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Energy Optimization with Bio-Inspired Heuristic Techniques in Smart Grid

by

Ibrar Ullah

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Energy Optimization with Bio-Inspired Heuristic Techniques in Smart Grid

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Dedicated to:

Hazrat Muhammad (Peace be upon Him)

My Parents, Teachers, Friends

My Wife

and

My Kids

Asma, Saad, Muhammad and Ayesha

(ASMA)

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List of Publications

It is certified that following publication(s) have been made out of the research work that has been carried out for this thesis:-

1. **I. Ullah** and S. Hussain, "Time-Constrained Nature-Inspired Optimization Algorithms for an Efficient Energy Management System in Smart Homes and Buildings," *Applied Sciences*, Vol. 9 (4), 792, 2019.

2. **I. Ullah** , Z. Khitab, M. N. Khan and S. Hussain, "An Efficient Energy Management in Office Using Bio-inspired Energy Optimization Algorithms," *Processes*, Vol. 7 (3), 142, 2019.

3. **I. Ullah** , I. Hussain and M. Singh, "Exploiting Grasshopper and Cuckoo Search Bio-Inspired Optimization Algorithms for Industrial Energy Management System: Smart Industries," *Electronics*, Vol. 9(1), 105, 2020.

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Abstract

Due to the exponential growth in the human population, the demand of energy is increasing with increased use of technology and smart appliances in every field of life. Energy consumers are increasing day by day due to their highly dependence on automatic operated appliances and power consuming devices. Because of this, reliable and high-quality electrical power system is extremely important to fulfill the residential, commercial and industrial sectors energy demand. Meanwhile there is a rapid increase in the global natural resources pressure. Throughout the world, major blackouts occur due to the consumer energy demand and supply mismatch and system automation deficiencies. Therefore, a transition process from traditional electric power grid to smart grid, to integrate communication and information technologies, is the demand of the future. To fulfill the energy demands, new resources of energy generation are necessary to keep the balance between demands and generation. However, due to the realization of the fact that, with increased carbon emission and scarcity of fossil fuels, optimized and efficient utilization of the existing resources of energy is very important in the near future. Therefore, search and integration of new green renewable energy resources is obligatory in such circumstances. But, integration of green renewable energy resources needs a wide sort of design, planning and optimization. Different conventional optimization techniques, such as Linear Programming (LP), Non-Linear Programming (NLP), Integer Linear Programming (ILP), Mixed Integer Linear Programming (MILP), Dynamic Programming (DP) and Constrained Programming (CP) etc. have already been practiced in the near past. However, in the present situations, when integration of renewable energy resources is mandatory, and problems are non-linear and have numerous local optima, such conventional optimization techniques become obsolete. In the last decade, bio-inspired modern heuristic optimization techniques are getting popularity due to their stochastic nature of search mechanisms and avoidance of large convergence time for exact solution. In this research work, we have explored and analyzed different bio-inspired algorithms for energy optimization problem, such as; Ant Colony Optimization

(ACO), Antlion Optimization (ALO), Bacterial Foraging Optimization (BFO) algorithm, Cuckoo Search Optimization Algorithm (CSOA), Firefly Algorithm (FA), Genetic Algorithm (GA), Grasshopper Optimization Algorithm (GOA) and Moth-Flame Optimization (MFO) algorithm. We also proposed a hybrid version of Genetic and Moth Flame Optimization algorithms, named as, Time-constrained Genetic-Moth Flame Optimization (TG-MFO) algorithm. Three main objectives of the use of the aforementioned bio-inspired algorithms; (a) minimization of the consumed energy cost by shifting the appliances from high energy price hours (on-peak hours) to low energy demand or low price hours (off-peak hours), (b) minimization of the peak to average power ratio (PAR) for stability and further reduction of the energy cost, (c) Reduction in the consumer waiting time due to shifting/scheduling of the appliances. Simulation results show that, the use of bio-inspired energy optimization algorithms gave comparative results in terms of the aforementioned objectives. Renewable energy sources (RESs) and battery storage units (BSUs) are also integrated for further reduction of total load and its cost. For analysis and validation of the proposed bio-inspired algorithms, we applied these algorithms on consumer's different real life scenarios, such as; single home for one day, single home for thirty days, thirty different size homes for one day and thirty different size homes for thirty days in a residential sector, an office in the commercial sector and a woolen mill in the industrial sector. We considered different size homes with different power rating appliances and different length of operational times (LOTs) to make our algorithms more practicable. We put constraints on appliances starting times and their operation ending times to minimize the end user discomfort and frustration along with the reduction of electricity bill. In a single home, we categorized the appliances as; Fixed Load (i.e., non-shift able or non-interruptible load) and shiftable Load (i.e., shift-able or interruptible load) to minimize consumer electricity bill. We also divided the consumers into three types as; (a) non-active users (that are fully depended on utility and do not have their own energy generation or battery storage units, (b) semi-active users (that are partially dependent on utility due to their own renewable energy sources and (c) full-active users (those users who have their own energy generation from any renewable energy sources and battery storage units in their own premises). We proposed three different system models (residential, commercial and industrial) for considering all aforementioned parameters to make a reliable and sustainable demand side management (DSM) system in a Smart Grid (SG). Day ahead pricing (DAP) signals are applied for calculation of the consumed energy cost, to make the system more practicable. In most of our assumed system models, usually there is a trade-off between reduction of consumer's electricity cost and waiting time. Therefore, we proposed hybrid algorithm for achieving our objectives in an efficient way.

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Abbreviations

ACO	Ant colony optimization
ALO	Antlion Optimization
AOAs	Automatic Operating Appliances
BFO	Bacterial Foraging Algorithm
BSU	Battery Storage Unit
CAs	Commercial Areas
CP	Constrained Programming
CPP	Critical Peak Pricing
CSA	Cuckoo search algorithm
DA	Dragonfly algorithm
DP	Dynamic Programming
DR	Demand Response
DSM	Demand Side Management
SL	Shiftable Load
EMC	Energy Management Controller
EU	European Union
FA	Firefly Algorithm
FAU	Full-Active Users
FL	Fixed Load
GA	Genetic Algorithm
GOA	Grasshopper Optimization Algorithm
GSM	Global System for Mobile communication
HEMS	Home Energy Management System
IBR	Inclined Block Rate

ILP	Integer Linear Programming
LOT	Length of Operational Time
LP	Linear Programming
MAIFI	Momentary Average Interruption Frequency Index
MFO	Moth-Flame Optimization
MILP	Mixed Integer Linear Programming
MKP	Multiple Knapsack Problem formulation
NAU	Non-Active Users
NLP	Non-Linear Programming
OEC	Office energy consumption
OEMS	Office Energy Management System
OEMCS	Office Energy Management Control System
OTI	Operational Time Interval
PAR	Peak to Average power Ratio
PLC	Power Line Carrier
RES	Renewable Energy Sources
RTP	Real Time Pricing
SAU	Semi-Active Users
SG	Smart Grid
SM	Smart Meter
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
TEPG	Traditional Electric Power Grid
TG-MFO	Time-constrained Genetic-Moth Flame Optimization
TOU	Time Of Use
Un-sch	Un-scheduled load
WOA	Whale Optimization Algorithm

Symbols

ap_s	Each shiftable appliance	
ap_f	Each fixed appliance	
AP_s	Set of shiftable appliances	
AP_f	Set of fixed appliances	
C	The total electricity cost in sixty time slots	\$
E_s	Energy consumption of shiftable appliances	Wh
E_f	Energy consumption of fixed appliances	Wh
E_{FAU}	Energy consumption of Full-active users	Wh
E_{NAU}	Energy consumption of Non-active users	Wh
E_{SAU}	Energy consumption of Semi-active users	Wh
E_{RES}	Energy generated from RESs	Wh
E_{SAU}	Energy consumption of semi-active users	Wh
E_{rate}	Energy cost per hour	\$
E_{max}	Maximum energy consumption of all appliances	Wh
E_T	Total energy consumption of all appliances	Wh
$Load$	Power consumption of each appliance	W
P_s	Power consumption of shiftable appliances	W
P_f	Power consumption of fixed appliances	W
P_{rate}	Power rating of connected appliances	W
s	Each time slot	Hrs
S	Set of 60 time slots	Hrs
V_T	Threshold limit of total knapsack energy	Wh
X	ON (1) and OFF (0) state of an appliance	

X_{bat}	Charging and discharging state of the batteries	
α_s	Starting time of shiftable appliances	Hrs
α_f	Starting time of fixed appliances	Hrs
β_s	Ending time of shiftable appliances	Hrs
β_f	Ending time of fixed appliances	Hrs
η	The operational starting time of an appliance	Hrs
λ	Multiplying factors of two portions of objective function	
ρ_s	Power rating of shiftable appliances	W
ρ_f	Power rating of fixed appliances	W
τ_s	Length of operational time of ap_s	Hrs
τ_f	Length of operational time of ap_f	Hrs
τ_w	User waiting time of started appliances	Hrs
ζ_m	Electricity cost in each time slot	$

Chapter 1

Introduction

1.1 Motivation and Background

Since the human population of this bio-sphere is increasing day by day, therefore, energy resources are becoming scarce. Because of the traditional methods, most of the generated energy is wasted every year in distribution network and demand side. Therefore, in the field of "energy trading", researchers all over the world have taken keen interest in this issue and finally introduced the concept of the smart grid. Smart grid is an ultimate solution to all of the energy related problems of today's modern world. Since the creation of this biosphere, Nature is becoming a big cause of inspiration. Inspired from nature, numerous researchers all over the world have developed an immense set of algorithms [1] – [71] Table 1.1 and Table 1.2. Some of these algorithms are very efficient and successful in solving real life problems. That's why, these algorithms have become very popular, especially in the field of optimization. In the last decade, researchers are applying these nature-inspired algorithms in different fields of life.

Energy consumers are increasing day by day due to their dependence on power consumption devices. Because of this, reliable and high quality electrical power system is extremely necessary to fulfill the residential, commercial and industrial sectors energy demand. Meanwhile there is a rapid increase in the global natural

Table 1.1: List of bio-inspired algorithms

S. No.	Proposed Algorithm	Ref.	Authors
1	African buffalo opt. algorithm	[1]	Odili JB et al.
2	Ant colony optimization	[2]	Dorigo
3	Ant lion optimizer	[3]	Seyedali Mirjalili
4	Artificial bee colony	[4]	Karaboga and Basturk
5	Atmosphere clouds model	[5]	Yan and Hao
6	Biogeography-based optimization	[6]	Simon
7	Brain Storm Optimization	[7]	Shi
8	Bacterial foraging	[8]	Passino
9	Bacterial-GA Foraging	[9]	Chen et al.
10	Bat algorithm	[10]	Yang
11	Binary bat algorithm	[11]	Seyedali Mirjalili et al.
12	Bee colony optimization	[12]	Teodorovi'c and Dell'Orco
13	Bee system	[13]	Lucic and Teodorovic
14	BeeHive	[14]	Wedde et al.
15	Bees algorithms	[15]	Pham et al.
16	Bees swarm optimization	[16]	Drias et al.
17	Bumblebees	[17]	Comellas and Martinez
18	Cat swarm	[18]	Chu et al.
19	Chaotic Bat Algorithm	[19]	Aamir H. et al.
20	Chaotic cuckoo search	[20]	Wang GG et al.
21	Chaotic Krill Herd algorithm	[21]	Gai-Ge Wang et al.
22	Chicken swarm opt. algorithm	[22]	Meng X et al.
23	Consultant-guided	[23]	search Iordache
24	Cuckoo search	[24]	Yang and Deb
25	Differential evolution	[25]	Storn and Price
26	Dragonfly algorithm	[26]	Seyedali Mirjalili
27	Dolphin echolocation	[27]	Kaveh and Farhoudi
28	Eagle strategy	[28]	Yang and Deb
29	Eco-inspired evolutionary algorithm	[29]	Parpinelli and Lopes
30	Egyptian Vulture	[30]	Sur et al.
31	Elephant Search Algorithm	[31]	S. Deb et al.
32	Fish-school Search	[32, 33]	Lima et al.
33	Flower pollination algorithm	[34, 35]	Yang
34	Fast bacterial swarming algorithm	[36]	Chu et al.
35	Firefly algorithm	[37]	Yang

resources pressure. Throughout the world, major blackout occurs due to consumer demand and utility supply mismatch and system automation deficiencies. So, a transition process from traditional electric power grid (TEPG) to smart grid (SG), to integrate communication and information technologies, is the demand of

Table 1.2: List of bio-inspired algorithms

S. No.	Proposed Algorithm	Ref.	Authors
36	Fish swarm/school	[38]	Li et al.
37	Good lattice swarm optimization	[39]	Su et al.
38	Glowworm swarm optimization	[40, 41]	Krishnanand and Ghose
39	Gene expression	[42]	Ferreira
40	Grasshopper optimization algorithm	[43]	Shahrzad Saremi
41	Grey Wolf Optimization	[44]	S. Mirjalili et al.
42	Great salmon run	[45]	Mozaffari
43	Group search optimizer	[46]	He et al.
44	Human-Inspired Algorithm	[47]	Zhang et al.
45	Hierarchical swarm model	[48]	Chen et al.
46	Invasive weed optimization	[49]	Mehrabian and Lucas
47	Japanese tree frogs calling	[50]	Hern'andez and Blum
48	Krill Herd	[51]	Gandomi and Alavi
49	Lion optimization algorithm	[52]	Rajakumar BR
50	Marriage in honey bees	[53]	Abbass
51	Monkey search	[54]	Mucherino and Seref
52	Moth-flame optimization algorithm	[55]	Seyedali Mirjalili
53	Multi-objective grey wolf optimizer	[56]	Seyedali Mirjalili
54	OptBees	[57]	Maia et al.
55	Paddy Field Algorithm	[58]	Premaratne et al.
56	Particle swarm algorithm	[59]	Kennedy and Eberhart
57	Queen-bee evolution	[60]	Jung
58	Roach infestation algorithm	[61]	Havens
59	Salp Swarm Algorithm	[62]	Seyedali Mirjalili et al.
60	Shuffled frog leaping algorithm	[63]	Eusuff and Lansey
61	Social spider algorithm	[64]	Yu JJQ and Li VOK
62	Spider monkey opt. algorithm	[65]	Bansal JC et al.
63	Termite colony optimization	[66]	Hedayatzadeh et al.
64	Virtual ant algorithm	[67]	Yang
65	Virtual bees	[68]	Yang
66	Weightless Swarm Algorithm	[69]	Ting et al.
67	Whale optimization algorithm	[70]	Seyedali Mirjalili
68	Wolf search	[71]	Tang et al.

the future. To fulfill the energy demands, new resources of energy generation are necessary to keep the balance between demands and generation. Due to the realization of the fact that, with increased carbon emission and scarcity of fossil fuels, optimized and efficient utilization of the existing energy resources is very important in the near future. Secondly, search and integration of new green renewable energy resources is obligatory in such circumstances. The integration of green renewable energy resources needs a wide sort of design, planning and optimization. Different conventional optimization techniques, such as LP, NLP, ILP, MILP, DP and CP etc. have been practiced so for. But in the present situations, when integration of renewable energy resources is mandatory, and problems are non linear and have numerous local optima, such conventional optimization techniques become obsolete. In the last decade, bio-inspired modern heuristic optimization techniques are getting popularity due to their stochastic search mechanisms and avoidance of large convergence time for exact solution.

In this work, we have given an overview of all proposed bio-inspired algorithms in literature. Then we have analyzed and applied some of these bio-inspired algorithms like, ACO, ALO, BFA, CSOA, FA, GA, GOA and MFO algorithms for energy optimization problem in smart grids (SG). We implemented these algorithms in residential, commercial and industrial sectors for energy optimization by scheduling end-user appliances and machines. Our objectives are reduction of energy cost and PAR, while considering high end-user comfort level. To reduce user frustration due to waiting time by scheduling the appliances, we also combined GA with MFO, and proposed hybrid version TG-MFO (time-constrained genetic moth-flame optimization) algorithm.

1.2 Research Challenges

Traditional electric power grids are unable to fulfill today's electricity demand. This deficiency has raised the demand for an energy management system. By exploiting various computational techniques and algorithms, the aforementioned problem could be solved comfortably. Researchers have applied different bio-inspired algorithms, however, they did not consider the end-user comfort by reducing their waiting time along with the reduction of energy cost and PAR. Therefore, in this research work, we use different bio-inspired techniques for three main sectors of consumers, i.e. residential, commercial and industrial. In residential sector, different home appliances with different power ratings and length of operational times (LOTs) are considered. While, in commercial sector, eight appliances have been considered, named as automatically operating appliances (AOAs). In industrial sector, we have divided our load in different load units. For residential and industrial sectors, 24 hrs are considered, while in commercial applications 12 hrs are considered. The scheduling of appliances is one of the most important requirements to optimize the performance of smart homes. The objectives of scheduling are to reduce; the electricity bill, PAR, aggregated power consumption and appliances waiting time in order to maximize the end user comfort etc. In this regard, the current research in SG majorly focuses on optimization techniques for power scheduling. Numerous researchers all over the world have proposed different system models for energy cost minimization and reduction of peak to average power ration. These techniques have efficiently reduced consumer electricity bills and PAR, however, they have the limitations of comfort in terms of appliances waiting time of end user (which should be kept minimum), i.e., when and which appliance a consumer wants to start, it must be start with minimum waiting time. In the present era of electricity dependent modern technologies, user wants to finish his job quickly, instead of waiting for his appliances to start. On the other hand, the consumption has to be minimized in order to reduce the cost as well. But unfortunately, these research attempts have ignored frequency of interruptions and aggregated power consumption, as these issues threaten the reliability, stability, sustainability and security of SG.

1.3 Objectives

There are four main objectives of our work as listed below:

1. Minimization of consumer's frustration in terms of waiting time due to scheduling of their appliances;

2. Reduction of consumer's electricity bill by shifting their load from on-peak hours to off-peak hours;

3. Minimization of peak to average power ratio (PAR);

4. Integration of renewable energy resources (RESs) and batteries storage units (BSUs).

The mathematical formulation of our objective function is given by:

$$E_T^N = \sum_{n=1}^{N} W_n \times X_n \tag{1.1}$$

where, W_n is the power of n^{th} appliance, N shows the total no of appliances, X_n is the ON-time in a time slot of n^{th} appliance and E_T^N is the total energy calculated for all appliances in a single time slot.

Now the total cost C_{Sch} for all scheduled appliances can be calculated by multiplying total energy $E_{T,m}^N$ calculated in m^{th} time slot with respective energy price ζ_m in that time slot.

$$C_{Sch} = \sum_{m=1}^{M} E_{T,m}^N \times \zeta_m \tag{1.2}$$

C_{unsch} is the total energy price for all slots of Unscheduled appliances calculated in the similar manner, then the normalized C_{Norm} of scheduled appliances can be calculated as:

$$C_{Norm} = \frac{C_{Sch}}{C_{Sch} + C_{unsch}} \tag{1.3}$$

1.3.1 User's Waiting Time (τ_w)

User's comfort in terms of waiting time is important for end-users. Waiting time must be minimized to have a high comfort level so that the end-user's frustration can be avoided. It is that interval of time when a consumer wants to switch-ON an appliance, however, due to the scheduling limitations of the system, consumer has to wait for starting its operation. As we have defined the starting time α and the latest ending time β of an appliance, then another parameter η will be the operational starting time of the same switched-ON appliance. This is shown diagrammatically in Figure 1.1. Where, β - α is the time span, defined by the consumer. The figure shows that a consumer's maximum waiting time could be up to η_{max}. Since length of operational time (LOT) is already defined by the consumer, so at η_{max}, the algorithm will have to start the appliance to complete its operation up to the final time β.

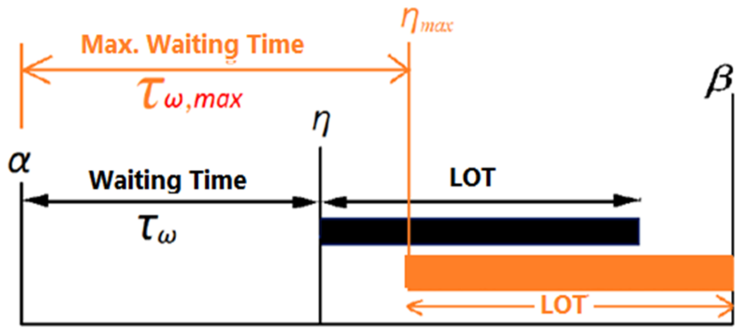

FIGURE 1.1: Starting time, ending time, LOT and waiting time.

Here, LOT is the length of the operational interval of time, in which an appliance completes its task. To elaborate it further, let a user wants to start his/her washing machine. As given in Table 1.3, its starting time (α)= 09.00 and ending time (β)= 12.00. So, its Time-span ($\beta - \alpha$)= 12-9= 3 hrs. However, its LOT= 1.5 hrs. Now this washing machine can start its operation from 9.00, 09.30, 10.00 Or at most 10.30, because it needs 1.5 hrs to complete its operation. Now, if this washing machine started at 09.00, so waiting time is zero. If it starts its operation at 09.30, the waiting time will be 0.5 hr and so on. The maximum starting time η_{max} could be 10.30 to complete its operation LOT=1.5 hrs.

Now, since,

$$(\beta - \alpha) \geq LOT \tag{1.4}$$

Therefore, the range of waiting time can be α to η_{max}, as shown in Figure 1.1.

