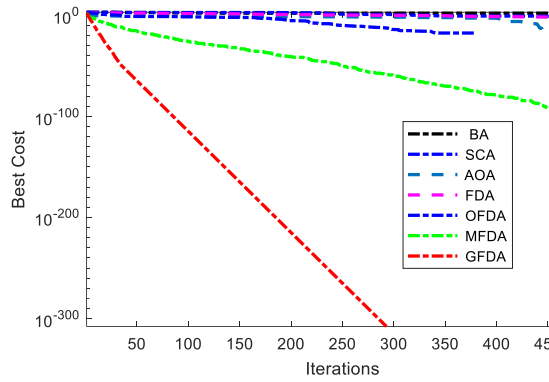
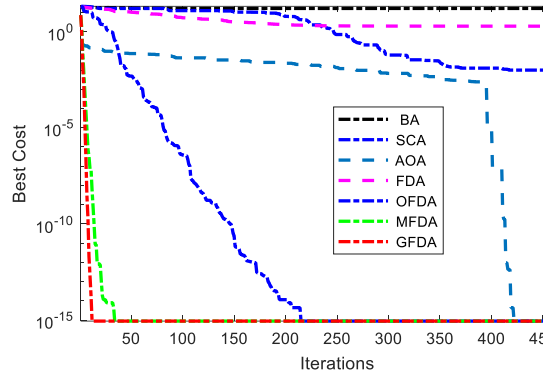


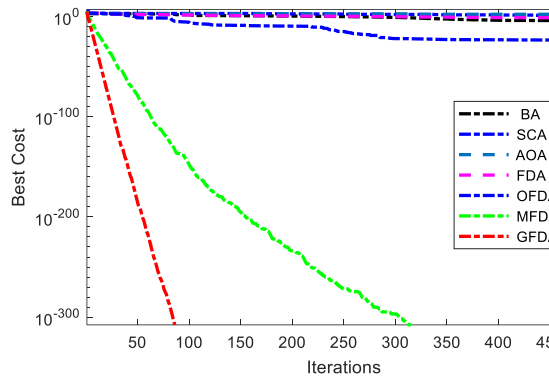
Figure 5: Convergence curves of various uni-model functions.



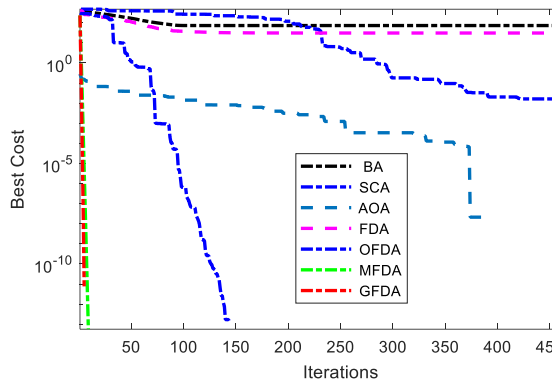
F8



F10



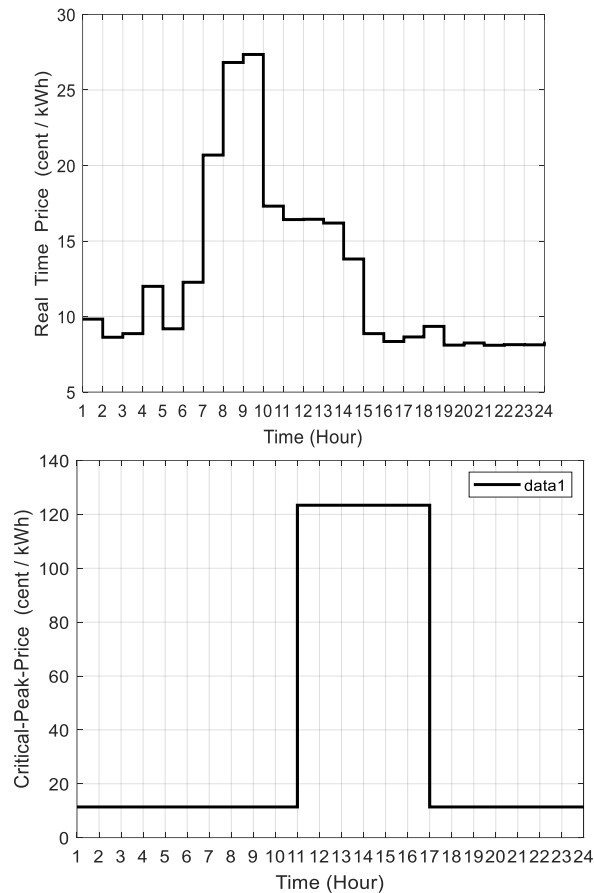
F12



F14

Figure 6: Convergence curves of various multi-model functions.**Optimum Energy Management in Smart Home:**

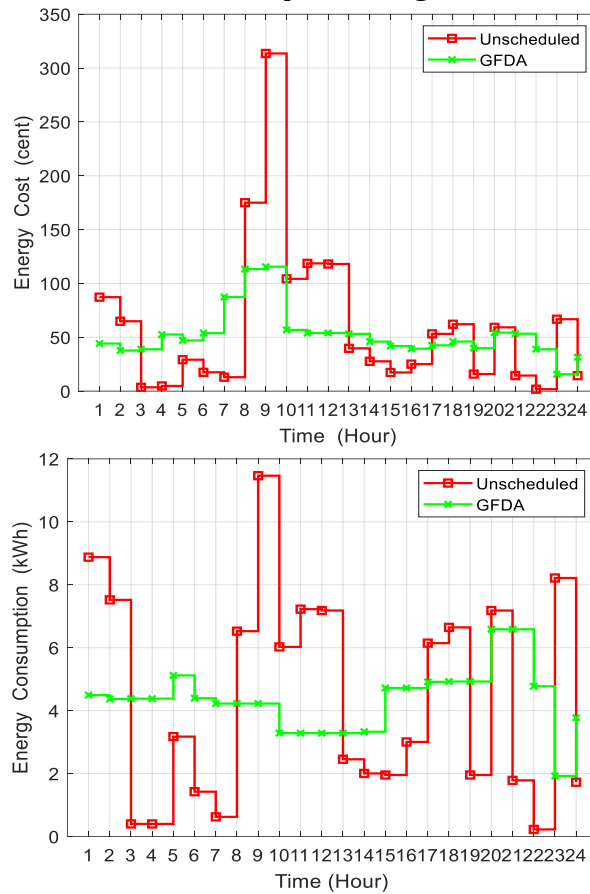
In this section, an empirical simulation was performed to evaluate the performance of proposed algorithm in terms of electricity cost minimization, PAR reduction, and improvement the comfort of end-user by reducing the waiting time of appliances. In this work, the smart home consists of twelve kinds of household appliances ($D = 15$). All appliances and their power rating with length of operation time (LOT) are given in Table 6.

**(a) Real Time Pricing tariff****(b) Critical-Peak-Price tariff****Figure 7: Histogram of pricing tariffs.****Table 6: Detail description of appliances used in simulations.**

Appliance Class	Appliance Name	Power Rating (kW)	LOT (slots)
Interruptible	Vacuum cleaner	1.2	6
	Water heater	2.6	8
	Air conditioner	1.5	14
	Dish washer	2.5	4
	Water pump	1	8
	Steam Iron	1.2	3
Non-interruptible	Washing Machine	3	5
	Tumble Dryer	3.3	4