Appliances' normalized waiting time (τ_w) can be calculated as:

$$\tau_w = \frac{\eta - \alpha}{\eta_{max} - \alpha} \tag{1.5}$$

Equation (1.5) shows that the normalized waiting time can be from "0" (when $\eta = \alpha$) to "1" (when ($\eta = \eta_{max}$). Now, the final expression for minimization function is given by the following equation:

$$min\Bigg((\lambda_1 \times C_{Norm}) + (\lambda_2 \times \tau_w)\Bigg) \tag{1.6}$$

Our proposed objective function aims to reduce electricity cost, while maintaining higher end user comfort level by minimization of waiting time. λ_1 and λ_2 are multiplying factors of two portions of our objective function. Their values varies between '0' and '1' so that $\lambda_1 + \lambda_2$=1 . It reveals that either λ_1 and λ_2 could be 0 to 1. That is, if an end user does not want to participate in the load scheduling process, then his multiplying factors will be λ_1 =1 and λ_2 =0 in the objective function.

Table 1.3 illustrates the typical electricity demand of a single home and multiple homes, with different power ratings and types of appliances, their LOTs and (α) and (β) constraints [72]. Since different end-users have different habits and life routines, with different sizes and power ratings of appliances, we have assumed four types of homes and randomly selected through the proposed algorithm, to have randomness in the consumed energy when taking multiple, i.e., 30 homes.

1.3.2 Peak to Average Power Ratio (PAR)

It is the ratio of the "peak load of the consumer" to the "average load" of the consumer, in every interval of time and is denoted by PAR. PAR can be minimized by reducing the peak load demand W_{max} of a consumer using the proposed scheduling algorithms, which is in favour of both the utility and consumer for maintaining demand-supply balance. Mathematically, it is defined as in [102]:

$$PAR = \frac{Load_{peak}}{Load_{avg}} = \frac{W_{peak}}{\frac{1}{T}\sum_{n=1}^{T} W_{t,n}} \tag{1.7}$$

where, W_{peak} is the peak load demand of a consumer during 24 hrs interval of time. Now the purpose of demand side management (DSM) is, to reduce this peak load by shifting some load to low demand (Off-peak) hours, by using some optimization algorithms, while keeping in view the user frustration in terms of waiting time.

TABLE 1.3: Appliances and their running time constraints [72]

S. No.	**Appliance**	**Category**	**Power Rating $\rho_{e,n}$ (KW)**	**Starting time (α)**	**Ending time (β)**	**Time-span ($\beta - \alpha$) (hrs)**	**LOT (hrs)**
1	Fridge-1	Fixed	0.3	00	24	24	24
2	Interior Lighting-1	Fixed	0.84	18	24	06	6.0
3	Dish Washer-1	Shiftable	2.0	09	17	08	2.0
4	Washing Machine-1	Shiftable	0.6	09	12	03	1.5
5	Spin Dryer-1	Shiftable	2.5	13	18	05	1.0
6	Cooker Hob-1	Shiftable	3.0	08	09	01	0.5
7	Cooker Oven-1	Shiftable	5.0	18	19	01	0.5
8	Microwave-1	Shiftable	1.7	08	09	01	0.5
9	Lap top-1	Shiftable	0.1	18	24	06	2.0
10	Desk Top-1	Shiftable	0.3	18	24	06	3.0
11	Vacuum cleaner-1	Shiftable	1.2	09	17	08	0.5
12	Electrical car-1	Shiftable	3.5	18	08	14	3.0
1	Fridge-2	Fixed	0.25	00	24	24	24
2	Interior Lighting-2	Fixed	0.9	19	24	07	7.0
3	Dish Washer-2	Shiftable	1.9	11	15	04	2.0
4	Washing Machine-2	Shiftable	0.5	10	14	04	2.0
5	Spin Dryer-2	Shiftable	2.0	10	16	06	2.0
6	Cooker Hob-2	Shiftable	3.5	09	10	01	0.5
7	Cooker Oven-2	Shiftable	5.4	17	20	03	1.5
8	Microwave-2	Shiftable	1.9	07	09	02	0.8
9	Lap top-2	Shiftable	0.09	16	23	07	3.0
10	Desk Top-2	Shiftable	0.28	14	20	06	2.0
11	Vacuum cleaner-2	Shiftable	1.4	10	16	06	1.5
12	Electrical car-2	Shiftable	3.3	16	09	17	4.0
1	Fridge-3	Fixed	0.5	00	24	24	20
2	Interior Lighting-3	Fixed	0.62	17	06	13	13
3	Dish Washer-3	Shiftable	2.5	10	16	06	2.5
4	Washing Machine-3	Shiftable	0.8	08	14	06	1.8
5	Spin Dryer-3	Shiftable	2.5	13	19	06	1.0
6	Cooker Hob-3	Shiftable	3.2	07	09	02	0.5
7	Cooker Oven-3	Shiftable	5.3	16	18	02	1.5
8	Microwave-3	Shiftable	1.9	10	14	04	1.0
9	Lap top-3	Shiftable	0.2	16	24	08	2.5
10	Desk Top-3	Shiftable	0.4	18	20	02	1.0
11	Vacuum cleaner-3	Shiftable	1.3	11	12	01	0.5
12	Electrical car-3	Shiftable	3.4	16	07	11	5.0
1	Fridge-4	Fixed	0.4	00	24	24	18
2	Interior Lighting-4	Fixed	0.7	19	08	13	13
3	Dish Washer-4	Shiftable	2.3	08	19	11	4.0
4	Washing Machine-4	Shiftable	0.9	11	14	03	1.0
5	Spin Dryer-4	Shiftable	2.0	14	20	06	1.0
6	Cooker Hob-4	Shiftable	3.5	10	12	02	1.2
7	Cooker Oven-4	Shiftable	5.5	10	11	01	0.8
8	Microwave-4	Shiftable	1.9	10	14	04	1.5
9	Lap top-4	Shiftable	0.15	11	23	12	4.0
10	Desk Top-4	Shiftable	0.4	09	24	15	6.0
11	Vacuum cleaner-4	Shiftable	1.5	11	16	05	1.2
12	Electrical car-4	Shiftable	4.0	10	22	12	4.0

1.3.3 Renewable Energy Source (RES) Model

Photovoltaic (PV) cells and wind turbines can be used as local power generators, also known as distributed RESs, on consumer premises. These RESs can be used for the local energy generation, as well as for charging the batteries in BSUs. The RESs' generated energy, denoted by E_{RES} (Figure 1.3), can be calculated as in [73], by approximating a local Gaussian function (Figure 1.2) as follows:

$$E_{RES}(t,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{(-\frac{(t-\mu)^2}{2\sigma^2})} \tag{1.8}$$

where t denotes the prospection variable (time), μ is the mean or central value and σ is the standard deviation.

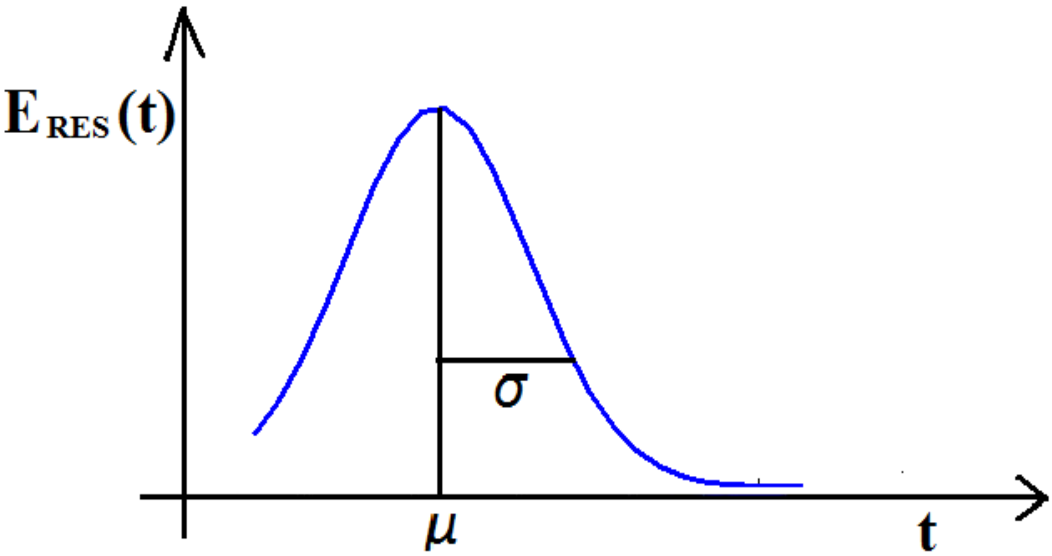

FIGURE 1.2: Gaussian function representing the approximate PV cells' energy generation (Wh) [73].

The total daily energy generated from RESs must be positive, i.e., greater than zero and on daily basis, it is given by:

$$0 \leq E_{RES} \leq E_{RES_{(max)}} \tag{1.9}$$

where $E_{RES_{(max)}}$ is the maximum available RESs' generated energy capacity. If in any time interval, the renewable energy source (RES) generated energy exceeds

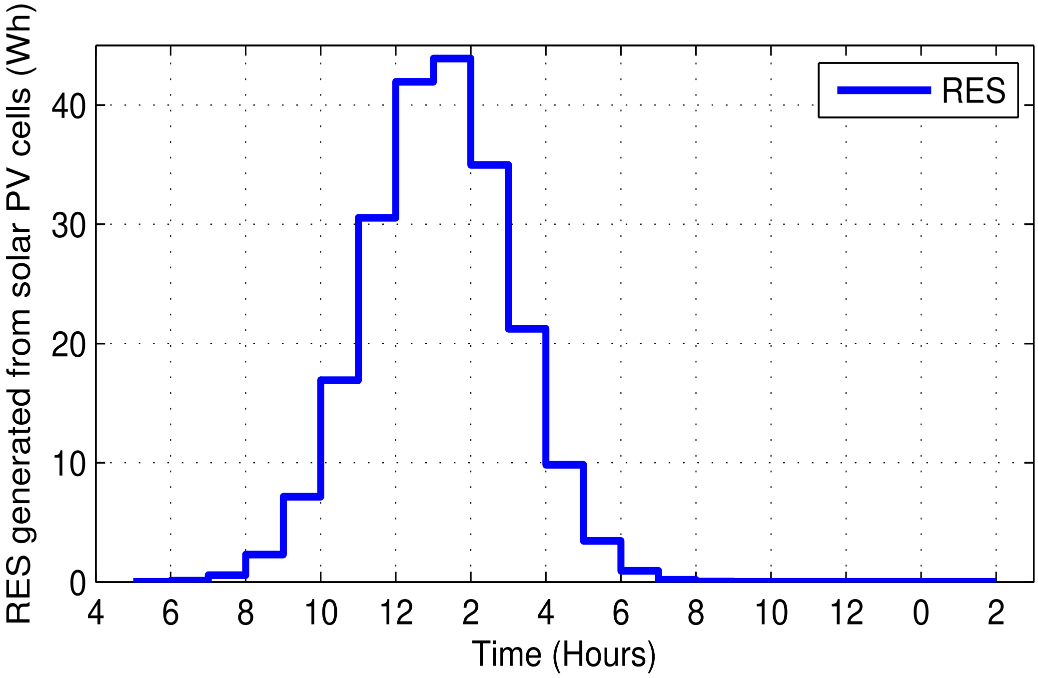

FIGURE 1.3: RES-generated energy E_{RES} for a single home.

the end-user energy demand E_T, i.e.,

$$E_{RES} > E_T \tag{1.10}$$

then it is sold back to the grid as per their prior agreement or can be used for charging batteries in BSUs for later use, particularly during peak hours.

1.3.4 Batteries Storage Units (BSUs) Model

When RESs' generated energy exceeds the consumer energy demand, it is stored in the batteries using BSUs, which can be used during on-peak hours or night-time, when RESs are not available. This can be modeled using a binary variable X_{bat} as:

$$X_{bat} = \begin{cases} 1 & \text{for charging} \\ 0 & \text{for discharging} \end{cases} \tag{1.11}$$

where X_{bat} shows the charging and discharging states of the batteries. In this model, I ignore the energy losses during the charging and discharging process.

1.4 Smart Grid and its Benefits

A Smart grid (SG) is generally a combination of information technology (IT) and traditional electric power grid (TEPG). SG networks can combine the proceedings of all attached generators, transmission and consumers intelligently. Recently, the traditional grids are transformed to smart digitized power grids due to several factors. They were energy inefficient, tendency to regular transmission failures and insecure. SG involves communication, control system, automation, computer technology, power electronics, distributed generation, energy storage systems and information flow. Traditionally, the flow of electric power is unidirectional, i.e. from the supply to demand side. Conversely, SG purpose is to make the flow of electricity supply and demand possible in bidirectional way.

1.4.1 Smart Grid Networks

For the flourishing functionality of SG, an integrated reliable, secure, high performance, scalable and robust SG communication network is necessary. This will make possible gathering distant and real time information from different grid remote terminal units (RTUs) as well as to support various applications.

1.4.2 Traditional Electric Power Grid to Smart Grid

With the passage of time energy consumers are increasing due to their dependence on power consumption devices. Because of this, reliable and high quality electrical power system is extremely necessary to fulfill the consumer energy demand. Meanwhile there is a rapid increase in the global natural resources pressure. Throughout the world, major blackout occurs due to consumer demand and utility supply mismatch & system automation deficiencies. So, a transition process from Traditional Electric Power Grid to Smart Grid (TEPG) to Smart grid (SG), to integrate communication and information technologies, is the demand of the future. Figure 1.4 shows the schematic view of up-gradation of conventional grid to smart grid. The figure shows that, along with power lines, each section of the existing grid is connected to another section using different types of communication means, like, WiFi, WiMax, GSM, Power Line Communication (PLC) etc. In SG, to reduce the cost of the consumed energy by the end user, during peak hours, the consumers also known as prosumers can produce energy from solar, wind and other possible sources. So, the goal of SG is to accomplish proficient energy consumption level by different end users.

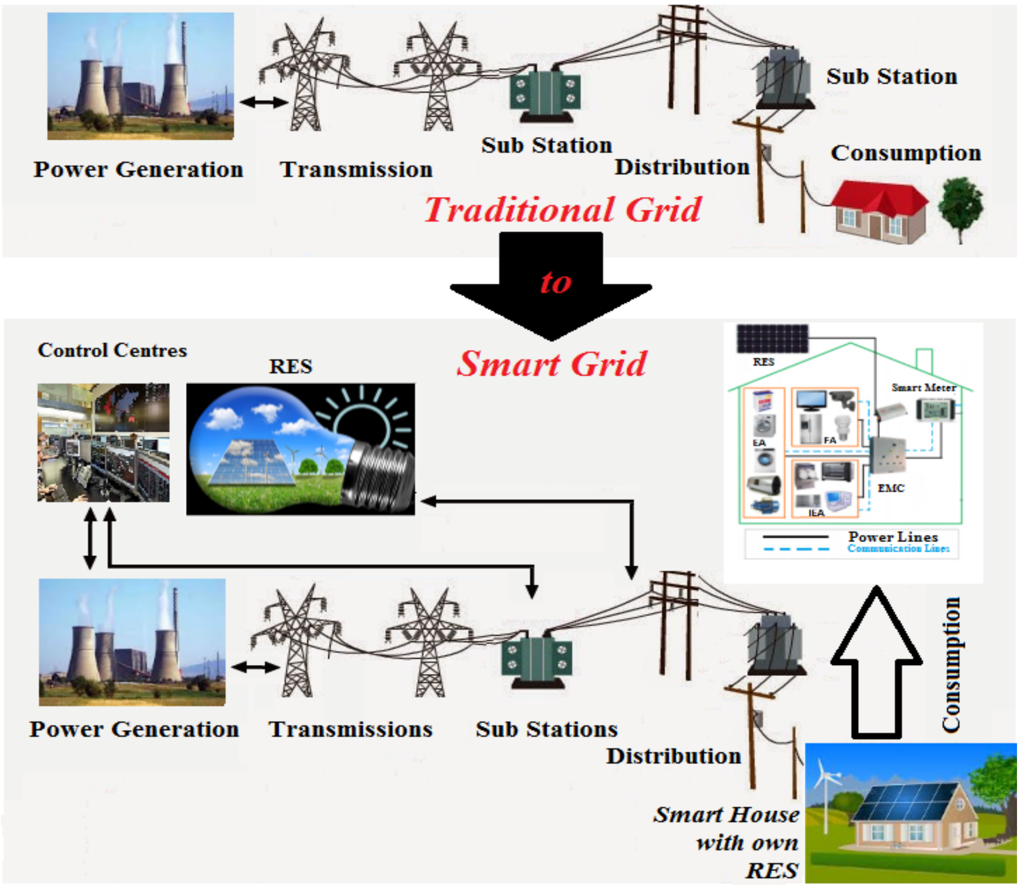

FIGURE 1.4: Traditional Grid to Smart Grid

1.4.3 Smart Meter (SM)

Smart meter (SM) is an energy measuring device installed at consumer end. It uses advanced metering infrastructure (AMI) for its communication with the power grid. SMs are used to make possible two-sided stream of information between the end electricity user and power providing companies.

1.4.4 Home Energy Management System (HEMS)

To keep demand-supply balance, HEMS is an extension of SG. Using AMI and sensors, HEMS is used to help end user to minimize total electricity bill and curtail peak load, hence reduction in PAR. By rescheduling the energy usage pattern of end user's house hold appliances, electricity bill can be highly reduced. During peak hours, energy consumption and load can be reduced by HEMS in smart grid, known as demand side management (DSM). With a proficient DSM system, major blackout and risk of power system failure can be avoided in both utility and consumer. So the main purpose of HEMS is to decrease electricity bill by minimizing the consumer's contribution to the peak hours energy demand i.e. PAR and household carbon emission reduction. Throughout the world, many researchers are investigating to apply artificial intelligence (AI) with HEMS in SG, to have a reliable and energy efficient system. The appearance of SG intelligent HEMS is made possible due to advancement in AI field. It means to put intelligence in the machines through software for self-healing and self-supporting of the system.

1.4.5 Demand Side Management (DSM)

Electric power providers use the terminology of DSM in SG to manage the usage of electric power by the consumers. For DSM, various terminologies are used like demand response (DR) and energy efficiency (EE). DR is a program name. In DR, electric power consumers are encouraged for reduction in their electricity demand for short intervals particularly during peak hours. This reduction in electricity demand will be either in response to electricity pricing schemes or utility operator triggers end user appliances by giving them some incentives. This interval is usually ranges from 1 to 4 hours. This can be achieved by either lighting reduction or HVAC levels adjustment. This can also be achieved by integration of some RES at consumer end to minimize the electricity demand. For end user's consumed energy cost calculation, different pricing schemes are available. In DSM, consumers are encouraged for efficient utilization of electricity permanently through different incentives provided by the utilities. DSM can be achieved by saving energy using energy saver lights, fans, inverter air conditioners (AC), up-gradation of building automation and improvements of HVAC system etc. Demand side management (DSM) has many strategies which help to solve the energy optimization problem by peak clipping, load shifting, strategic conservation, flexible load shifting, strategic load growth and valley filling [74]. All these strategies are shown in Figure 1.5.

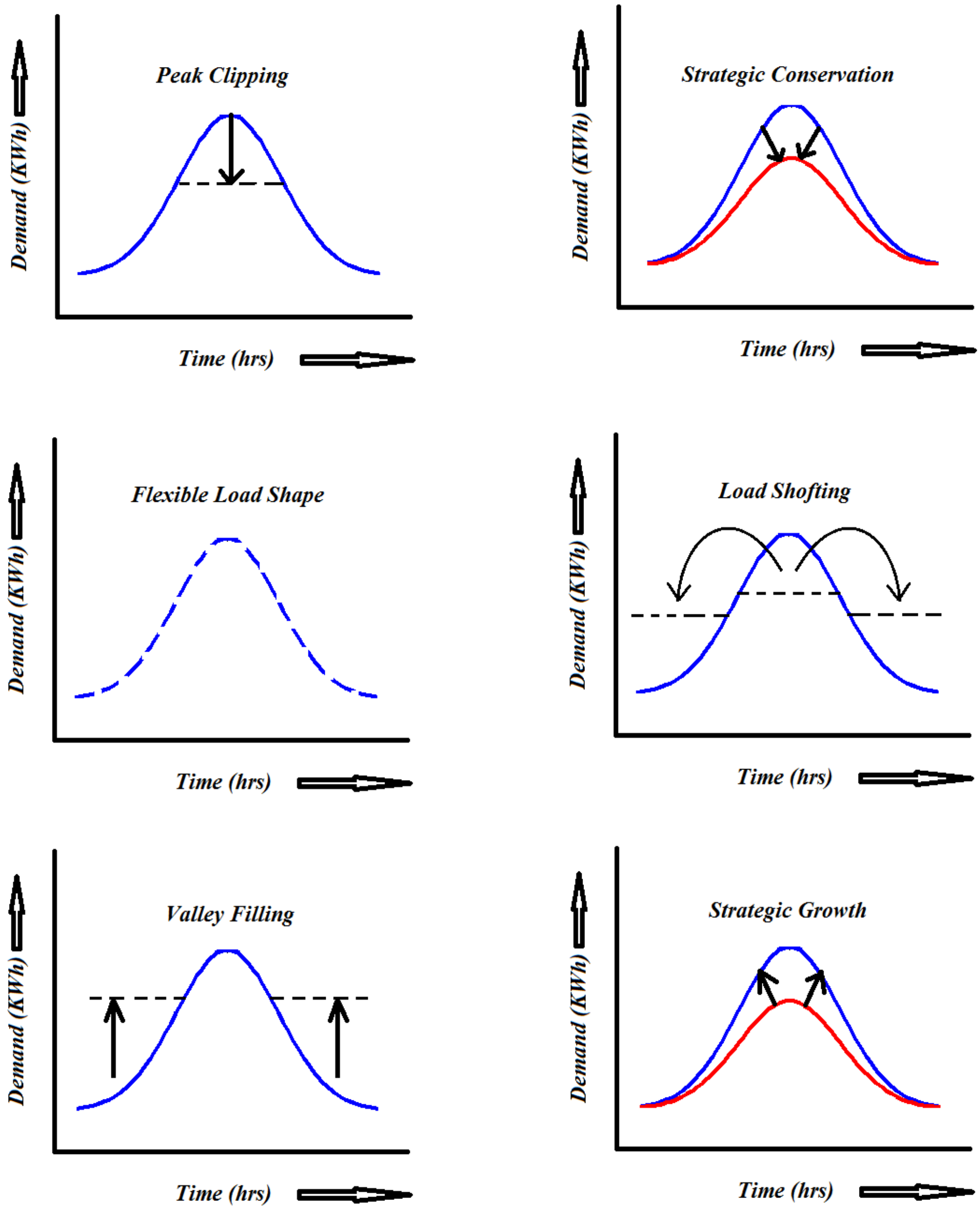

FIGURE 1.5: DSM categories in a SG [74]

1.4.5.1 Peak Clipping

Peak clipping means, decreasing the load on utility for the duration of peak hours. It reduces the need of extra generation capacity of electricity, and hence reduction in the electricity cost.