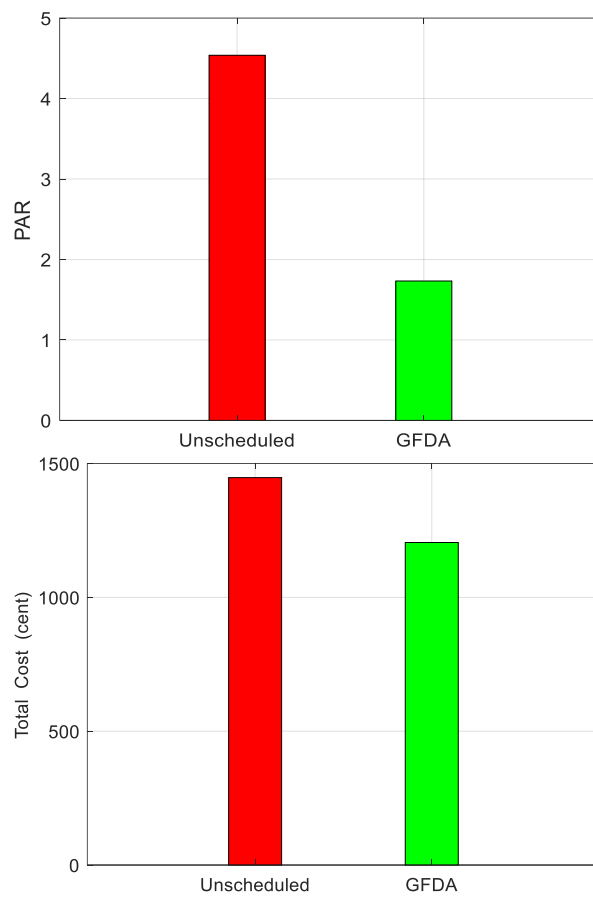
Base	Refrigerator	0.225	20
	Oven	1.23	4
	Blender	0.3	2
	Ceiling fan	0.1	12
	Desktop PC	0.3	10
	TV	0.3	9
	Laptop	0.1	8

Load consumption using RTP:



(a) Energy Cost Profile

(b) Energy Consumption Profile

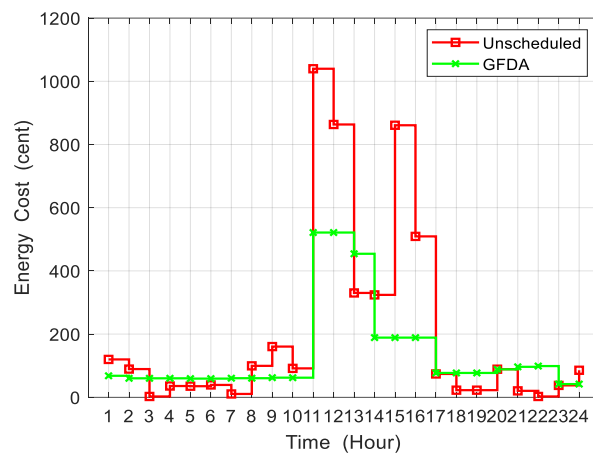


(c) Peak to Average Ratio

(d) Total Electricity Cost

Figure 8: Graphical results using RTP tariff for operational one hour period.

Load consumption using CPP:



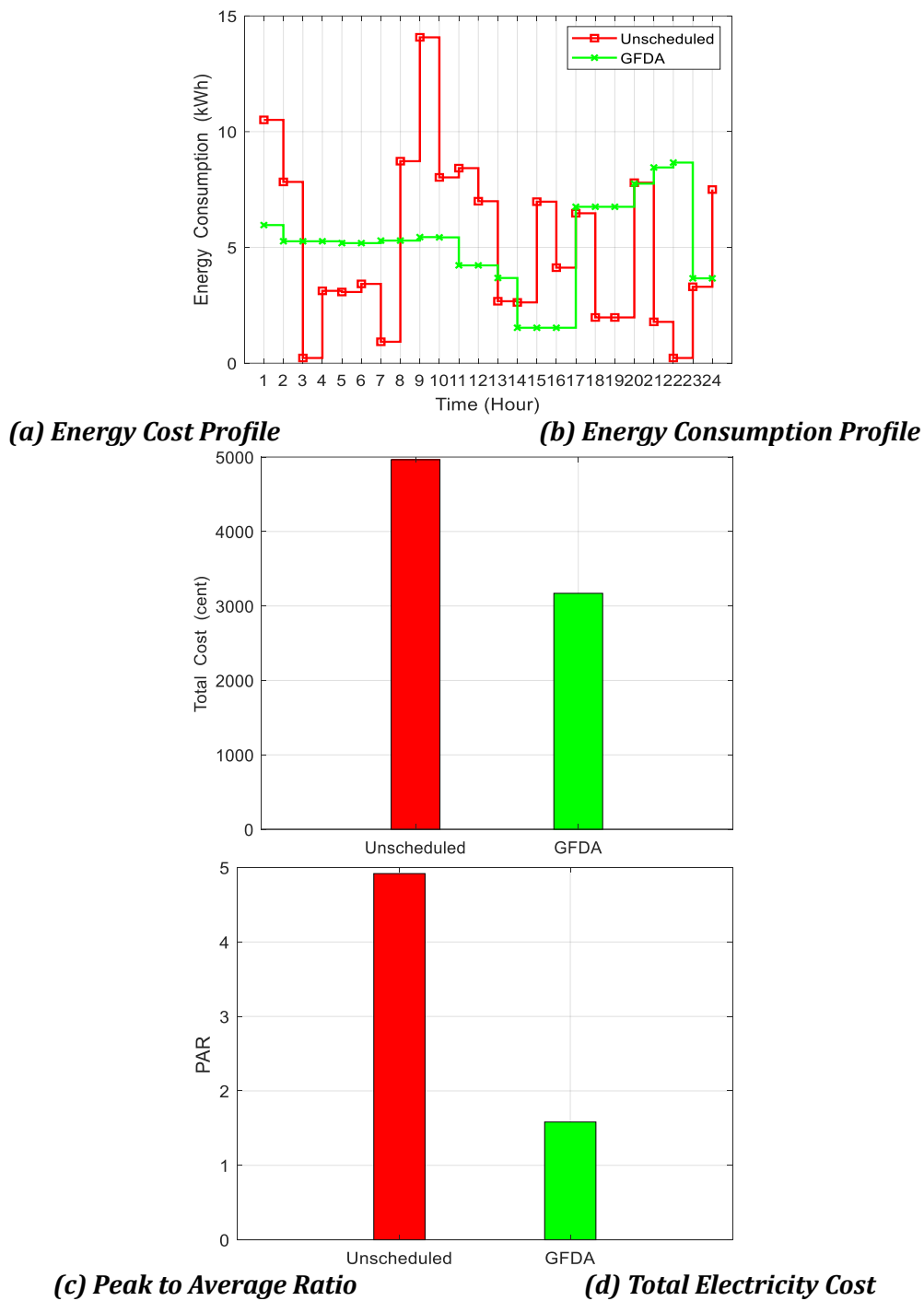


Figure 9: Graphical results using CPP tariff for operational one hour period.

Load consumption patterns using RTP and CPP are shown in Figures 7 (a) & (b) respectively. Figures 7 (a) & (b) show their behaviours to: peaks reduction, electricity cost profile and average waiting times. In RTP signal, on-peak and shoulder-peak hours are within 7–10 and 11–14 respectively, whereas off-peak hours are set between 1–6 and 15–24.

Table 7: Comparison of PAR.

	PAR	Cost	Waiting Time (hours)	Total Load
RTP				
Un-scheduled	5.9002	1447.8	--	104.140
GFDA	1.7324	1205.0396	3.4399	104.140
CPP				
Un-scheduled	5.9002	4956	--	122.800
GFDA	1.5821	3169.5086	3.621	122.800

The table shows that GFDA method has a significantly lower PAR (1.7324 compared to 5.9002 for Un-scheduled, resulting in a lower cost (1205.0396 compared to 1447.8) and total load 122.8, the GFDA method has a significantly lower PAR (1.5821 compared to 5.9002 for Un-scheduled, resulting in a lower cost (3169.5086 compared to 4956).