1.4.5.2 Valley Filling

In valley filling, direct load control is applied to construct the off peak demand and decrease burden on utility. By using these strategies we can shift load from those hours during which utility faces high load to those hours during which utility has less load.

1.4.5.3 Load Shifting

In order to decrease load on the grid, load is shifted from peak load hours to off peak load hours.

1.4.5.4 Strategic Load Growth

It changes the load pattern according to rise in sales and is stimulated by utility.

1.4.5.5 Flexible Load Shape

The management of smart grid identify those consumers which have flexible loads and that load can be controlled during on-peak hours, in order to get incentives.

1.4.5.6 Strategic Conservation

For energy efficient utilization, consumers are motivated to use less energy during on-peak hours, while use their routine appliances during off-peak hours.

1.4.6 Energy Pricing Models

Different energy pricing schemes are used in the literature to give energy cost either on daily basis or hourly basis like real time pricing (RTP), critical peak pricing (CPP), time of use (TOU), critical peak rebate (CPR) and Inclined block rate (IBR) etc. as shown in the Figure 1.6.

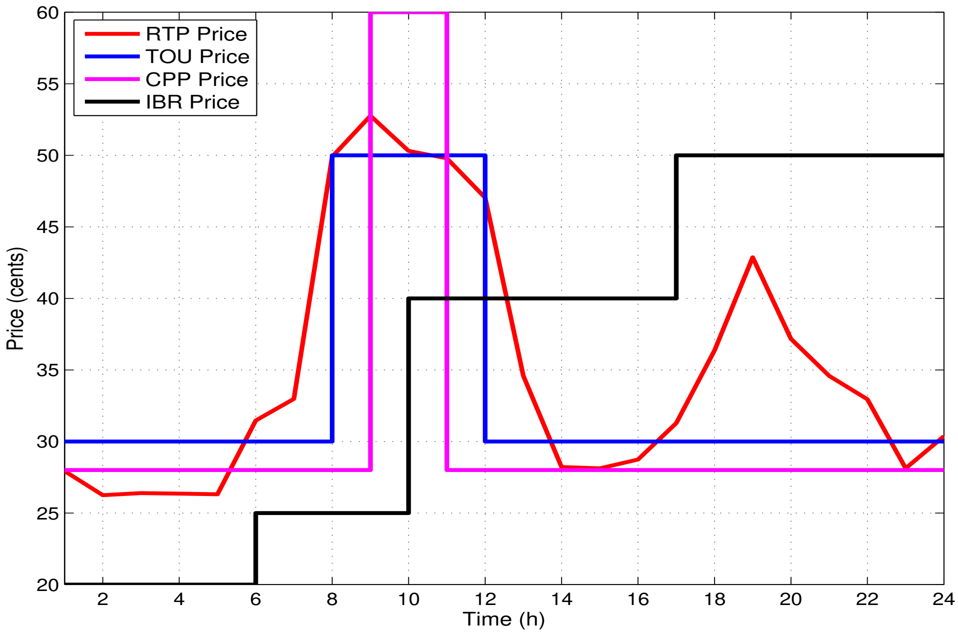

FIGURE 1.6: Pricing signals

1.4.6.1 Real Time Pricing (RTP)

RTP is the hourly consumption rate of electricity. It is regulated by utility in two parts, base bill and hourly prices.

1.4.6.2 Inclining Block Rate (IBR)

Inclining Block Rate (IBR) is the electricity pricing model which divides the pricing scheme into several steps. The first step has low cost and then cost increases or decreases step wise. Mostly, high units cost more, compared to low units.

1.4.6.3 Time of Use (TOU)

TOU is the energy pricing scheme which is used for a wide block of hours.

1.4.6.4 Critical Peak Pricing (CPP)

CPP is the electricity pricing signal which shows the high electricity rate in specific peak duration.

1.5 Interruption Frequency Indexes

1.5.1 System Average Interruption Frequency Index (SAIFI)

SAIFI is also a term used by electric utilities which indicates the distribution system reliability. It gives the average no. of sustained interruptions faced by the electricity consumers in a period of one year.
Mathematically, SAIFI can be calculated as;

$$SAIFI = \frac{\text{Total no. of consumers interruptions}}{\text{Total served consumers}} = \frac{\sum_{n=1}^{N} \mu_n M_n}{M_T} \tag{1.12}$$

where μ_n is the rate of failures, M_n shows the no. of consumers for n locations, and M_T gives the total no. of served consumers.

1.5.2 Momentary Average Interruption Freq. Index (MAIFI)

MAIFI is a term used by electric utilities which indicates the power system reliability. MAIFI gives the average no. of transitory interruptions faced by the electricity consumers in a period of one year. This interruption may lasts for 1 to 5 minutes duration.

$$MAIFI = \frac{\text{Avg. duration of consumers interruptions}}{\text{Total served consumers}} \tag{1.13}$$

1.5.3 System Average Interruption Duration Index (SAIDI)

SAIDI indicates the distribution system reliability. It gives the average duration of interruptions faced by the electricity consumers in a period of one year.

$$SAIDI = \frac{\text{Avg. duration of consumers interruptions}}{\text{Total served consumers}} \tag{1.14}$$

1.6 Main Contributions of this Work

The main contributions of this research work are summarized as follow:

1. We have proposed a new Time-constrained genetic moth flame optimization (TG-MFO) algorithm, as the main contribution of this work.
2. We have explored and compared different bio-inspired algorithms for energy optimization problem, such as; ACO, ALO, BFA, CSOA, FA, GA, GOA and MFO with our proposed hybrid TG-MFO;
3. We applied our proposed hybrid TG-MFO algorithm in all three sectors, i.e., residential, commercial and industrial consumers, and proposed system models for all scenarios.
4. Through simulations, we have shown that, bio-inspired optimization algorithms outperform in terms of minimization of:
   (a) Total energy cost,
   (b) Waiting time of the user appliances and
   (c) Peak to Average power Ratio (PAR).
5. We integrated renewable energy sources (RESs) for further minimization of total load and its cost;
6. We considered different size homes with different power rating appliances and different length of operational times (LOTs);
7. We used DAP electricity pricing signal to make the system more practicable.

8. For analysis and validation of the proposed nature inspired algorithm, we applied it on different consumer scenarios, such as:
   (a) single home for one day,
   (b) single home for thirty days,
   (c) thirty different size homes for one day and
   (d) thirty different size homes for thirty days in residential sector;
   (e) an office in commercial sector and
   (f) woolen mill in industrial sector.

9. We also used constraints on user appliances starting time and operation ending time to get maximum comfort level of end user;

10. We proposed three system models for considering all aforementioned parameters to make a reliable and sustainable feasible DSM in a smart grid;

1.7 Outline of the Thesis

The rest of the thesis work is structured as follows:
Chapter 2 gives the related work. This chapter summarizes the researchers work in the field of energy optimization.
Chapter 3 gives a detail description and mathematical modeling of the state-of-the-art bio-inspired algorithms, e.g. ACO, ALO, BFA, CSOA, FA, GA, GOA, MFO and our proposed new hybrid algorithm TG-MFO.
Chapter 4 applies bio-inspired algorithms in a residential sector for all possible scenarios of a consumer. Both algorithms are applied on a single home and multiple homes (i.e. 30 in our case), for a single day and thirty days to compare their performance as compared to un-scheduled load. Then a hybrid version of these two algorithms, GA and MFO, i.e. TG-MFO, named as, Time-constrained genetic-moth-flame optimization algorithm is proposed to achieve three main objectives: energy cost reduction, minimization of peak to average ratio (PAR), and user discomfort minimization due to scheduling of the house appliances. At the end, performance of the proposed algorithm is compared to the state-of-the-art

algorithms in terms of three aforementioned objectives.

Chapter 5 applies five bio-inspired algorithms for energy optimization in commercial applications. An office is taken as an example. Both algorithms performances are compared to an un-scheduled load, and again with state-of-the-art algorithms, ant colony optimization (ACO), genetic algorithm (GA), cuckoo search algorithm (CSA), and fire fly algorithm (FA) in terms of three main objectives of energy cost reduction, minimization of PAR and user discomfort.

Chapter 6 applies five bio-inspired algorithms, their mathematical modeling and application in an industrial sector. Again their performance in terms of the aforementioned objectives is compared with un-scheduled load. Different machines are scheduled for reduction of energy cost, so that their performance and working hours (i.e. 24 hours) cycle remain the same. At the end of this chapter, the whole work is concluded and future work is mentioned.

Chapter 7 gives the conclusion and future work. At the end a rich list of references is given.

Chapter 2

Literature Review

2.1 Introduction

For smart grid (SG) many algorithms have been proposed for energy optimization problem in residential, commercial and industrial areas. Numerous researchers around the world are investigating different technologies in order to fulfill the needs of energy efficient and intelligent smart homes. Many algorithms have been proposed for optimal use of existing energy resources. In this regard, I illustrate some prior state of the art challenges and the corresponding research work in SG.

2.2 Present Challenges and Their Solution

The researchers in the energy trading and optimization area have done lot of work and proposed different algorithms for solving the issue of reducing the energy cost and peak to average power ratio (PAR). This section depicts a comprehensive literature review of the state of the art work and challenges in this field of study. We have categorized the past work w.r.t. DR programs. Mainly three types of DR programs are mentioned, i.e.,(a) energy cost reduction based DR programs, (b) end user Comfort based DR programs and (c) trade-off between end user comfort and electricity cost reduction based DR programs.

2.2.1 Energy Cost Reduction Based DR Programs

In [75], the authors have proposed an approach to optimize their objective function using the Genetic Algorithm (GA). Electricity prices are varying between on-peak hours and off-peak hours. Therefore, an optimized task scheduling module is used in smart homes, which can reduce the consumption of the entire energy. The problem of optimal scheduling of household appliances has been explored in [76]. The authors used the day-ahead changeable peak pricing technique for the minimization of the consumer's energy consumption cost using a combination problem approach. This approach enables customers to schedule their household appliance using MKP (Multiple knapsack problem) formulation.

In [77], the authors implemented GPSO (Gradient-based Particle Swarm Optimization) for DR in smart homes by considering load and energy price uncertainties. The authors implemented the 0/1 multiple knapsack problem with the genetic algorithm to find a good solution in [78]. A simple fitness function is evaluated for each appliance in every time slot to obtain the desired results. The authors proposed a Demand-Side Management (DSM) strategy. This technique is based on a load shifting strategy during peak hours to reduce electricity bills using an Evolutionary Algorithm (EA). The authors discussed the strategy of the load shifting-based generalized technique, from on-peak hours to off-peak hours of a day, to minimize energy cost. This mechanism can support a large number of controlled devices of numerous types to minimize end-user electricity bills.

An adaptive energy model for DSM in smart homes has been proposed by the authors in [79]. Distributed RESs' usage is optimized using the ACO algorithm to minimize the electricity bill of end user. In [80], Kusakana et al. used the TOU pricing model along with the integration of RESs and BSUs to minimize the end-user's electricity bill and achieve energy consumption balancing. The authors proposed a model to sale extra generated energy back to the utility, as per their prior agreement. For minimization of the end-user electricity bill, Bharathi et al. suggested a model in [81], which works in all three sectors of society, i.e., industrial, commercial and residential areas. For optimization, the authors used

GA. They also compared the different EA with GA and found that it gave a maximum decrease of 21.9% in the consumption of energy. In [82], the authors proposed objective function generalization using the DR program to minimize the residential consumer electricity bill. The authors showed that by shifting the load, unexpected peaks were observed in off-peak hours. They evaluated this later peak formation with multi-CPP and multi-TOU pricing schemes combined with DAP concepts. In [83], authors presented a DSM strategy, by shifting the load from on-peak hours to off-peak hours, using DAP signal and Evolutionary Algorithm (EA). However, consumer comfort is not considered. In [84], the authors proposed a Quality of Experience (QoE)-based home energy management system. They gave the priority to the end-user's frustration. Two algorithms that run the HEM system are: "QoE-aware Cost Saving Appliance Scheduling (Q-CSAS)" for scheduling of controlled load and "QoE-aware Renewable Source Power Allocation (Q-RSPA)" for management of appliances for renewable energy sources' surplus energy. They reduced energy cost to 30–33% without RES and 43–46% with RESs for the end-user annoyance rates of 1.67–3.36 and 1.70–3.43, respectively.

In [85], authors have presented an optimal scheduling scheme for residential appliances, using DAP signal in smart homes. This algorithm has reduced peak cost to 22.6% and normal price to 11.7%. This approach does not lie on the energy optimization approach. In [86], the authors have discussed load shifting, cost minimization and energy storage system (ESS). They proposed a system which enables the user to buy energy during low demand timings and sale-out their storage energy to utility during on-peak hours. In [87], gradient based particle swarm optimization (GPSO) technique for demand response (DR) in smart homes, considering the load and energy price uncertainties is discussed. The authors in [88] have discussed cooperative multi-swarm particle swarm optimization (PSO) technique for achieving their goals of cost minimization, however, they have not considered PAR. In [89] authors have used GA with the DAP scheme for optimally scheduling the load demand. In [90] authors have introduced a load balancing mechanism in commercial, residential and industrial areas. They have compared the usage of electricity with GA and without GA in DSM. By using GA based DSM, they have reduced the electricity usage during peak hours. However, PAR and end-user discomfort are not discussed. In [91], authors have proposed enhanced differential evolution (EDE) and harmony search algorithm (HSA) for scheduling home appliances for reduction of electricity cost and PAR. They have hybridized both algorithms for achieving their objectives. However, user comfort is ignored. Table 2.1 depicts the achievements and limitations of the energy cost reduction based DR programs research work.

TABLE 2.1: Critical analysis of the energy cost reduction based DR programs

Mechanisms/ Techniques	**Objectives/ Requirements**	**Achievements**	**Limitations**
GA [75]	Minimization of electricity bills.	Reduced electricity bill.	No PAR is considered.
MKP with DAP [76]	Minimization of total energy and electricity bill.	Reduced power consumption and electricity bill.	Less end-user comfort level.
GPSO with DR [77]	Minimization of PAR and electricity bills.	PAR and minimization of electricity bill.	No end-user comfort level and no RES and congestion problem.
0/1 MKP and GA [78]	Minimization of PAR and electricity bills.	Minimization of PAR and peak load shifting.	Less end-user comfort level and no RES.
ACO [79]	Distributed RES usage is optimized.	Minimization of PAR and peak load shifting.	End-user comfort has been compromised.
TOU along with RES and BSUs [80]	To minimize the end-user electricity bill.	Energy consumption balancing.	User comfort has been compromised.
GA-based DSM [81]	Bill minimization for industrial, commercial and residential consumers.	Compared with EA, 20.9% reduction in bill.	End-user comfort has been compromised.
DR with CPP and ToU [82]	Objective function generalization using the DR program to minimize bill.	Minimized residential consumer electricity bill.	End-user comfort is ignored.
EA with DAP [83]	Energy bill minimization.	Bill is minimized.	User comfort has been compromised.
Q-CSAS and Q-RSPA [84]	Energy bill minimization.	Bill is minimized.	User comfort has been compromised.
optimal scheduling scheme [85]	To minimize the end-user electricity bill.	minimized the end-user electricity bill.	Less end-user comfort level and no RES.
ESS [86]	Electricity bill reduction.	Minimization of PAR and peak load shifting.	Less end-user comfort level and no RES.
GPSO [87]	Electricity bill reduction.	Electricity bill is reduced.	End-user comfort has been compromised.
PSO [88]	To minimize the end-user electricity bill.	minimized the end-user electricity bill.	End-user comfort has been compromised.
GA with DAP [89]	To minimize the end-user electricity bill.	Electricity bill is reduced.	End-user comfort is ignored.
GA [90]	Reduction of elect. bill.	Reduction of elect. bill is achieved.	PAR and user comfort have been compromised.
EDE and HSA [91]	Minimization of electricity bills.	Reduced cost.	No user comfort is taken into consideration.

2.2.2 End User Comfort Based DR Programs

Yi Peizhong et al. [92] have proposed the Optimal Stopping Rule (OSR) for energy-efficient scheduling of home appliances. The limitation of this work is that OSR runs on a threshold-based strategy. The end-user has to wait until the price comes down below the threshold level. In [93], the authors proposed a distributed algorithm for shifting the load from on-peak hours to off-peak hours. They used the game theory approach for scheduling the residential load. The Nash equilibrium convergence rate was also accelerated by the Newton technique. PAR and end-user discomfort were minimized. A smart community based energy optimization technique is discussed in [94]. The authors have focused on the end-user high comfort level and less energy usage with integration of renewable energy sources using particle swarm optimization (PSO).

In [95], the authors have discussed optimal operation methods for a micro-grid. They have used improved adaptive evolutionary algorithm (IAEA) and swarm optimization algorithm (SOA) for end user comfort maximization. In [96] authors have used PSO for scheduling of smart electric appliances for electricity cost minimization. They have taken different cases of changing the renewable energy consumption rate and user comfort level, and applied it in a smart community as a case study. Table 2.2 depicts the achievements and limitations of the end user comfort based DR programs research work.

TABLE 2.2: Critical analysis of the end user comfort based DR programs

Mechanisms/ Techniques	**Objectives/ Requirements**	**Achievements**	**Limitations**
Threshold based OSR [92]	Minimization of electricity bills.	Reduced cost.	Threshold-based cost minimization.
Game theory, Nash equilibrium [93]	Used distributed algorithm, minimization of PAR and discomfort.	PAR and end-user discomfort have been minimized.	No RES integration.
PSO [94]	Maximization of user comfort and electricity bills.	Reduced cost and user discomfort .	PAR is not considered.
IAEA and SOA [95]	Minimization of total energy and electricity bill.	End user comfort maximization.	Electricity cost is increased.
PSO [96]	Energy bill and user discomfort minimization.	Bill is minimized.	PAR has been compromised.

2.2.3 Trade-off Between End User Comfort and Electricity Cost Reduction Based DR Programs

The authors in [97] discussed the strategy for scheduling appliances in order to reduce carbon emissions along with the reduction of the electricity bill and waiting time. They applied the cooperative multi-swarm PSO technique to achieve their goals; however, they did not consider PAR. Having an optimal scheduling of power, a heuristic-based GA was used for Demand-Response (DR) in Home Energy Management (HEM) systems in [98]. The authors proposed GA-, TLBO- (Teaching Learning-Based Optimization), EDE (Enhanced Differential Evolution) and EDTLA- (Enhanced Differential Teaching Learning-based Algorithm) based approaches, which are used for minimization of the residential total energy cost and maximization of the end-user comfort level.

The authors employed GA and BPSO (Binary Particle Swam Optimization) for optimal scheduling of home appliances in [99]. They proposed GAPSO (Genetic Algorithm with Particle Swam Optimization), a hybrid scheme of both these techniques, to obtain better results in terms of reducing PAR, minimization of electricity cost and especially end-user discomfort. Day-Ahead Pricing (DAP) and Critical Peak Pricing (CPP) are used as pricing schemes for single and several days. The authors used GA and TLBO and their hybrid TLGO (Teacher Learning-based Optimization with Genetic algorithm) for appliance scheduling in [100]. They categorized flexible appliances as time flexible and power flexible for proficient energy consumption of consumers in SG. This approach enables energy consumers to schedule their appliances to obtain optimized energy consumption. This approach also maximizes the comfort level of customers with restricted total energy consumption. In [101], in order to lessen the end-user electricity cost and minimize the end-user discomfort, Ogunjuyigbe et al. developed a GA-based optimization technique for scheduling of appliances. In [102], the authors introduced three heuristic-based algorithms: GA, ACO and BPSO, to maximize user comfort, minimize PAR and minimize electricity cost, as well. In [103], the authors proposed a hybrid GA-PSO, which is a combination of the GA and PSO algorithm, for energy management and obtaining maximum end-user comfort in smart homes. K. Muralitharan et al. [104] presented multi-objective EA for the minimization of electricity bill and appliances waiting time. As soon as the running appliances' load increases from a threshold, they are switched off.