Table 8: Comparison of PAR and Cost results of proposed algorithms

	RTP			CPP		
	PAR	Difference	Reduction percentage in PAR	PAR	Difference	Reduction percentage in PAR
Un-scheduled	5.9002	--	--	5.9002	--	--
GFDA	1.7324	4.1678	70.63	1.5821	4.31815	73.18
	PAR	Difference	Savings percentage in cost	PAR	Difference	Savings percentage in cost
Un-scheduled	1447.8	--	--	4956	--	--
GFDA	1205.0396	517.16	30.02	3169.5086	1786.4914	36.04

The Table 7 shows values for PAR, including differences and reduction percentages in PAR, as well as cost savings. For instance, GFDA shows a notable reduction in PAR by 70.63% for one scenario and 73.18%. In terms of cost savings, GFDA also demonstrates significant reductions in costs 30.02% and 36.04%; this analysis gives a clear indication that GFDA outperforms Un-scheduled in terms of both PAR reduction and cost savings.

Cost using RTP:

The load profiles of GFDA algorithm are almost same in all of 24 h except of unscheduled case were showing that energy consumption is higher during 1–2 h and 9–10 h which resulting to high cost and PAR in unscheduled case. From this figure clearly showing that the load is transferred from On-peak hours to off-peak hours throughout the day (24 h). In addition, the proposed GFDA algorithm shows most successful scheme of energy consumption as compared to other algorithms, of which avoids peak formation and keeps the load on the medium level contrary to other pairs which having the small shoulder peak hours.

In case of unscheduled load, the maximum peak equal to 11.46 kWh while maximum scheduled is 6.85 kWh. Hence, a difference of 4.61 kWh is registered, which leads to reduce PAR. Furthermore, between 23–24 h and 10–15 h, GFDA consumes less power which significantly reduces overall cost. Meanwhile within 20–22 h, GFDA algorithm

show an increase of energy consumption, where energy level pass from 4.92 kWh to 6.58 kWh. Only reason that GFDA technique shifts more load in these time slots is the lower electricity prices in end of the day.

Cost using CPP:

The load profiles of GFDA algorithm are almost same in all of 24 h except of unscheduled case were showing that energy consumption is higher during 9–10 h and 1–2 h which resulting to high cost and PAR in unscheduled case. From this figure clearly showing that the load is transferred from On-peak hours to off-peak hours throughout the day (24 h). In addition, the proposed GFDA algorithm shows most successful scheme of energy consumption as compared to other algorithms, of which avoids peak formation and keeps the load on the medium level contrary to other pairs which having the small shoulder peak hours.

In case of unscheduled load, the maximum peak equal to 14.07 kWh while maximum scheduled is 8.665 kWh. Hence, a difference of 5.405 kWh is registered, which leads to reduce PAR. Furthermore, between 14–17 h, GFDA consumes less power which significantly reduces overall cost. Meanwhile within 21–23 h, GFDA algorithm show an increase of energy consumption, where energy level pass from 1.53 kWh to 8.665 kWh. Only reason that GFDA technique shifts more load in these time slots is the lower electricity prices in end of the day.

Conclusions:

This paper presented a Gaze Cues Learning Flow Direction Algorithm for scheduling home energy-management-system under various operational and peak power constraints. The proposed algorithms were evaluated using two pricing models: RTP and CPP. In addition, two one-hour time period was considered to evaluate the consumer's demand and behaviour of the suggested scheme. In this original research paper, the performance of GFDA was examined on the basis of electricity-cost, energy-consumption, PAR value, and users-comfort (in regards to waiting-time). The results showed that GFDA can provide both costs and peak demand reduction, with acceptable comfort level to consumers. Simulation results showed that the proposed scheme giving higher reduction in the total energy cost. In terms of PAR reduction, giving higher reduction. The shows that the GFDA proves a greater performance in terms of waiting time reduction, end-users' payments reduction and PAR, however, a trade-off between user comfort and cost was still exists to be addressed. In the future, the authors can propose the possibility to study the energy consumption reduction cost with integration of renewable energy source and storage system.

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