A multi-residential energy scheduling issue with multi-class appliances in a smart grid was discussed in [105]. The authors proposed a PL-generalized Benders algorithm (Property (P) and L-Dual-Adequacy) for bill minimization and bounded user comfort. Hybrid Bacterial Foraging and Genetic (HBG) algorithm based DSM for smart homes is proposed by the authors in [106]. They focused on peak load reduction, cost minimization, user comfort maximization and load shifting. Through HBG cost, PAR and waiting time are reduced compared to GA and BFA. A time constrained nature inspired algorithms based HEM system is proposed by the authors in [107]. Genetic algorithm (GA), Moth-flame optimization algorithm (MFO) and their hybridization is proposed for energy bill reduction and achieving end user high comfort level. A HEM system using Cuckoo search is proposed in [108]. Performance of GA and cuckoo search algorithm is compared with respect to the reduction of energy cost, PAR and user discomfort by using the DAP signal. Cuckoo search incorporation with levy flights of some kind of birds and fruit-flies are considered for breading strategy in [109]. In many optimization problems, because of its generic and robust nature, the cuckoo search is superior to GA and PSO. The authors have used GA, TLBO (teacher learning-based algorithm), LP (linear programming) and TLGO (teacher learning genetic optimization) algorithms for appliances scheduling in [110]. They have categorized flexible appliances as "time flexible" and "power flexible" for proficient energy consumption of consumers in SG. This approach enables energy consumers to schedule their appliances to get optimized energy consumption. This approach also maximizes the comfort level of customers with restricted total energy consumption. Having an optimal scheduling of power, the heuristic-based Genetic Algorithm (GA) is used for demand response (DR) in HEM systems in [111]. In this paper, authors used GA, TLBO (teaching learning-based optimization), EDE (enhanced differential evolution) and proposed EDTLA (enhanced differential teaching learning algorithm) for minimization of the residential total energy cost and end user discomfort level. In [112], authors have used optimal stopping rule (OSR) theory for appliances scheduling in a house to achieve minimization of electricity cost, PAR and user discomfort. They developed a multi-agent control system for residential energy management using RTP signals. In [113], authors have reduced electricity cost, PAR and user discomfort using a hybrid algorithm BGA, a combination of bat algorithm (BA) and genetic algorithm (GA). They have applied time of use (TOU) pricing signal, while load is categorized as base load, shift-able and non shift-able interrupt-able loads. Table 2.3 depicts the achievements and limitations of the trad-off between end user comfort and electricity cost reduction based DR programs research work.

2.3 Future Challenges and Research Gaps

Numerous researchers all over the world have proposed different system models for energy cost minimization and reduction of peak to average power ration. These techniques have efficiently reduced consumer electricity bills and PAR, however, they have the limitations of comfort in terms of appliances waiting time of end user, i.e. when and which appliance a consumer wants to start, it must be start with minimum waiting time. Table 2.2 showed a few papers that have taken user comfort into consideration. In the present era of electricity dependent modern technologies, user wants to finish his job quickly, instead of waiting for his appliances to start. On the other side, electricity consumption is to be minimized to reduce cost as well. Also, these research attempts have ignored frequency of interruptions and aggregated power consumption, as with these issues, reliability, stability, sustainability, and security of grid may be threatened. Now the need of the day is, to have an adoptive system, having the provision for use in all three sectors of life, i.e., residential (single and multiple homes and buildings), commercial and industrial. Therefore, in this research work, I have not only explored and analyzed the world of bio-inspired algorithms for energy optimization problem, but also combined two bio-inspired algorithms GA and MFO to make their hybrid

Table 2.3: Critical analysis of the trade-off between end user comfort and electricity cost reduction based DR programs

Mechanisms/ Techniques	Objectives/ Requirements	Achievements	Limitations
PSO [97]	Optimization of the appliances.	Carbon emission, bill and waiting time minimization.	Less end-user comfort level and no RES.
GA, TLBO [98]	Minimization of PAR and electricity bills.	Reduced cost and PAR with RES.	No end-user comfort priority.
MKP with GA, PSO and GAPSO [99]	Minimization of total energy and electricity bill.	Minimization of electricity bill.	Less end-user comfort level and no RES.
GA and TLGO algorithm [100]	Cost minimization plus congestion control.	Minimization of electricity bill.	Waiting time increased.
GA [101]	Bill minimization keeping consumers' maximum satisfaction.	Managed the load as per end-user budget.	PAR has been compromised.
GA, ACO and BPSO [102]	Cost minimization plus congestion control.	Minimization of electricity bill.	Less end-user comfort level.
GA-PSO [103]	Bill minimization keeping consumers' maximum satisfaction.	Minimized electricity bill.	Less end-user comfort.
Multiobjective EA [104]	Minimization of electricity bill and appliances waiting time.	Minimized electricity bill and appliances waiting time.	Appliances' interruptions increased.
PL -generalized Benders algorithm [105]	Multi-residence and multi-class appliance.	Bill minimized with upper and lower bounds on user comfort.	No RESs and BSUs are integrated.
HBG [106]	Minimization of electricity bills and PAR.	Reduced cost and PAR.	No. RES integration.
GA and MFO [107]	Minimization of electricity bills and User Discomfort.	Reduced electricity bill and PAR.	high convergence time
CSA and GA [108] CSA, GA and PSO [109]	Minimization of total energy and electricity bill. Minimization of PAR and electricity bills.	Reduced power consumption and electricity bill. PAR and minimization of electricity bill.	Less end-user comfort level. No end-user comfort level and no RES and congestion problem.
GA, TLBO and TLGO [110]	Minimization of total energy and electricity bill.	Minimization of electricity bill.	Less end-user comfort level and no RES.
GA, TLBO and EDE [111]	To minimize the end-user electricity bill.	Electricity bill is reduced.	No RES integrated.
OSR[112]	Minimization of electricity bills and PAR.	Reduced cost and PAR.	No RES integration.
BA, GA and BGA [113]	Minimization of electricity bills and PAR	Reduced electricity bill and PAR.	User comfort is ignored

algorithm TG-MFO for achieving a user comfort-based cost and PAR reduction. I introduced the time constrained factor for scheduling the appliances. I.e., an appliance in a home or a machine in the industrial sector will be scheduled not on the basis of low energy pricing criterion, but according to the consumer specified time interval low energy cost threshold. Simulation results show that using bio-inspired optimization algorithms gave comparative results in terms of minimization of; total energy cost, waiting time of the user appliances and PAR. Renewable energy sources are also integrated for further minimization of total load and its cost. For analysis and validation of the proposed bio-inspired algorithms, I applied these algorithms on different consumer scenarios in residential, commercial and industrial sectors.

2.4 Methodology

For scheduling, I therefore, planned to use bio-inspired heuristic algorithms, like ACO, ALO, BFA, CSOA, FA, GA, GOA and MFO. I also proposed the hybridization of GA and MFO, named Time-constrained Genetic-Moth-Flame Optimization (TG-MFO) algorithm because of its unique features; elasticity for particular limitations, execution simplicity, less convergence time and less computational complexity, to perform the scheduling process of end user appliances optimally using DSM programs.

To achieve our goal, the smart electric grid is modeled as a residential sector comprised of 30 homes having different size, different LOTs and appliances power ratings. The appliances power rating is different due to their home size requirements. For example, a small size home runs 12000 BTUs air conditioner (AC), as compared to a large size home who runs 18000 BTUs ACs. Various types of appliances in a home, that use electricity, are known as home loads. Each home also has a RES and BSU. Each home is connected to the sub-utility, which is further connected to the main utility and hence to the power generation system through transmission lines. The utility provides the electricity to those homes whose power demand exceeds their own power generation through any RES. However, if their power generation exceeds their power demand, it is stored in the BSU, and may be sell back to the power grid. In our model, we have forty eight (48) operational time intervals (OTIs) in a day, by dividing one hour into two time slots of thirty minutes each. In each OTI, a smart home checks the appliances power demand,

i,e. whether an appliance is ON (1) or OFF (0). According to the appliances status the energy management controller (EMC) check the availability of the RES and BSU to fulfill the appliances power demand. If it is available, the appliance will be turned-ON, and the consumer will not wait for appliance scheduling. If the own generation and stored energy are insufficient for running the load, the proposed algorithms will check the economical slot (time interval) for that appliance keeping in view the maximum user comfort, i.e. minimum waiting time. In order to achieve this objective, constraints have been put for maximum interval of time in which an appliance has to complete its operation. For example, a user wants to switch-ON a washing machine at 09:00 hrs, and there is no possibility of providing power to it immediately, due to either no RES and BSU or peak hours constraints, and the user can wait for a maximum of three hours only, so the algorithm schedule it from 09:00 to 12:00 hrs definitely. Due to this the cost may be less affected, but maximum user comfort is achieved.
Consequently, if the utility give incentives to the user in the form of real time lower prices in off-peak hours, the end user will be encouraged to produce their own energy from RES and schedule their loads accordingly. To summarize, the following steps are followed:

1. In the first phase of this work, a thorough literature review of the bio-inspired energy optimization algorithms in the field of energy trading has been conducted. Furthermore, the literature study is categorized according to the demand response programs and our main objectives.

2. Critical analysis of the literature review is given, limitations and challenges of state-of-the-art energy optimization algorithms are summarized, based on which, future challenges and research gaps are defined.

3. Mathematical models are developed for selected bio-inspired algorithms, which are used to achieve our objectives.

4. The performance of the mathematical modeled bio-inspired heuristic algorithms is examined and are compared with stat-of-the-art algorithms in the research area of energy optimization through extensive simulations.

2.5 Summary

The optimization techniques mentioned in the literature have achieved either the energy cost minimization and PAR reduction by loosing the end-user comfort or considered user comfort while loosing energy cost minimization. Also, most of the research work have considered residential consumers. Therefore, in this work, I have explored and analyzed bio-inspired algorithms for the energy optimization problem in the residential, commercial and industrial sectors. I have taken into consideration minimization of energy cost and PAR along with user comfort. For this purpose, I have developed a hybrid algorithm named as, time-constrained genetic-moth flame optimization algorithm, to achieve aforementioned objectives. This is because of the algorithms developed on the perfect optimization behavior of naturally available organisms. Through simulations, I have shown that using bio-inspired optimization algorithms the energy cost and PAR can be reduced, while keeping user comfort in first priority compared to unscheduled load. I, not only compared the performance of numerous bio-inspired algorithms in terms of electricity cost, PAR and user waiting time reductions in all three sectors of energy consumers, but also integrated RESs and BSUs for further improvements in our objectives.

Chapter 3

Contributions of Our Work

In this chapter, we discuss the main contributions of this research work, the new proposed bio-inspired algorithm named as, Time-constrained genetic moth flame optimization (TG-MFO) in detail along with different bio-inspired algorithms and their mathematical models. Various classical programming techniques like LP, ILP, MILP, DP and CP have already been used by researchers for optimal scheduling of home appliances. The convergence time of these classical techniques is very large due to the exact solution, and to schedule a large number of appliances, they cannot be used. Furthermore, classical algorithms usually show the best results for local optimization, as compared to the global point of view. Therefore, due to their probabilistic nature, bio-inspired meta-heuristic algorithms give good results in the case of local, as well as global solutions.

Heuristic means "to discover", or "to find" or "to hit upon" by experiment, trial and error approaches. The solution of an optimization problem can be found in a realistic interval of time. However, such optimization techniques cannot guarantee the optimal solution. Meta-heuristic means "to find on a higher level" or "to find ahead of" local optimization. This means its performance is superior to straightforward heuristics techniques. All such algorithms use the process of local search and randomization, which further provides a path to global search and optimization. In this way, the problem of global optimization is solved. However, this form of optimization algorithms do not give exact solution.

3.1 TG-Moth Flame Optimization (TG-MFO)

Time-constrained genetic moth flame optimization (TG-MFO) is the new proposed bio-inspired algorithm, as the main contribution of this work. In this algorithm, we apply the bio-inspired algorithms GA and MFO, then not only hybridize these two algorithms, but putting a new concept of time constraints for achieving tremendous results in terms of almost zero waiting time by minimizing the energy cost and PAR. We compare their results with some of the existing techniques like ACO, CSA and FA on randomly-generated data. To apply the strategy of the time constraints of end-users, i.e., for each appliance to switch-ON, we give some time span as the initial and final thresholds for all appliances. A user initiates the operation of an appliance, but usually, it is allowed to remain OFF for a certain time interval, in which the user has no problem or frustration. We apply this time threshold policy, to have a zero end-user waiting time. As TG-MFO is based on the hybridization of GA and MFO with time constraints. Therefore, initially, MFO is applied on randomly-generated data for the optimization problem to obtain the local best positions for home appliances. Then, GA is applied to compare MFO's local best solution with the new random data, to find the global best solution in each iteration. The fitness functions are updated accordingly. This process continues until the termination criterion is fulfilled. Figure 3.1 depicts the steps involved in the TG-MFO implementation process, while, Algorithm 1 gives the pseudocode to show the step-by-step working of the proposed TG-MFO algorithm.

3.2 Ant Colony Optimization (ACO)

ACO is a bio-inspired meta-heuristic iteration-based optimization technique. Using pheromone trails, chemicals as signals to other ants left on the ground known as the Stigmergy principle, starting from their nest, in search of food, ants find the shortest routes between their origins to the destination. If an ant wants, with a certain probability, to follow a particular path, it follows the pheromone trail. It reinforces the other ants by laying more pheromone on the same trail. As

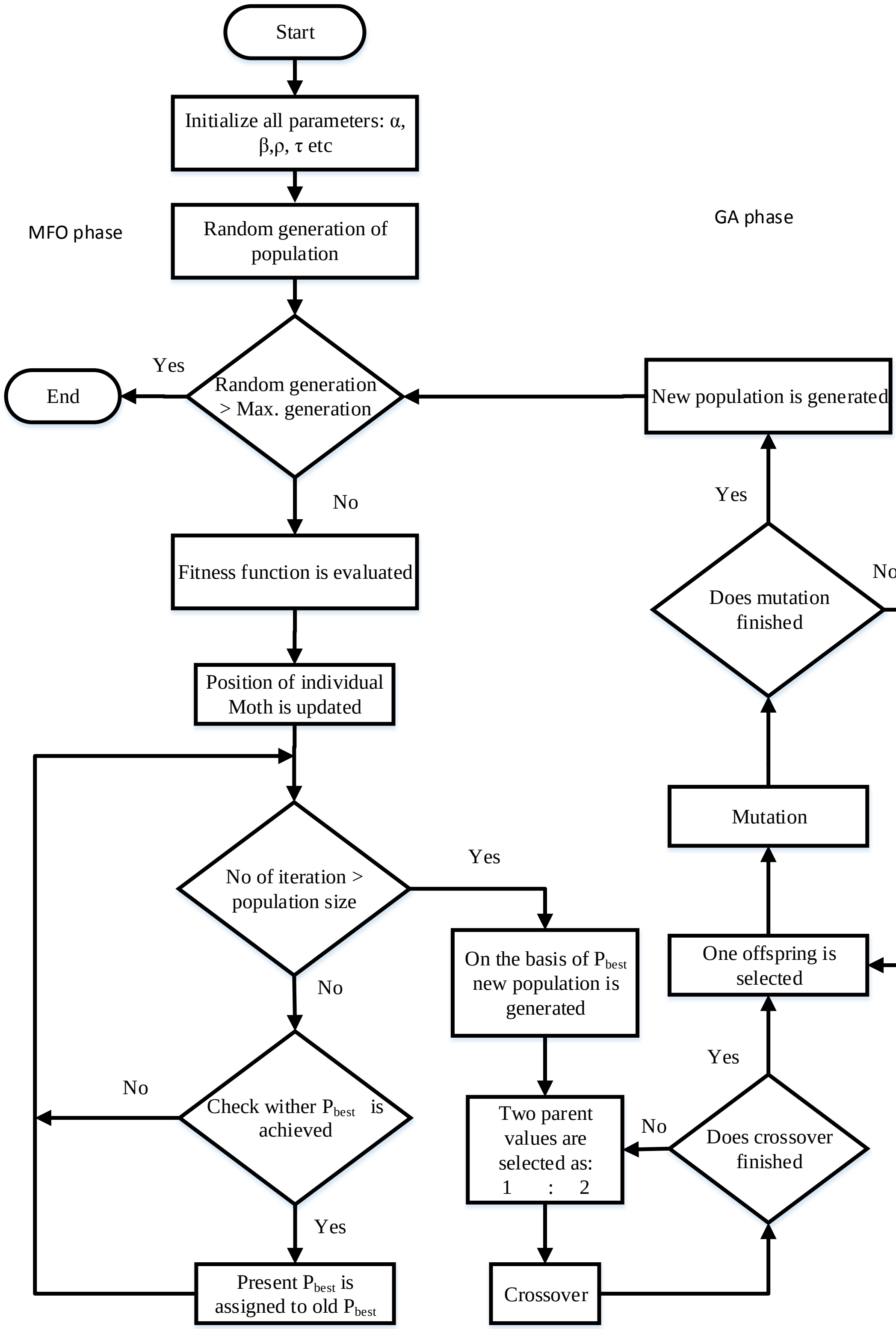

Figure 3.1: Flowchart for the proposed algorithm Time-constrained Genetic-MFO (TG)-MFO.

Algorithm 1: Pseudocode of the proposed TG-MFO algorithm.

Initialization: GA parameters, MFO parameters, the maximum size of the population, No. of iterations.
Input: RTP ζ_n, $AP, \rho, X, \alpha, \beta, V_T, X_{bat}, \lambda$.
MFO phase:
Random generation of the initial population of moths $Q_{i,j}$ matrix using Equation (16)
Random generation of the initial population of flames $U_{i,j}$ matrix using Equation (17)
Fitness function O_M is evaluated by objective function $f(M) = (U_b(i) - l_b(i)) * rand() + l_b(i)$
Position of individual moths $Q_{i,j}$ is updated as per the position of flame $U_{i,j}$
while *No. of iterations* $<$ *population size* **do**
  for i *=1:M* **do**
    for j *=1:N* **do**
    end
    New solution is evaluated
    Present P_{best} is assigned to the old P_{best}
    GA phase:
    On the basis of P_{best}, generate chromosomes x_i for i = 1,2,...,n
    Two parent values are selected as 1:2
    if *(The crossover is done* **then**
      One offspring is selected
      Mutation is done
    else
      Two parent values are selected again till the crossover is finished
    end
  end
  if *(Mutation is finished* **then**
    The new population is generated
  else
    One offspring is again selected until the mutation is finished
  end
  Present P_{best} is assigned to old P_{best}
end
Output: $E_T, E_{RES}, \tau_w, \mu$

the movement of ants increases on a route, the amount of pheromone increases. Since pheromones' nature is volatile, so the shortest path has more pheromone as compared to the longer one. As a result, ants' movement increases on the shortest route. Figure 3.2 shows the basic principle of ACO shortest path selection.

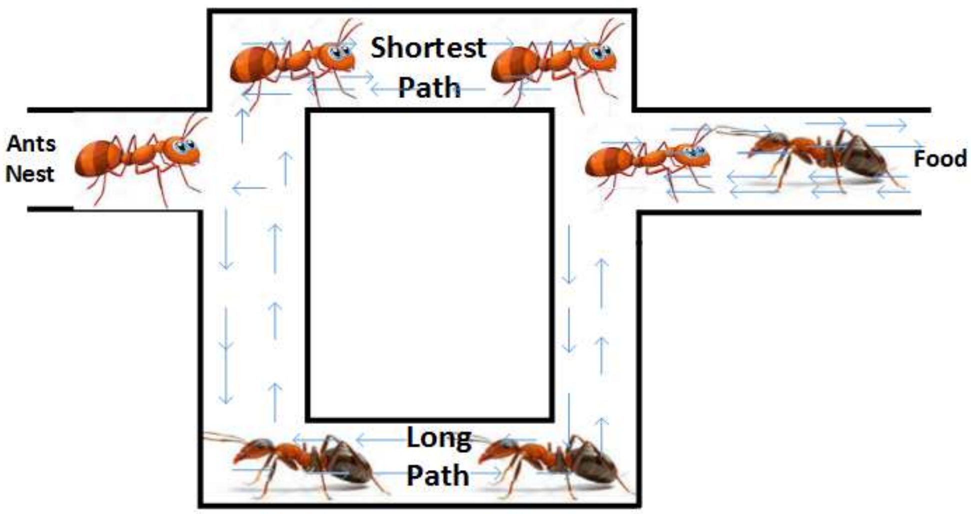

FIGURE 3.2: Paths followed by ants in ACO algorithm

Using this principle, ACO is used for the solution of discrete combinatorial search optimized-solution problems. Self-organization and self-healing are the distinguishing properties of ACO. ACO is used for the residential consumer's energy optimization, which is a novel scheme for such energy management problems [114]. The ACO parameters are given in Table 3.1.

TABLE 3.1: ACO parameters.

S. No.	Parameter	Value	S. No.	Parameter	Value
1	No. of Ants	12	4	Evaporation rate	5
2	Pheromone intensity factor α_1	2	5	Trail decay factor	0.5
3	Visibility intensity factor β_1	6	6	Max. iterations	600

3.3 Ant Lion Optimization Algorithm (ALO)

The ALO is a bio-inspired and population based algorithm proposed by S. Mirajlili in 2015 [115]. In ALO, the antlion search for food randomly in the search space. For caching prey there needs to perform some steps to achieve the optimal solution in ALO are: first, random walk in which the ants are randomly moving in the search space. Second, building traps in which the antlion digs circular traps in sands. The size of trap is a function of level of hunger and shape of moon. Third, entrapment of prey in trap in which the prey comes inside the trap. Fourth, catching in which antlion tries to catch the prey. Fifth, rebuilding traps in which antlion rebuild the traps to get a chance of new prey.

Step 1: The random walk of ants in the search space is given by:

$$X(t) = [0, cumusum(2u(t_1) - 1), cumusum(2u(t_2) - 1), ..., cumusum(2u(t_i) - 1)] \tag{3.1}$$

Where i shows total number of iterations, cumusum stands for cumulative sum and u(t) is a random function defined as:

$$u(t) = \begin{cases} 1 & if rand > 0.5 \\ 0 & if rand \leq 0.5 \end{cases} \tag{3.2}$$

To keep the walk of ants inside the search space, the updated position is normalized with the following equation:

$$X_i(t) = dfrac(x_i(t) - a_i)(b_i - c_i(t))(d_i(t) - a_i) - \alpha + C_i \tag{3.3}$$

Step 2: The effect of antlion traps on the random walk of ants in the search space are mathematically modeled with the following equation:

$$c_i(t) = (Antlion_i(t) + c_i)d_i(t) = (Antlion_i(t) + d_i) \tag{3.4}$$

Step 3: A roulette wheel operator is used to evaluate the fitness of antlion during optimization. The roulette wheel operator gives us high probability to select the fitter antlion for hunting preys. Using this mechanism antlion become able to build traps according to its fitness value.
Step 4: When an ant goes inside the trap, the ant lion trying to catch it shoot sands outside from center of trap with his massive jaws. Catching prey occur when the fitness value of ant becomes greater than its corresponding ant lion. For an ant lion it is required to change its position to increase the probability of catching new prey, this assumption is modeled with the following equation:
Step 5: The evolutionary algorithm allows him to get the optimal solution during the optimization process and saved as an elite one. The elite ant lion change the random walk of ant inside the search space. The ant walks around the selected antlion inside the search space.
All the steps mentioned above are shown in the Figure 3.3

3.4 Bacterial Foraging Algorithm (BFA)

BFA was proposed by Kevin Passino in 2002 [116]. In this algorithm, the group foraging strategy of a swarm of *Escherichia coli (E. coli)* bacteria is the key point. Bacteria forage for food and nutrients, to maximize their energy per unit time. By sending a signal, bacteria also communicate with each other. Because of predators,

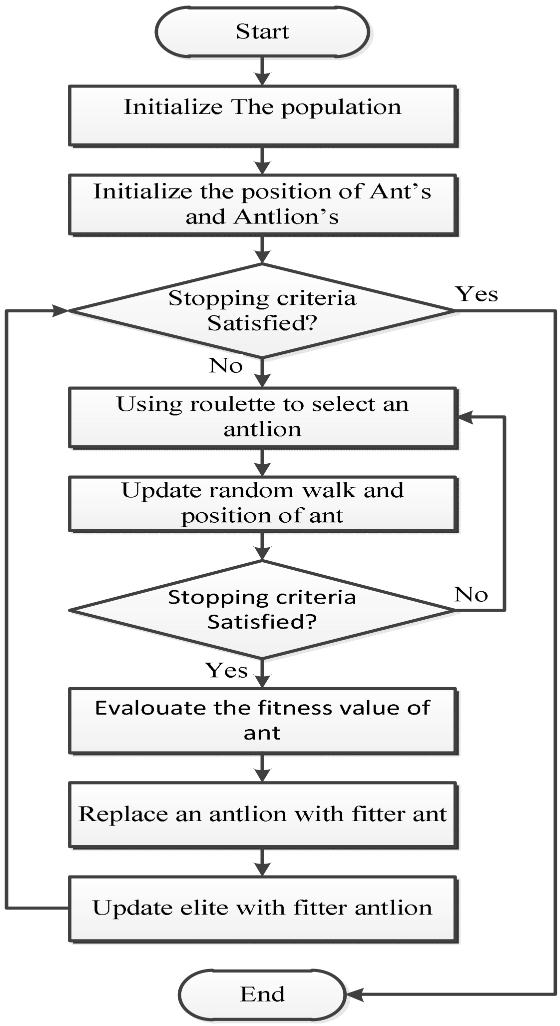

Figure 3.3: Flowchart of ALO

the prey may be mobile. Therefore, it is chased by the bacterium in an optimal way. When a bacterium maximizes its energy by getting sufficient food, then it does other activities like sheltering, mating, fighting, etc. Four steps are needed in order to explain BFA, i.e., (a) Chemotaxis, (b) Swarming, (c) Reproduction and (d) Elimination.

3.4.1 Chemotaxis

In the chemotaxis step, the *E. coli* move from one place to another through flagella. According to the biological point of view, its motion is observed in two different ways: it may either swim or tumble.

To consider the chemotaxis movement of bacteria, we have the following equation:

$$\delta^j(i+1,k,l) = \delta^j(i,k,l) + Q(j)\frac{\Delta(j)}{\sqrt{\Delta^T(j)\Delta(j)}} \tag{3.5}$$

In the above equation, $\delta^j(i,k,l)$ shows the position of the j^{th} bacterium at the i^{th} chemotactic, the k^{th} reproductive and the l^{th} elimination-dispersal step. $Q(i)$ represents the size of the step taken by the bacterium in a random direction when it tumbles. Δ shows the vector in random direction [−1,1].

3.4.2 Swarming

The *E. coli* bacterium is blessed with swarming behaviour. In this step, bacteria cells form a ring-shaped structure and move in search of nutrients. A high level of succinate usage stimulates the cells, due to which attractant-aspartate is released by the cells, which helps them to bind in groups.

3.4.3 Reproduction

When a bacterium is in a feasible and nutritious environment, it reproduces, splits into two bacteria and keeps the number of cells in a swarm fixed.

3.4.4 Elimination and Dispersal

The scarcity of nutrients kills the bacterium or disperses them into another environment. They are also killed due to high temperature. If there is a poor condition in the environment, the bacteria may place themselves near a good food source, hence assisting the process of chemotaxis (first step).

To calculate the fitness of each bacterium, the following equation can be used:

$$F_j[i,k,l] = F_j[i,k,l] + F_{cc}(\delta_j[i,k,l], P[i,k,l]) \tag{3.6}$$

In the above equation, F_j shows the fitness of the bacterium and δ_j is the position of the bacterium.

$$F_{cc} = \sum_{d=1}^{d-1} (100 \times (\delta(j,d+1) - (\delta(j,d))^2)^2 + (\delta(j,d) - 1)^2) \tag{3.7}$$

In order to achieve the time-varying objective, we must put the objective function J_{cc} into the actual objective function F_j. The steps involved in the bacterial foraging algorithm (BFA) are given in Algorithm 2 and are depicted in the flowchart diagram shown in the Figure 3.4.

Algorithm 2: Bacterial Foraging Algorithm (BFA).

```
1  Initialization: Generation of the price signal according to the scheme used, LOTs' specification of
     appliances, power ratings of appliances
2  Input: Give initial values to variables; pop, N_p, N_e, N_c, N_r, N_s, D, C.
3  Evaluate fitness for each bacterium (J_last).
4  for l = 1 to N_e do
5      for k = 1 to N_r do
6          for j = 1 to N_c do
7              for i = 1 to N_p do
8                  Find new position of the bacterium
9                  Find the fitness
10                 for s = 1 to N_s do
11                 end
12                 if J_i < J_last then
13                     Replace the previous position of the bacterium with the new position
14                     Go back to line 10
15                 else
16                     Assign a random direction
17                     Evaluate the fitness
18                     Go back to line no. 10
19                 end
20             end
21         end
22         Evaluate the fitness of the bacterium
23         Select the best one Random elimination and dispersal
24     end
25     if 1 < N_e then
26     else
27         Go back to the initial elimination step
28     end
29 end
30 Output: E_T, load, PAR.
```

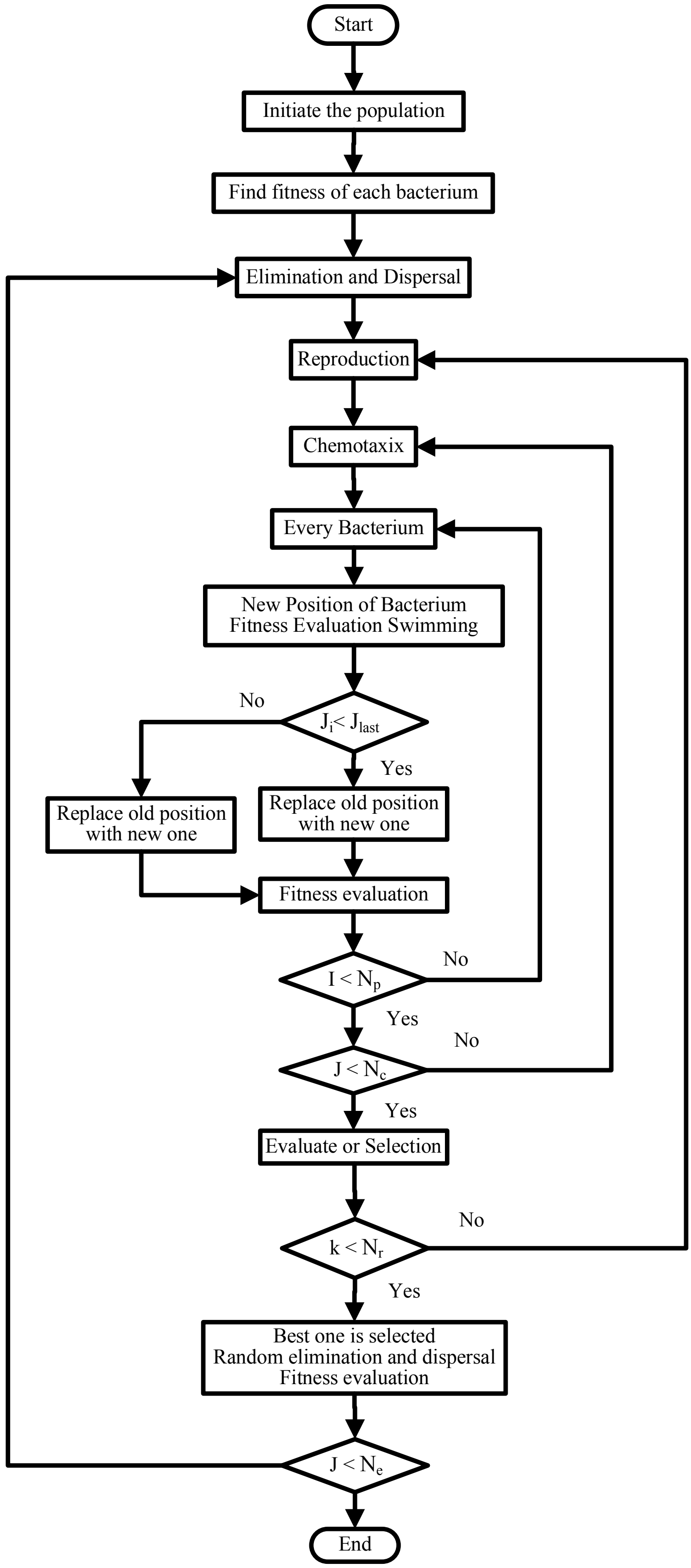

FIGURE 3.4: Flowchart of BFA

3.5 Cuckoo Search Optimization Algorithm (CSA)

The cuckoo search optimization algorithm was proposed by [117] and belongs to the family of bio-inspired meta-heuristic algorithms. It is used to solve the optimization problems using the mating and production behavior of some cuckoo species and the characteristics of Lèvy flights of some birds and fruit flies. *Lévy* flights are performed to find the global best solution.

$$X_i^{t+1} = X_i + \alpha \oplus L\acute{e}vy(\lambda) \tag{3.8}$$

In the above equation X_i^{t+1} is the new solution, X_i is the current status, α is the transition or step size. Frye and Reynolds have recently found *Lévy* with the recent study of fruit-fly flight. The fruit-fly explores its landscape by a series of straight flights with a sudden turn of 90°, leading to $L\acute{e}vy - flight - style$ intermittent scale free search pattern. The step-by-step process of CSA algorithm is given in Algorithm 3.

3.6 Dragonfly Algorithm

Dragonfly is a decorative insect, its scientific name is Anisoptera and belongs to kingdom Animalia, and it is classified to phylum Arthropoda. The average life span of a dragonfly is 6 months. Dragonfly insect is found in 3000 different species around the world [118]. There are two main phases in the life-cycle of a dragonfly which includes: nymph and adult. Dragonfly spends most of his lifespan as nymph and then become adult after passing metamorphism stage as shown in the Figure 3.5 .

Dragonflies are placed in the class of small predators, they rely on other small insects for their survival. They also prey aquatic flies and even small fishes. The swarming nature is an interesting fact of dragonflies. The purpose behind the

Algorithm 3: Pseudocode of proposed CSA Algorithm

```
Parameters initialization: The cuckoo position, maximum size of the
  population, and maximum number of iterations.
Input: The Pricing signal, power rating of machines, LOTs for all machines,
Define variables i.e. Nn, D, Count, n, Tol
while No. of iterations < population size do
    for i =1:M do
        for j =1:N do
        end
    end
    Find Electricity Cost;
    Find E-Cost of all Machines LOTs
    Find P_best
    Assign P_best to L_best
    Find the best nest
    Update the LOTs of Machines
    New solution is evaluated
    Find P_best and L_best
    Assign L_best to G_best
    Output: E_T, τ_w, PAR
end
```

swarming of dragonflies is: hunting and migration. Hunting is static (stationary) swarm and migration is dynamic (traveling) swarm.

In static behavior of swarm dragonflies in small groups over a specific area to make prey of all other flying insects such as butterflies, mosquitoes and many other small insects [119]. On other hand in dynamic swarm a large number of dragonflies migrate from one place to another place over a long distance for finding a best habitat for their living [120]. The mentioned two swarming behavior are

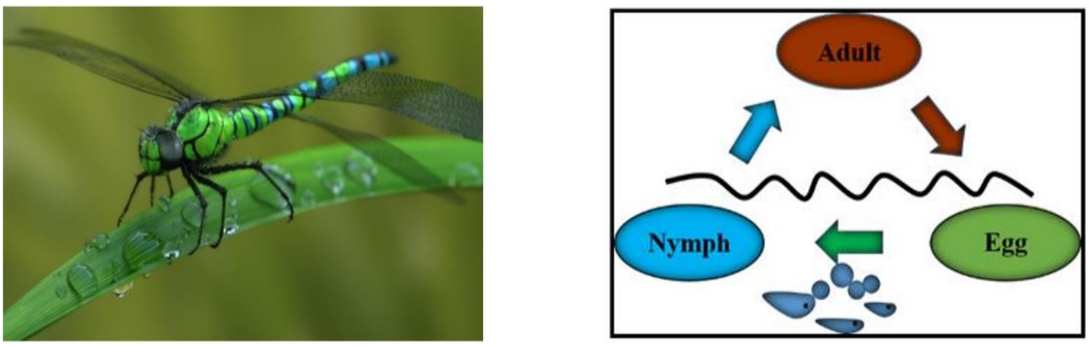

FIGURE 3.5: **(a)** Real dragonfly, **(b)** Life-cycle of dragonfly [118]

similar to the main phases of optimization using meta-heuristics: exploration and exploitation. Static swarm is the main goal of exploration, while dynamic swarm is favorable in exploitation phase. The two swarming styles are briefly explained and mathematically represented in the next section.

- Separation represents the static collision prevention of dragonflies in the swarm from other dragonflies of the nearby vicinity.
- Alignment shows the velocity matching of one dragonfly in the swarm to other individual dragonfly in the same swarm of dragonflies.
- Cohesion represents the struggle of dragonflies toward the center of the mass of the nearby individual dragonflies.

All the individual dragonflies should attract their selves toward the food sources and prevent their selves from the enemies to survive which is the main goal of the swarming nature of dragonflies. In consideration to these two behavior five main position updating factors are shown in the equation below: Separation can calculated by the following equation:

$$S_i = -\sum_{k=1}^{N} Z - Zk \tag{3.9}$$

where Z represents the position of the current dragonfly while Zk represents the position of k-th nearby dragonfly and N is the number of all other nearby individual dragonflies.

Alignment can calculated by the following equation:

$$Ai = \frac{\sum Nk = 1Vk}{N} \tag{3.10}$$

where Vk is the velocity of k-th nearby dragonfly.

Cohesion can calculated by the following equation

$$Ci = \frac{\sum Nk = 1Xk}{N} Z \tag{3.11}$$

where Z shows the position of the current dragonfly while Zk represents the position of k-th nearby dragonfly and N is the number of all other nearby individual dragonflies.

Attraction toward the food can be calculated by the following equation:

$$Fi = Z^{+} - Z \tag{3.12}$$

where Z shows the position of the current dragonfly , and Z^{+} Represents the position of the target food.

Distraction from the enemy can be calculated by the following equation:

$$Ei = Z^{-} + Z \tag{3.13}$$

where Z shows the position of current dragonfly and Z^{-}Represents the position of the enemy.

Two vector are used for updating the position of dragonflies and simulations of their movement, that two vectors are: step (ΔZ) and position (Z). The ΔZ represent the direction of the motion of dragonfly and the step vector is represented mathematically by the following equation:

$$\Delta Z_{t+1} = (sSep_i + aAlig_i + cCoh_i + fFood_i + eEnemy_i) + w\Delta Z_t \tag{3.14}$$

where (s, a, c, f, e, w) are the swarm factors during an optimization process.

The step vector is represented mathematically by the following equation:

$$Z_t + 1 = Z_t + \delta Z_t + 1 \tag{3.15}$$

In above two equations t shows the present iteration.

For the arbitrariness, stochastic nature and exploration of dragonflies, the flying over the search area is necessary, using arbitrary walk (levy flight) in case when there is no nearby solution for finding the position of individual in the swarm, for solving this issue the position of an individual can be calculated by the following equation:

$$Z_{t+1} = Z_t + Levy(d) \times Zt \tag{3.16}$$

In above equation t shows the present iteration, and d is the dimension of the position vector.

The levy flight can be find by the following equation:

$$Levy(Z) = 0.01 \times \frac{c1_{|c2|\beta}}{\times} 1^{\sigma} \tag{3.17}$$

where c1 and c2 are two randomly selected constants between 0 and 1, β is also a constant number which is selected according to the situation of the problem. The step by step process of the proposed DA is depicted in Figure 3.6 (flow-chart).

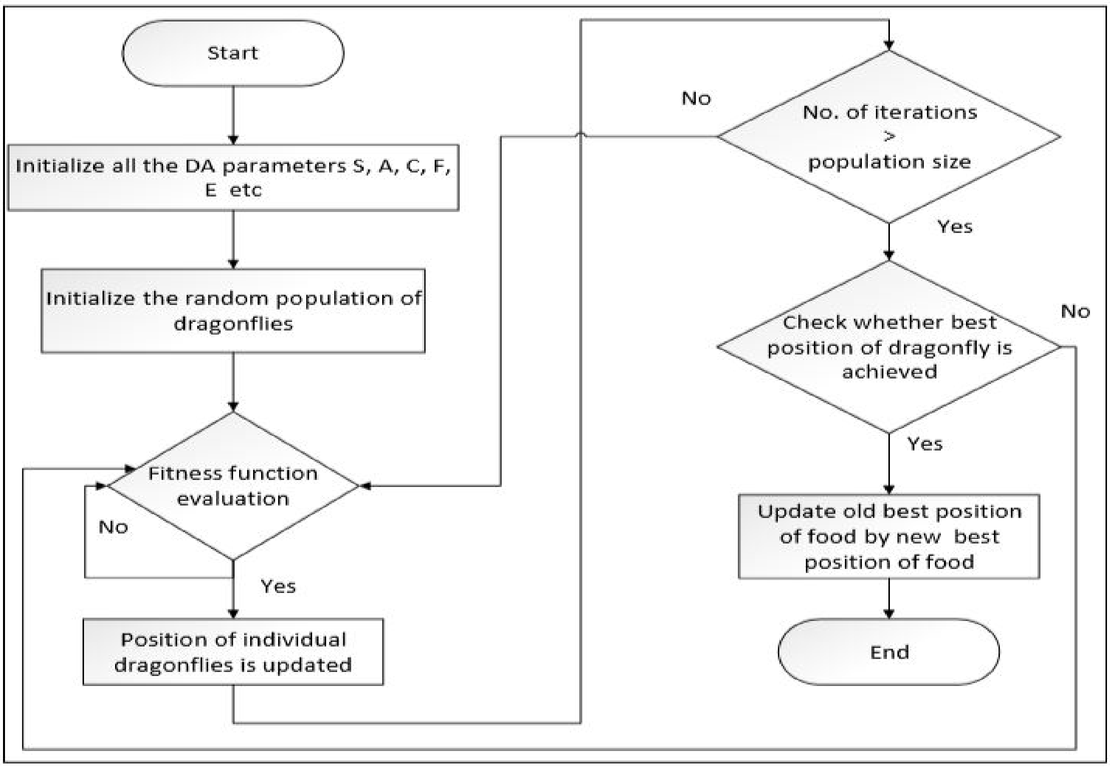

FIGURE 3.6: Step by step process of the DA

3.7 Firefly Algorithm (FA)

Fireflies are in the insect family. They live mostly in humid environments. They generate green, yellow and pale-red limited intensity flashing lights chemically. There are more than 2000 different species. Their unique flashing light pattern is used for communication, i.e., to attract partners and probable prey and as a defensive cautionary mechanism. Some female species apply the flashing light mating pattern for the hunting of other species [121]. Like PSO, in FA, inspired by nature, three assumptions are made: (a) all fireflies must be of the same sex, (b) the attractiveness of a firefly is directly proportional to its brightness and inversely proportional to the square of the distance between two fireflies and (c) brightness is calculated by an objective function: the brighter one will attract the less bright ones. The firefly's flashing light intensity in complete darkness is related to the solution quality. The brighter firefly will attract less bright ones, depending on the brightness intensity, which is calculated as follows:

$$I(I_o, r_{i,j}) = \frac{I_o}{r_{i,j}^2} \tag{3.18}$$

where I_o is the flashing light intensity at the origin and $r_{i,j}$ is the distance of firefly j from firefly i. Let γ be the coefficient of the firefly's flashing light absorption in a medium, then, in the above equation, the light intensity I will vary with the distance between fireflies $r_{i,j}$ using the following equation:

$$I(I_o, \gamma, r_{i,j}) = I_o e^{-\gamma r_{i,j}} \tag{3.19}$$

Both Equations (3.18) and (3.19) can be combined using the Gaussian form as follows:

$$I(I_o, \gamma, r_{i,j}) = I_o e^{-\gamma r_{i,j}^2} \tag{3.20}$$

The following approximation can be used for a slower rate of decrease in the light intensity between the origin and the target.

$$I(I_o, \gamma, r_{i,j}) = \frac{I_o}{1 + \gamma r_{i,j}^2} \tag{3.21}$$

As the less bright firefly will be attracted to the brighter firefly, this attractiveness β between two fireflies can now be mapped as:

$$\beta(\beta_o, \gamma, r_{i,j}) = \beta_o e^{-\gamma r_{i,j}^2} \tag{3.22}$$

where β_o is the attractiveness at the zero distance. For $\beta = \beta_o$ at the zero distance, $r_{i,j} = 0$. Therefore, for a characteristic distance of $r = \dfrac{1}{\sqrt{\gamma}}$, Equation 3.22 becomes:

$$\beta(\beta_o, \gamma, r_{i,j}) = \beta_o e^{-1}$$

The distance between any two fireflies x and y at positions i and j is calculated by:

$$r_{i,j} = Dist.(x_i, y_j) = ||x_i - y_j|| = \sqrt{\sum_{k=1}^{n} (x_{i,k} - y_{j,k})^2} \tag{3.23}$$

The firefly movement towards another firefly has two parts, i.e., (a) the movement for finding a better solution using attractiveness, and (b) the random movement.

$$x_i = x_i + (Attractiveness * Distance) + Randomness \tag{3.24}$$

$$x_i = x_i + \beta_o e^{-\gamma r_{i,j}^2}.(y_j - x_i) + \alpha(Rand() - 0.5) \tag{3.25}$$

where α is the randomness parameter and $Rand$ is a random number generated lying between zero and one. Two extreme points are that when γ is zero, attractiveness will be constant, and when γ is ∞, attractiveness will almost be zero. Practically, γ lies between zero and ∞, so FA gives good results in finding local, as well as global optima [121]. Table 3.2 depicts the FA parameters.

Table 3.2: FA parameters.

S. No.	**Parameter**	**Value**
1	Randomness parameter (α)	0.2
2	Attractiveness (β)	2
3	Absorption coefficient (γ)	1

3.8 Genetic Algorithm (GA)

GA, based on Darwin's theory of natural selection, is in the family of evolutionary algorithms. This algorithm's name is due to, it being inspired by the genetic progression of living organisms. It has a quick rate of convergence. GA carries out parallel search operations in the provided solution space, which reduces the chances of being trapped in the local optimal solution.
For complex non-linear problems' formulation, GA is the best option, especially where the global optimization is a challenging job. For any solution deployment, as GA is probabilistic in nature, the optimality is usually not guaranteed [122]. Every time, when it is run, it gives different solution due to its stochastic behavior. The parameters used in GA are;
Chromosome: A design point made by string of zeros(0s) and ones(1s),
Gene: A scalar component, i.e., either zero (0) or one (1), of the design vector,
Population/population size: The set of design points at the current iteration and
Generations: Iterations.
Besides these parameters, three genetic operators are;
Reproduction: Also known as selection process, in which an old pattern is copied into a new pattern,
Crossover: The process of combining two different design points (set of bits) as shown in Figure 3.7, and
Mutation: Mutual change of 1 to 0 or vice versa, in any random location, as shown in Figure 3.8.

The optimization process of the GA is such that, it initiates a random population known as chromosomes, and then, in every iteration, the generated population is updated. The fitness function of a given problem is evaluated by the suitability of each chromosome. Then, in every iteration, the population is updated by storing the present local best solution, known as elitism. After elitism, in order to reproduce new chromosomes, two parent chromosomes are chosen using the

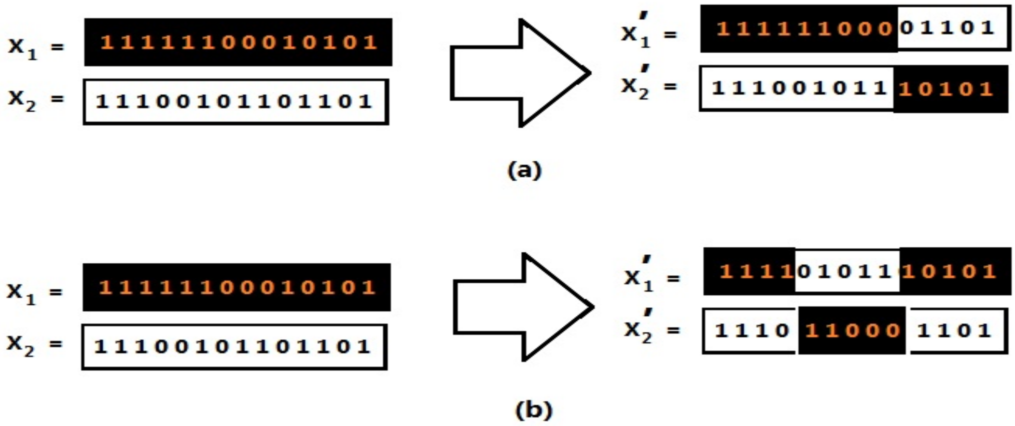

FIGURE 3.7: Process of crossover **(a)** One-cut point **(b)** Two-cut point

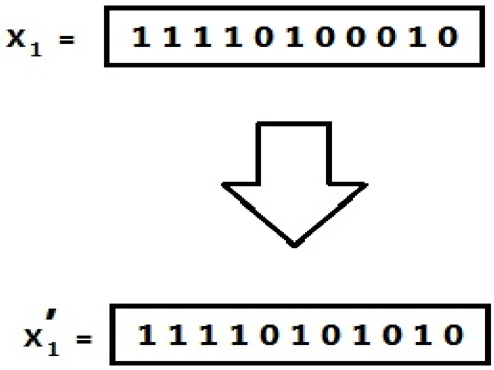

FIGURE 3.8: Process of mutation (changed 0 into 1 at random location 8)

tournament-based selection technique. Then, on the basis of selected chromosomes, the crossover procedure is performed. New offspring are added to update the present population [123]. **Pros:** (a) GA utilizes only the function values for finding a solution.
(b) GA can be used to apply all types of search problems, wither continuous problems, discrete problems or non-differentiable problems.
(c) GA is best for finding global best as compared to local best.
Cons: (a) Using GA, it is not usually possible to get an optimal solution.
(b) Even a simple problem can take a large amount of time to converge.
To overcome the 1st drawback, i.e., to get an optimal solution, usually the process is repeated. However, to handle the second drawback, parallel computing can help or the termination criterion is made adoptive.

Stopping criterion: Adoptive, either (a) local best is not further improving greater than the threshold μ or (b) max. no. of iterations exceeds a threshold (here 800 in our case).

Mapping: In the case of a HEMS, home appliances are mapped with bits of chromosomes. Table 3.3 shows the GA parameters and their values.

Table 3.3: GA parameters.

S. No.	Parameter	Value
1	Population size	200
2	Crossover probability	0.8
3	Mutation probability	0.2
4	Maximum number of generations	800

3.9 Grasshopper Optimization Algorithm (GOA)

GOA is the Meta-heuristic population based optimization technique [124]. Grasshoppers are insects and are considered harmful to crops. The main property of grasshoppers is to form a swarm although they are seen separately in nature. The swarm assembled by grasshoppers, is one of the largest swarms of all the creature in the world and it is considered as the nightmare for farmers. The life cycle of grasshopper consists of egg, nymph and adult, i.e., when a grasshopper reaches its adult stage, it passes through the stages of eggs, nymph and adult as shown in the Figure 3.9.

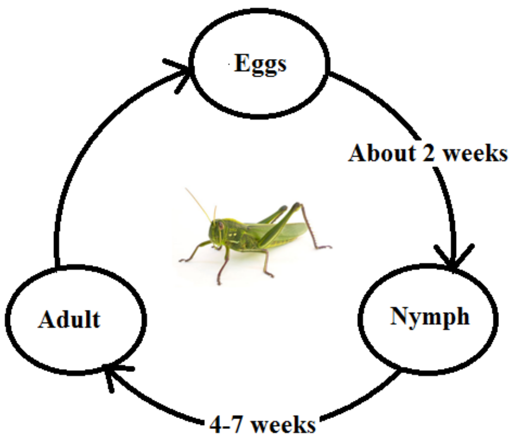

Figure 3.9: The life cycle of a grasshopper

The eggs hatched for ten months, the nymph grasshopper born. Nymph grasshoppers jump over each other and start rolling and eat everything that comes in its way. After sometime, it becomes an adult and start swarming in air.
GOA is basically focusing on the social behavior of grasshoppers. Every member of the swarm consists of a single insect, positioned in a search space ’S’ and moving within its bound as shown in Figure 3.10. Here we are considering the two important motions of grasshopper. The first is the cooperation of grasshoppers which show slow movements when it is in larvae-phase and dynamic movements, when it is in insect-form. The second movement is foraging of food.

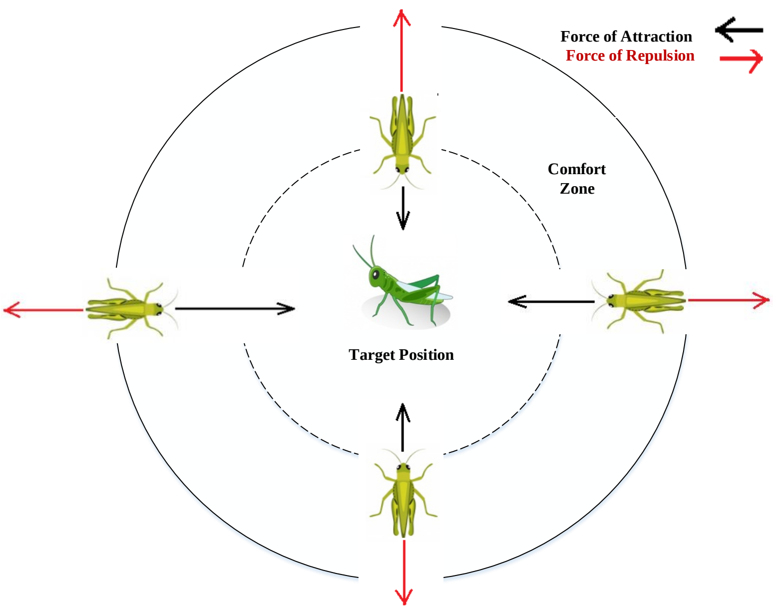

FIGURE 3.10: Behavior of grasshoppers in a swarm

Usually, grasshoppers can be seen in the form of a swarm in nature. They attack agricultural lands and become a nightmare for formers. The swarming behaviour is found in both adult and nymph grasshoppers [125, 126]. Generally, a locust swarm contains five billion of grasshoppers and spread over an area of 60 square miles. Nature-inspired algorithms have a unique search mechanism for food. This consists of two techniques: exploration and exploitation.

3.9.1 Exploration

The process in which the algorithm finds a new solution from the current solutions in the search space.

3.9.2 Exploitation

The process in which algorithm searches the surrounding search space. The mathematical model of GOA, which carries the swarming behaviour of a grasshopper, is given as in [127]. The best search agent is selected on the basis of fitness value evaluation. The best grasshopper agent starts moving toward another individual in its surrounding. Thus all the search agents start motion toward the best grasshopper search agent.
M_i shows the migration of i^{th} search agent towards the target search agent. Mathematically it is given as follows;

$$M_i = S_i + G_i + A_i \tag{3.26}$$

In the above equation A_i shows the direction of wind, G_i shows the gravitational force on i^{th} grasshopper and S_i is the social interaction, which is considered as the main movement part in grasshopper motion. Mathematically it is given as follows;

$$S_i = \sum_{i=1}^{N} S(d_{ij})\hat{d_{ij}} ....j \neq i \tag{3.27}$$

Where, $\hat{d_{ij}}$ is the position vector from i^{th} grasshopper to j^{th} grasshopper and d_{ij} is the distance between two grasshoppers, which is given by;

$$d_{ij} = |m_j - m_i| \tag{3.28}$$

and S is the social interaction force which is given as:

$$S(r) = fe^{\frac{-d}{a}} - e^{-d} \tag{3.29}$$

Where a is attractive scale length, d grasshoppers in-between distance and f is the strength of social forces.

In Equation 3.26, the gravitational force G_i is calculated as follows:

$$G_i = -g\hat{e}_g \tag{3.30}$$

where g denotes the constant of gravitational force and $\hat{e}_g$ is the unit vector.

Now A_i component in Equation 3.26 is given as follows;

$$A_i = v\hat{e}_v \tag{3.31}$$

where v is the constant drift velocity and $\hat{e}_v$ denotes the unit vector.

According to proposed mathematical model in [124];

$$M_i = \sum_{j=1, j\neq i}^{N} S(|P_j - P_i|)\frac{(P_j - P_i)}{d_{ij}} - g\hat{e}_g + v\hat{e}_v \tag{3.32}$$

We modify this model for the purpose of our energy optimization problem as follows;

$$M_i = \gamma\left(\sum_{j=1, j\neq i}^{N} \gamma\frac{u_u - u_l}{2} S(|m_j - m_i|)\frac{(m_j - m_i)}{d_{ij}} - g\hat{e}_g + v\hat{e}_w\right) + \hat{\tau}_d \tag{3.33}$$

Where u_u and u_l are the upper and lower bounds respectively in the D dimension, γ is the decreasing parameter which shrink the comfort zone and $\hat{\tau}_d$ is the value of D dimension of the target agent. The gravitational force has been neglected and wind force is considered in the direction of target agent. γ can be calculated as follows;

$$\gamma = \gamma_{max} - I_i(\frac{\gamma_{max} - \gamma_{min})}{I_{max}}) \tag{3.34}$$

Where, γ_{max} is the upper-limit and γ_{min} is the lower-limit of γ, I_i is the number of iterations and I_{max} is the maximum number of iterations. We utilize the above equations for the creation of swarm in free space and use in simulation to describe the interaction between grasshopper in a swarm. The algorithm working steps are given in Algorithm 4 and are depicted in Figure 3.11.

Algorithm 4: GOA Algorithm

Initialization: Generation of price signal according to the used scheme
LOTs' specification of appliances
power ratings of appliances
Input: variables u_b, l_b, dim, N
Initialize position of Grasshopper
for $h = 1$ *to* H **do**
    Find Electricity Cost
    Find Cost of all appliances LOTs
    Find F_{best}, L_{best} and G_{best};
    for $It = 1$ *to* It_{Max} **do**
        for $i = 1$ *to* N_{VAR} **do**
        end
        Find the best position
    end
    Update the LOTs of Appliances
end
Output: $E_T, Load, PAR.$

3.10 Moth Flame Optimization (MFO)

The nature-inspired algorithm MFO was proposed by Seyedali Mirjalili in 2015 [128]. Moths are butterfly-like insects, having 160,000 plus different species in nature. They have their unique navigation mechanism known as transverse orientation

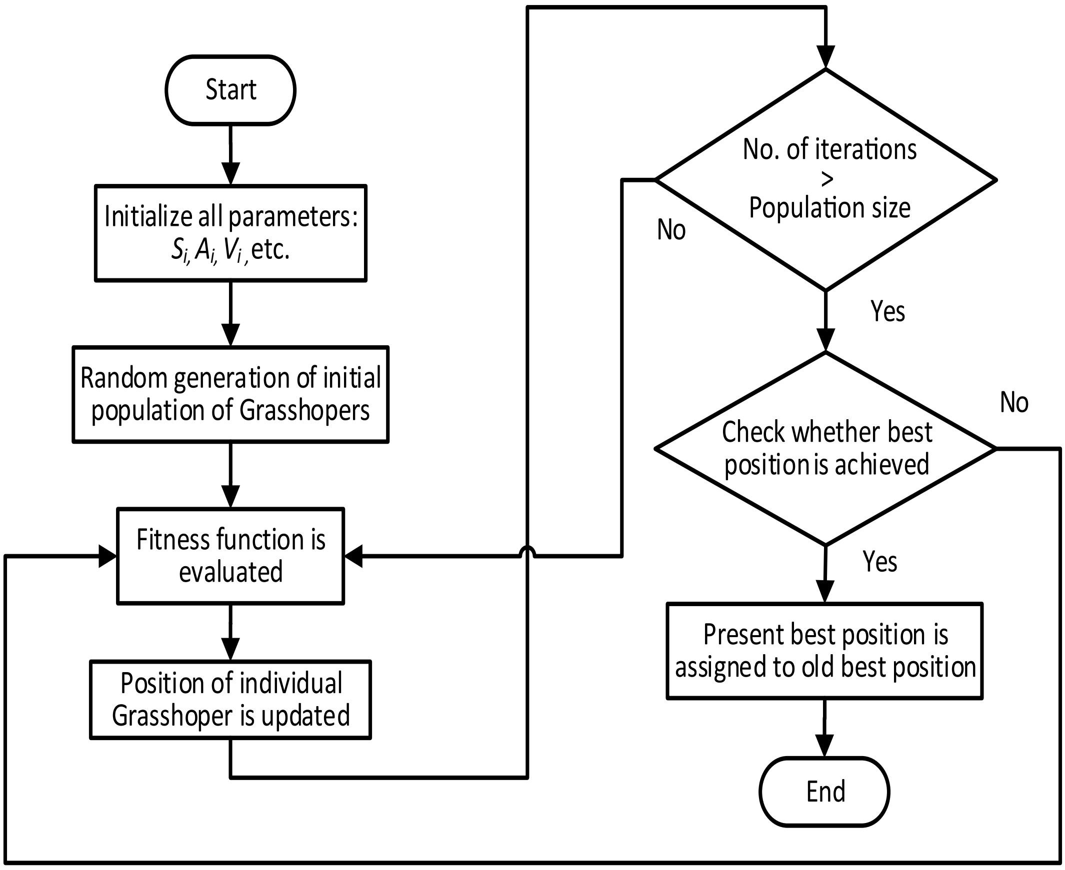

Figure 3.11: Step by step process of the GOA

when flying in the moonlight. When they fly in a spiral, they maintain a constant angle related to the moon, ultimately converging in the direction of light. The spiral articulates the searching region, and it assures the exploitation of the optimum solution.

Since MFO is a population-based algorithm, the movement of m moths in n dimensions (variables) is given in the position matrix form as follows:

$$Q = \begin{bmatrix} q_{1,1} & \dots & q_{1,n} \\ \dots & \dots & \dots \\ q_{m,1} & \dots & q_{m,n} \end{bmatrix} \tag{3.35}$$

The resultant fitness values, for "m" number of moths, are stored in an array. The fitness function (objective) evaluates each moth's fitness value. Each moth's position vector, i.e., matrix Q's first row, is evaluated on the fitness function, and its output is then allocated to its respective moth.

Similarly, a matrix U_F is assigned to the corresponding flames as follows:

$$U_f = \begin{bmatrix} u_{1,1} & \dots & u_{1,n} \\ \dots & \dots & \dots \\ u_{m,1} & \dots & u_{m,n} \end{bmatrix} \tag{3.36}$$

Now, in mapping our problem of the optimum scheduling of home appliances, moths act as searching agents, and flames are the optimum positions. In each iteration, a moth searches for an optimum flame, with updates in the next iteration for the best solution by comparing with the previous one. Moths follow the logarithmic spiral for their update positions, where moths start from some initial position, following some limited fluctuating search space, and reach their destination flames. In MFO, the logarithmic spiral is:

$$S(X_i, P_j) = d_i.e^{bt}.cos(2\pi t) + P_j \tag{3.37}$$

where $d_i = |P_j - X_i|$ is the ith moth distance from jth flame, b is the spiral shape defining the constant and the random number t lies between -1 and one. When $t = -1$, this means the moth is closest to its destination flame, while $t = 1$ indicates that its farthest position from the flame. Therefore, the moth is always assumed to be in a hyper-ellipse space, which guarantees the exploitation and exploration of search space. Table 3.4 depicts the MFO parameters.

Table 3.4: MFO parameters.

S. No.	**Parameter**	**Value**
1	Number of moths and flames	12
2	Max. No. of Iterations	1000
3	Lower bound L_b	-100
4	Upper bound U_b	100

3.11 Whale Optimization Algorithm (WOA)

Whale optimization algorithm (WOA) - a naturally inspired optimization algorithm provided by Mirjalili et al. [70]. WOA is inspired by Humpback whales behavior survival and hunting. The whale can only live alone or in crowds and can be up to 30 meters in length. WOA imitates automated behavior to simulate wildlife hunting as a random or optimistic search agent, for hunting (exploration) and using intelligence kits as a spiral bubble-net attack mechanism.

In addition, Humpback whales typically involve the formation of bubbles around the spinning circle around the predator (exploitation). As with every optimization technique, WOA involves two stages: exploration and exploitation. Exploration is a global search for optimal solutions, but exploitation is related to local search.

Expected to explore the limited prospects of the search engines, hopes to expand the already-known 'S' solution. This will then speed up the search for a "C" solution. On the other hand, exploitation is a major part of the search field, which hopes to find other stimulating solutions that are still being processed. This requires diversification of search to avoid local optimization.

Whale optimization algorithm is similar to hunting optimization techniques and the location of the hunt resembles the best solution. In addition, the WOA begins with a randomly generated whale (solutions) randomly generated position. During the initial iteration, search negotiators upgrade their locus on an arbitrarily selected search negotiator. However, from the second iteration, intermediaries change their state of mind about the best solution ever.

Arbitrary search negotiator is performed if —A— > 1 will help this discovery. If the finest solution is nominated, —A— < 1 is set. This will exploit all exploitation, as all search agents approach. Therefore, WOA can be considered as a good global optimization. Hunting behavior can be summarized in three stages: Encircling, attacking prey and searching of prey.
Figure 3.12 shows the bubble-net attacking strategy of Humpback Whale, i.e., it depicts its hunting mechanism.

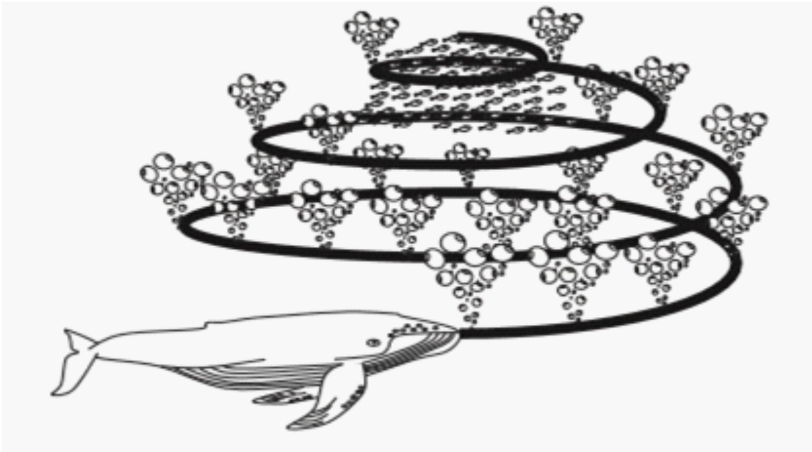

FIGURE 3.12: Bubble-net attacking strategy of Humpback Whale

3.12 Summary

In this chapter, we have discussed, analyzed and mathematically modeled different bio-inspired optimization algorithms. Also, we have made flowcharts and Pseudo-codes of these algorithms, to show that, how these algorithms are working. Although, there are so many bio-inspired algorithms listed in Tables 1.1 and 1.2, however, we have used ACO, ALO, BFA, CSOA, DA, FA, GA, GOA, MFO, WOA and proposed a hybrid version of GA and MFO named as TG-MFO in detail to achieve our three main objectives; minimization of energy cost, PAR and end user discomfort in all three sectors of energy consumption; residential, commercial and industrial. In successive chapters 4,5 and 6, these algorithms are applied and simulated for the aforementioned objectives and their performance is compared in different scenarios.

Due to the random numbers' generation at the beginning, and stochastic nature of the bio-inspired algorithms, every time the algorithm runs, it will give new solution. Therefore, infinite number of solutions is possible, as in each iteration, the algorithms look for local best, and then assign that best solution to the previous achieved and stored global best solution if applied. Therefore, the performance of an algorithm is measured on taking an average of more than ten (10) times repetition on different consumer scenarios. Based on this strategy, the proposed algorithms have been compared and analyzed with the state-of-the-art algorithms used for energy optimization.

Chapter 4

Use of Bio-inspired Optimization Algorithms for Efficient EMS in Residential Sector (Homes and Buildings)

4.1 Motivation

This chapter proposes two bio-inspired heuristic algorithms, the Moth-Flame Optimization (MFO) algorithm and Genetic Algorithm (GA), for an Energy Management System (EMS) in smart homes and buildings. Their performance in terms of our objectives; energy cost reduction, minimization of the Peak to Average power Ratio (PAR) and end-user discomfort minimization are analysed and discussed. Then, a hybrid version of GA and MFO, named TG-MFO (Time-constrained Genetic-Moth Flame Optimization), is proposed for achieving the aforementioned objectives. TG-MFO not only hybridizes GA and MFO, but also incorporates time constraints for each appliance to achieve maximum end-user comfort. Different algorithms have been proposed in the literature for energy optimization. However, they have increased end-user frustration in terms of increased waiting time for home appliances to be switched ON. The proposed TG-MFO algorithm is specially designed for nearly-zero end-user discomfort due to scheduling of appliances, keeping in view the timespan of individual appliances. Renewable energy sources and battery storage units are also integrated for achieving maximum end-user benefits. For comparison, five bio-inspired heuristic algorithms, i.e., Genetic Algorithm (GA), Ant Colony Optimization (ACO), Cuckoo Search Algorithm (CSA), Firefly Algorithm (FA) and Moth-Flame Optimization (MFO), are used to achieve the aforementioned objectives in the residential sector in comparison with TG-MFO. The simulations through MATLAB show that our proposed algorithm has reduced the energy cost up to 32.25% for a single user and 49.96% for thirty users in a residential sector compared to unscheduled load.

4.2 Introduction

Energy utilization efficiency is increasing with increased use of technology and smart appliances in every field of life in the residential, commercial and industrial sectors. At the same time, a reliable and high-quality electrical power system is extremely vital to fulfill the residential energy demand. Meanwhile, there is a rapid increase in demand for global natural resources. Throughout the world, major blackouts occur due to consumer demand and utility supply mismatch and system automation deficiencies. Hence, a transition process from the Traditional Electric Power Grid (TEPG) to the Smart Grid (SG), to integrate communication and information technologies, is the demand of the future. Presently, about 40% of the total generated energy is consumed by residential users, and approximately 30–40% of carbon emission is due to these residential areas [129]. The unnecessary and inefficient use of electrical energy brings sustainability issues to the forefront, such as economic growth, heavy pollution and global warming. Conventionally, the service provider power systems run on fossil fuel and add to global warming with high carbon emissions. Furthermore, in the present power systems, electricity power flow is uni-directional, i.e., from the supply- to the demand-side. Conversely, SG's purpose is to make the flow of electricity supply and demand bidirectional [130].

Secondly, the search for and integration of new green renewable energy resources are obligatory in such circumstances. The integration of green renewable energy resources needs a broader perspective of design, planning and optimization. Up to this time, different conventional optimization techniques, such as Linear Programming (LP) [114], Non-Linear Programming (NLP) [131], Integer Linear Programming (ILP) [132], Mixed Integer Linear Programming (MILP) [133], Dynamic Programming (DP) [134] and Constrained Programming (CP), have been practised. However, in the present situations, the integration of renewable energy resources is mandatory, and the problems are non-linear and have numerous local optima, making conventional optimization techniques obsolete. In the last decade, bio-inspired modern heuristic optimization techniques have grown in popularity due to their stochastic search mechanisms and avoidance of large convergence time for the exact solution [129].

In this chapter, we propose a new meta-heuristic optimization algorithm, named Time-constrained Genetic-Moth-Flame Optimization (TG-MFO), and applied it for efficient energy optimization in smart homes and buildings. We have also explored and analysed five bio-inspired heuristic algorithms for the energy optimization problem, namely the ACO, GA, Cuckoo Search Algorithm (CSA), Firefly Algorithm (FA) and MFO algorithms. For analysis and validation of the proposed algorithm, we applied these algorithms in different consumer scenarios, such as a single home for one day, a single home for thirty days, thirty different sizes of homes for one day and thirty homes for thirty days. Simulation results show that our proposed algorithm reduced the end-user discomfort in terms of appliance waiting time being nearly equal to zero, as compared to the bio-inspired optimization algorithms, along with minimization of total energy cost and minimum PAR. Renewable energy sources are also integrated for further minimization of the total load and its cost.

To achieve this goal, the SG is modeled as a residential sector comprised of 30 different size homes, different Lengths of Operational Time (LOTs) and appliance power ratings. Appliance power ratings are different due to the home size requirements. For example, a small-sized home runs a one-ton (12,000 BTU) air conditioner compared to a large-sized home that runs 1.5 tons (18,000 BTU) or even more. Some homes have a Renewable Energy Source (RES) and a Battery Storage Unit (BSU). In the considered model, we have forty-eight (48) Operational Time Intervals (OTIs) in a day, by dividing one hour into two-time slots of thirty minutes each. In each OTI, a smart home checks appliances' power demand, i.e., whether an appliance is ON or OFF. According to the appliances' ON/OFF status, the Energy Management Controller (EMC) checks the availability of RES and BSU to fulfill the appliances' power demand. If it is available, the appliance will be ON, and the consumer will not wait for appliance scheduling. If the generation and stored energy are insufficient for running the load, the proposed algorithm will check the time span, in which a user has no problem with appliance scheduling with the lowest energy price (time interval) for running that appliance. In order to achieve this objective, time constraints have been defined for a maximum interval of time in which an appliance has to complete its operation. Consequently, if the utility gives incentives to the user in the form of real-time lower prices in off-peak hours, the end-user will be encouraged to produce his/her own energy from RES and schedule the load accordingly.

4.2.1 Proposed System Model Architecture

Figure 4.1 shows the proposed system model architecture. In the proposed system model, the following assumptions are made;

1. Four different size homes, in which, one will be selected randomly
2. Small size homes are assumed to have low power rated appliances
3. Large size homes are assumed to have high power rated appliances
4. Two types of loads; (a) fixed and (b) shiftable
5. Three types of consumers; (a) Passive, (b)semi active and(c) full active
6. 24 hrs time slots are assumed, with no load shedding or black-out.

Smart Home (SH) consists of a smart meter along with the EMC, for a reliable bi-directional power and information flow between SG and SH [135].

All appliances, sensors, RESs and BSUs are connected to EMC through a Home Area Network (HAN), which is further connected to SG through a Wide Area Network (WAN). Different WAN solutions are available like PLC, Wi-Fi, Wi-Max and GSM [136]. End-users manage their energy consumption activities as per incentives offered by the utilities. In each SH, the end-user sets various parameters of all appliances in EMC. EMC is then responsible for the ON/OFF status of all appliances.

4.2.2 Problem Formulation

To formulate the problem, residential consumers have been categorized as follows:

4.2.2.1 Non-active Users (NAUs)

Non-active Users (NAUs) do not use RESs and/or BSUs. They fulfil their load demand only from the utility grid. They can reduce their electricity bill by transferring their loads to off-peak hours. The consumed energy of NAU is calculated using the following equation:

$$E_{NAU} = E_T \tag{4.1}$$

where E_{NAU} is the energy consumption of all non-active users and E_T is the total energy consumption of all appliances.

4.2.2.2 Semi-active Users (SAUs)

Semi-active Users (SAUs) may generate their own energy using RESs and get energy from the grid when needed, i.e., when their demand exceeds the RESs' generated energy or when RESs are not available. That is, the end-user energy

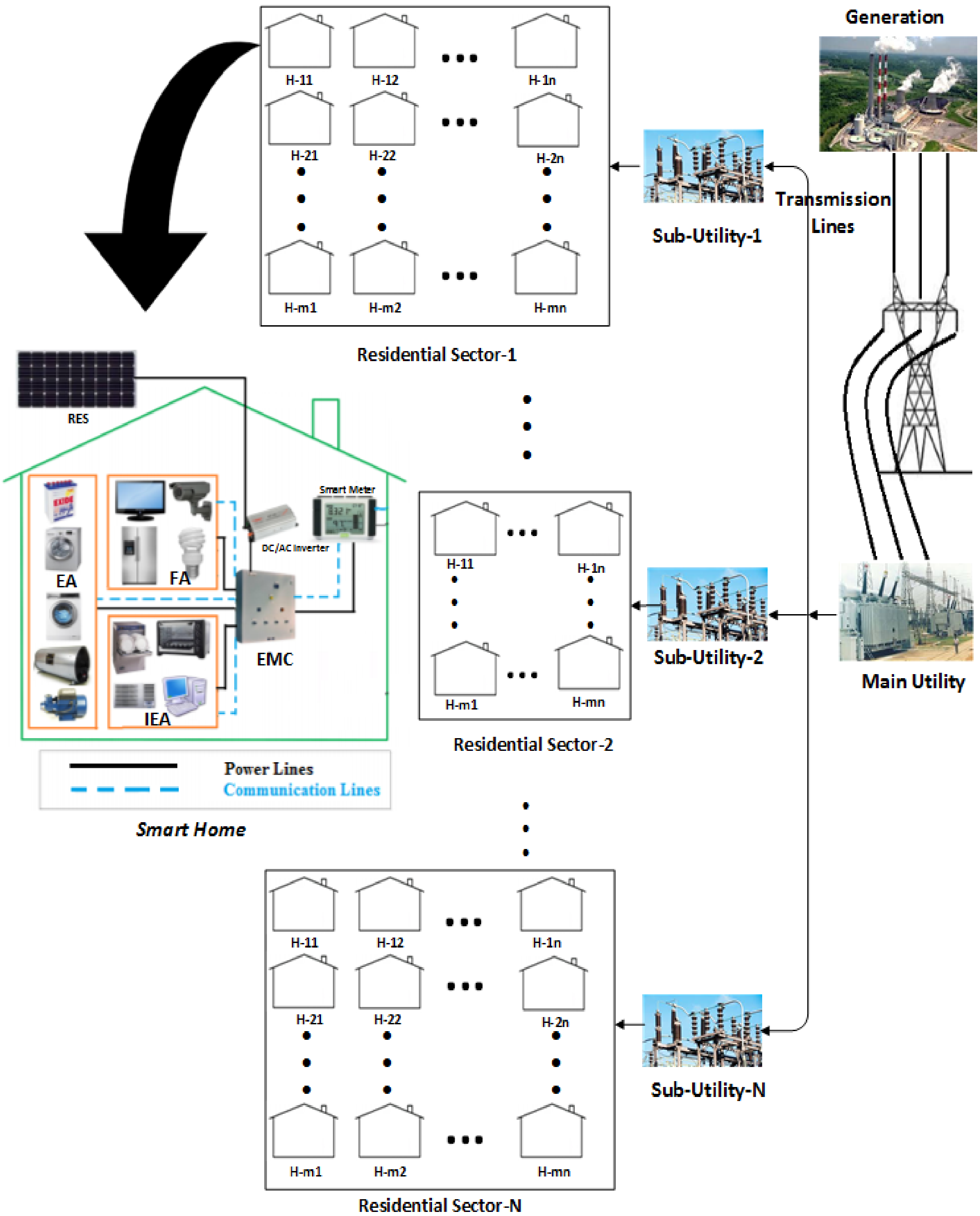

FIGURE 4.1: Proposed system model architecture.

demand from the grid will be the total used energy minus their self-generated RES energy.

SAUs consumed energy is calculated using the following equation:

$$E_{SAU} = E_T - \sum_{n=1}^{48} E_{RES,n} \tag{4.2}$$

where E_{SAU} is the energy consumption of semi-active users and E_{RES} is the energy generated from RESs.

4.2.2.3 Fully-active Users (FAUs)

Fully-active users (FAUs) generate their own energy using RESs and store the extra generated energy in the batteries using BSUs. They obtain energy from the grid when needed, i.e., when their demand exceeds the RESs' generated energy plus the BSUs' stored energy. Their energy consumption pattern is calculated using the following equation:

$$E_{FAU} = E_T - \sum_{n=1}^{48} \left(E_{RES,n} \pm E_{BSU,n} \right) \tag{4.3}$$

where E_{FAU} is the energy consumption of fully-active users, $E_{RES,n}$ is the nth consumer's RESs' generated energy and $E_{BSU,n}$ is consumers' stored energy using BSUs. Now, if E_{BSU} is positive, this means that RESs are charging the batteries, and if E_{BSU} is negative, this means batteries are discharging and providing energy to the load.

4.2.3 Load Categorization and Their Energy Models

To design an optimized model, the consumer load can be divided as follow:

4.2.3.1 Fixed Load

These are those regular appliances whose starting time remains fixed. That is, a consumer can start and stop these appliances any time. Refrigerator and interior lights are examples of Fixed Load (FL).

Most of the research works have considered 24 intervals for their energy calculations, which are usually not applicable to all appliances. Usually, an appliance, for example a microwave oven, a clothes dryer, etc., operates for less than an hour. Hence, further dividing an hour into two sub-intervals of thirty minutes each generates a total of forty-eight (48) time slots, which results in accurate manipulation. However, this slightly increased the manipulation time, but that can be ignored.

4.2.3.2 Shiftable Load

These are those appliances that can be fully managed, i.e., they can be shifted to any time slot and can also be interrupted at any time keeping in view the minimization of PAR and electricity bill [102]. These include: dish washer, washing machine, spin dryer, electric car, laptop, desktop computer, vacuum cleaner, oven, cook top and microwave oven [72]. The energy consumed by all shiftable appliances in the total time interval of 24 h with 48 time-slots and their cost can be found as:

$$E_T^N = \sum_{n=1}^{N} W_n \times X_n \tag{4.4}$$

where, W_n is the power of n^{th} appliance, N shows the total no of appliances, X_n is the ON-time in a time slot of n^{th} appliance and E_T^N is the total energy calculated for all appliances in a single time slot.

Now the total cost C_{Sch} for all scheduled appliances can be calculated by multiplying total energy $E_{T,m}^N$ calculated in m^{th} time slot with respective energy price ζ_m in that time slot.

$$C_{Sch} = \sum_{m=1}^{M} E_{T,m}^N \times \zeta_m \tag{4.5}$$

C_{unsch} is the total energy price for all slots of Unscheduled appliances calculated in the similar manner, then the normalized C_{Norm} of scheduled appliances can be calculated as:

$$C_{Norm} = \frac{C_{Sch}}{C_{Sch} + C_{unsch}} \tag{4.6}$$

In this work, we assumed a single home and thirty homes with different power ratings of appliances, as tabulated in Table 4.1. Our required objectives are:

- Consumers' high comfort level by reducing appliances' average waiting time

- Consumers' electricity bill minimization
- Minimization of PAR and
- Integration of RES and BSU in the system for further reduction of end-user waiting time.

These objectives can be achieved by the optimization of the energy consumption profiles of home appliances, using different scheduling techniques. In this chapter, we are using the MKP (multiple knapsack problem) scheduling technique. MKP is a capacity (resources) allotment problem. It consists of N number of capacities and Q number of objects [149].

MKP is a combinatorial problem. In MKP, stuff quantity, having different weights and values, can be kept into a knapsack of certain capacity, such that the worth of the knapsack should be maximum as shown in Figure 4.2. We consider U number of knapsacks, and using MKP as scheduling mechanism to map our problem as follows:

- Power capacities of consumers in every time interval are mapped as U number of knapsacks
- Appliances in an office are mapped as "Q" number of objects
- The weight of every object in MKP is mapped as appliances consumed energy in every time interval. This is assumed to be time invariant
- In MKP, the worth of each object in a particular time interval is mapped as the cost of appliances consumed energy in that interval of time [150].

$$E_T \leq V_T \tag{4.7}$$

Here E_T is the cumulative energy demand of the end-user and V_T is the maximum energy capacity in a particular interval of time available from the utility grid. MKP scheduling tells us to keep the total energy demand of end user less than or

FIGURE 4.2: Multiple knapsack problem (MKP) formulation

equal to this maximum energy capacity threshold.
Waiting Time (τ_w) and PAR can be calculated as discussed in chapter 1, Figure 1.1, Equations 1.4 to 1.7

4.2.4 Objective Function

Our proposed objective function aims to reduce electricity cost, while maintaining higher end user comfort level by minimization of waiting time. The final expression for our objective function is given by:

$$min\Big((\lambda_1 \times C_{Norm}) + (\lambda_2 \times \tau_w)\Big) \tag{4.8}$$

λ_1 and λ_2 are multiplying factors of two portions of our objective function. Their values varies between '0' and '1' so that λ_1 + λ_2=1 . It reveals that either λ_1 and λ_2 could be 0 to 1. That is, if an end user does not want to participate in the load scheduling process, then his multiplying factors will be λ_1 =1 and λ_2 =0 in the objective function.

TABLE 4.1: Home appliances and their running time constraints [72].

S. No.	Appliance	Category	Power Rating ρ (KW)	Starting Time (α)	Ending Time (β)	Time-Span ($\beta-\alpha$) (h)	LOT (h)
1	Fridge-1	Fixed	0.3	00	24	24	24
2	Interior Lighting-1	Fixed	0.84	18	24	06	6.0
3	Dish Washer-1	shiftable	2.0	09	17	08	2.0
4	Washing Machine-1	shiftable	0.6	09	12	03	1.5
5	Spin Dryer-1	shiftable	2.5	13	18	05	1.0
6	Cook Top-1	shiftable	3.0	08	09	01	0.5
7	Oven-1	shiftable	5.0	18	19	01	0.5
8	Microwave-1	shiftable	1.7	08	09	01	0.5
9	Laptop-1	shiftable	0.1	18	24	06	2.0
10	Desktop-1	shiftable	0.3	18	24	06	3.0
11	Vacuum Cleaner-1	shiftable	1.2	09	17	08	0.5
12	Electrical Car-1	shiftable	3.5	18	08	14	3.0
1	Fridge-2	Fixed	0.25	00	24	24	24
2	Interior Lighting-2	Fixed	0.9	19	24	07	7.0
3	Dish Washer-2	shiftable	1.9	11	15	04	2.0
4	Washing Machine-2	shiftable	0.5	10	14	04	2.0
5	Spin Dryer-2	shiftable	2.0	10	16	06	2.0
6	Cook Top-2	shiftable	3.5	09	10	01	0.5
7	Oven-2	shiftable	5.4	17	20	03	1.5
8	Microwave-2	shiftable	1.9	07	09	02	0.8
9	Laptop-2	shiftable	0.09	16	23	07	3.0
10	Desktop-2	shiftable	0.28	14	20	06	2.0
11	Vacuum Cleaner-2	shiftable	1.4	10	16	06	1.5
12	Electrical Car-2	shiftable	3.3	16	09	17	4.0
1	Fridge-3	Fixed	0.5	00	24	24	20
2	Interior Lighting-3	Fixed	0.62	17	06	13	13
3	Dish Washer-3	shiftable	2.5	10	16	06	2.5
4	Washing Machine-3	shiftable	0.8	08	14	06	1.8
5	Spin Dryer-3	shiftable	2.5	13	19	06	1.0
6	Cook Top-3	shiftable	3.2	07	09	02	0.5
7	Oven-3	shiftable	5.3	16	18	02	1.5
8	Microwave-3	shiftable	1.9	10	14	04	1.0
9	Laptop-3	shiftable	0.2	16	24	08	2.5
10	Desktop-3	shiftable	0.4	18	20	02	1.0
11	Vacuum Cleaner-3	shiftable	1.3	11	12	01	0.5
12	Electrical Car-3	shiftable	3.4	16	07	11	5.0
1	Fridge-4	Fixed	0.4	00	24	24	18
2	Interior Lighting-4	Fixed	0.7	19	08	13	13
3	Dish Washer-4	shiftable	2.3	08	19	11	4.0
4	Washing Machine-4	shiftable	0.9	11	14	03	1.0
5	Spin Dryer-4	shiftable	2.0	14	20	06	1.0
6	Cook Top-4	shiftable	3.5	10	12	02	1.2
7	Oven-4	shiftable	5.5	10	11	01	0.8
8	Microwave-4	shiftable	1.9	10	14	04	1.5
9	Laptop-4	shiftable	0.15	11	23	12	4.0
10	Desktop-4	shiftable	0.4	09	24	15	6.0
11	Vacuum Cleaner-4	shiftable	1.5	11	16	05	1.2
12	Electrical Car-4	shiftable	4.0	10	22	12	4.0

4.3 Results and Discussions

4.3.1 Consumer Scenarios

In the present work, four types of consumers' scenarios were simulated and presented. In the first case, a single home was taken, and its hourly load, hourly energy cost, PAR and waiting time were determined both in the unscheduled and scheduled (with ACO, CSA, GA, FA, MFO and TG-MFO) environment for a single day. In the second case, a residential building with thirty homes having users with different LOTs and power ratings of their appliances were considered. Again, their hourly average load, hourly cost, PAR and waiting time were determined both for unscheduled and scheduled (with ACO, CSA, GA, FA, MFO and

TG-MFO) scenarios for a single day. In the third case, we considered a single home, found all four of its parameters for unscheduled and scheduled scenarios for a complete month, i.e., thirty (30) days, and found its monthly bill. In the fourth case, a residential building with thirty homes was considered, where we determined its daily average load, daily cost, daily PAR and average waiting time for a complete month, i.e., thirty (30) days, as well as calculated its monthly electricity consumption and electricity bill. In all four cases, the RTP scheme was used.

For the system's stability, further reduction of electricity consumption and maximum user comfort, RES and BSUs were also integrated. Additionally, for photovoltaic cells' electricity generation, temperature, solar irradiance, battery charging/discharging rates and its storage system, different assumptions were considered from [73].

4.3.2 Pricing Signal

Many international energy system operators issue hourly day-ahead pricing (DAP) signals every day to the consumers. DAP signal is a key feature of smart meter which benefits the end user as well as the utility. DAP signal is provided to the users via smart energy meters, the users modify their daily needs according to the DAP signal and the EMC scheduled the smart appliances according to the proposed algorithm. The day-ahead energy price signal of New York Independent System Operator (NYISO), shown in Figure 4.3, accessed on 5th Jan. 2019, is reproduced and used for cost calculation [152].

4.3.3 Daily Basis Hourly Load Curves

Figure 4.4 depicts the daily basis hourly load curve for a randomly selected single home and thirty homes, for un-scheduled load and GA-, MFO-, ACO-, CSA-, FA- and TG-MFO-scheduled load, for 24 hours. According to the utility provided DAP signal, shown in the Figure 4.3, peak hours range from 16 to 20 hrs, during which the energy price is high. It is therefore clear from Figures 4.4 and 4.5, that

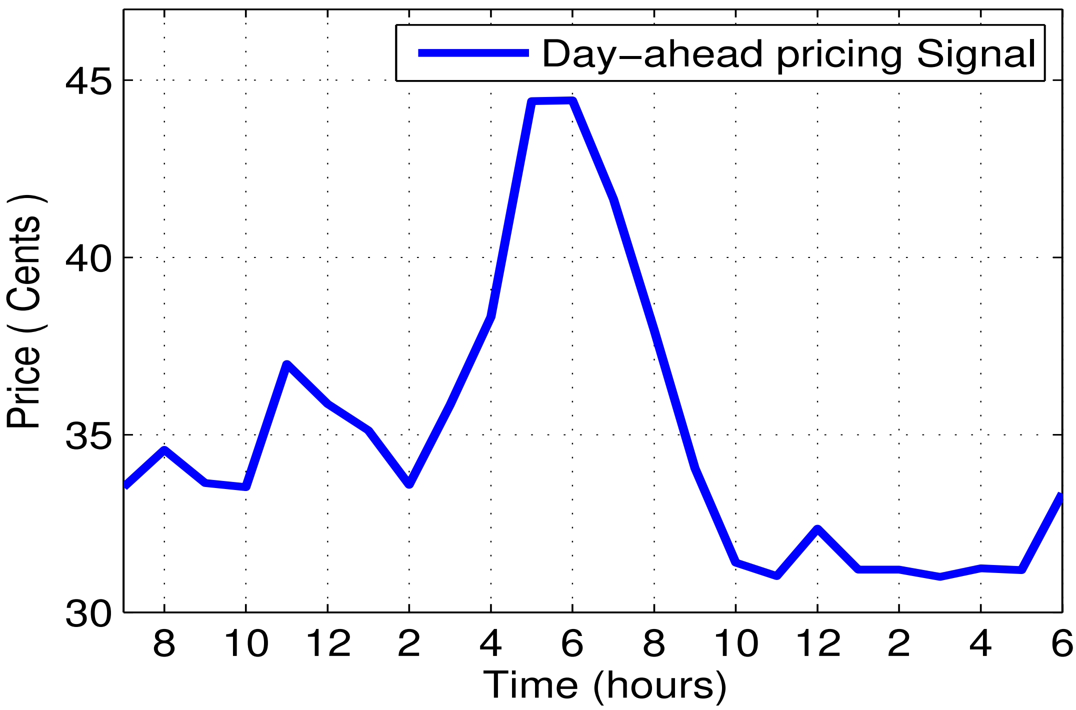

FIGURE 4.3: Day-ahead real-time pricing signal.

as compared to the unscheduled load, meta-heuristic algorithm-based scheduled load was shifted to the off-peak hours, where not only the price was low, but RES was also available, considering the end-user's time constraints for the maximum comfort level. The Figure shows that our proposed algorithm gave comparatively good results for both single and multiple homes with different sizes, power ratings and LOTs.

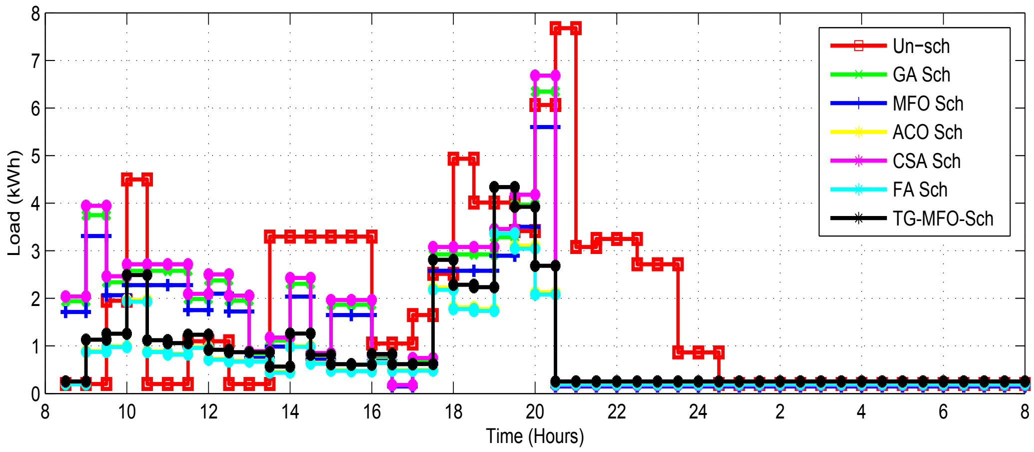

FIGURE 4.4: The hourly load for un-scheduled and GA-, MFO-, ACO-, CSA-, FA- and TG-MFO-scheduled load for a single home.

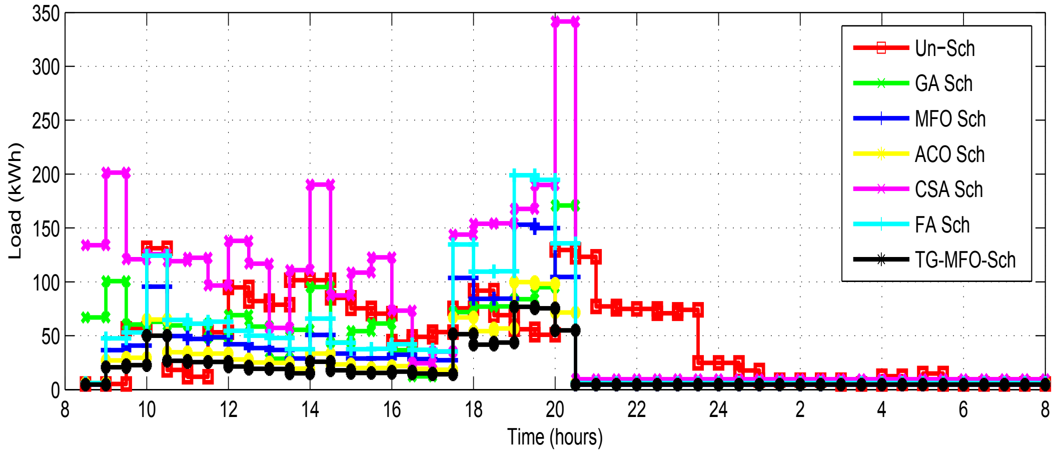

FIGURE 4.5: The hourly load for un-scheduled and GA-, MFO-, ACO-, CSA-, FA- and TG-MFO-scheduled load for 30 homes

4.3.4 The Total Electricity Cost

Figure 4.6 shows the total average cost for a randomly selected single home for one day, single home for thirty days, thirty homes for single day and thirty homes for thirty days, for the unscheduled and scheduled (with ACO, CSA, GA, FA, MFO and TG-MFO) load. Due to the shifting of load from ON-peak hours to OFF-peak hrs, it is clear from figures the electricity cost of the meta-heuristic algorithms-based scheduled load was very low as compared to the unscheduled load cost. In Figure 4.6, the operation of a single home for a single day is considered. In this case, ACO-based scheduling revealed better results as compared to all scheduled and unscheduled costs. Similarly, in Figure 4.7, the case of a single home for 30 days (one month) is shown, while, in Figure 4.8, 30 homes with different LOTs and power ratings for 30 days (one month), and in Figure 4.9, the case of 30 homes for 30 days; the scheduled cost was very less as compared to the un-scheduled cost. In all four cases, ACO outperformed all scheduling techniques.

4.3.5 Average Waiting Time

Figure 4.10 depicts the average waiting time of single and thirty homes. Waiting time is a very important feature of appliance scheduling for optimal energy

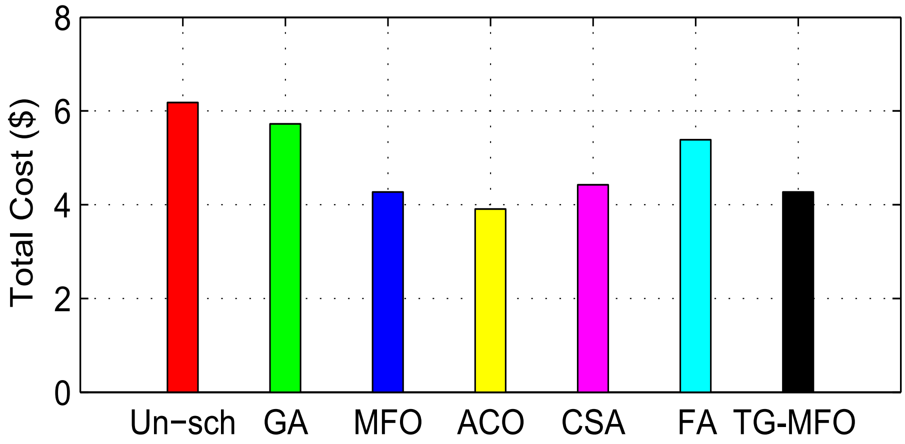

FIGURE 4.6: Total cost for un-scheduled, and GA, MFO, ACO, CSA, FA and TG-MFO Scheduled load for a single home for 1 day

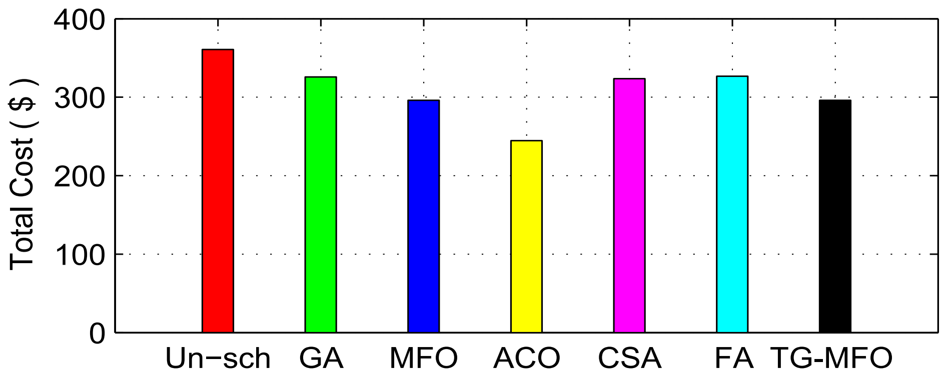

FIGURE 4.7: Total cost for un-scheduled, and GA, MFO, ACO, CSA, FA and TG-MFO Scheduled load for single home for 30 days.

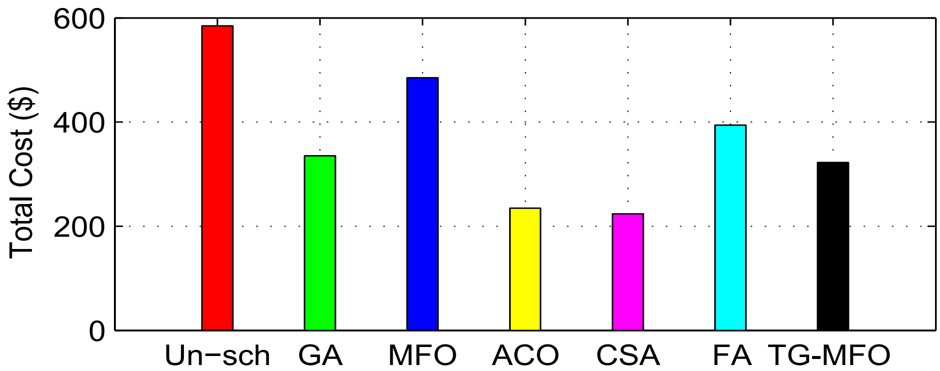

FIGURE 4.8: Total cost for un-scheduled, and GA, MFO, ACO, CSA, FA and TG-MFO Scheduled load for 30 homes for 1 day.

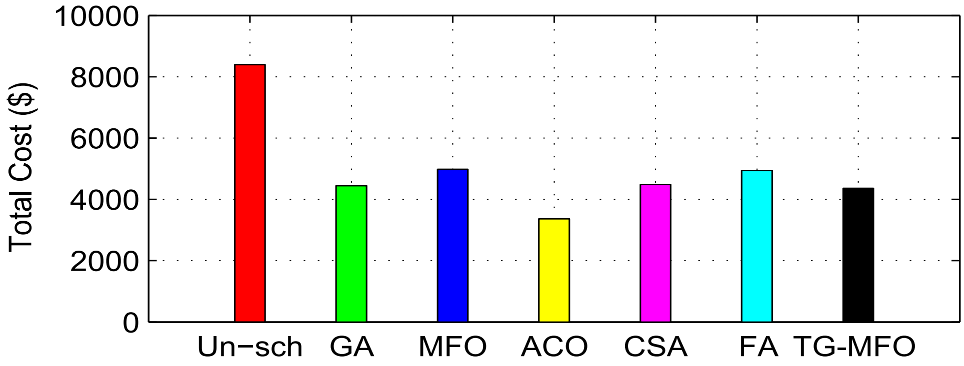

FIGURE 4.9: Total cost for un-scheduled, and GA, MFO, ACO, CSA, FA and TG-MFO Scheduled load for 30 homes for 30 days.

consumption in the smart grid. To reduce electricity cost, usually, waiting time increases. A user wants to start an appliance, but due to scheduling time constraints, the user has to wait for the starting of its operation. Our main objective in this work was to minimize the user electricity bill, keeping in view the maximum comfort level of the end-user. Figure 4.10 shows that we achieved our objective using heuristic techniques for optimal scheduling. The graphs show that TG-MFO outperformed ACO, CSA, GA, FA and MFO in achieving a nearly-zero waiting time for the end-user.

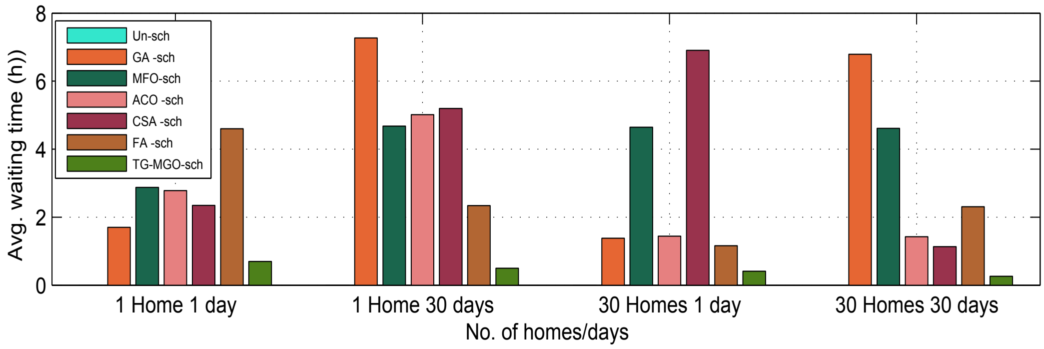

FIGURE 4.10: Average waiting time for a single home and 30 homes.

4.3.6 Peak to Average Power Ratio (PAR)

PAR plays an important role in the optimal scheduling of smart home appliances. Due to high PAR, the utility faces huge peak loads during peak hours, and the rest of the day, most of the generating units remain idle. Therefore, researchers try to reduce PAR for economical load dispatch in smart grids. Figure 4.11 and Figure 4.12 show that, in the case of a single home for a single day and thirty homes for a single day, MFO performed better than FA, while in the case of a single home for thirty days and thirty homes for thirty days, FA showed better results than MFO respectively. In our proposed hybrid model, we tried to not only schedule appliances optimally, economically and having maximum end-user comfort, but also gave the lowest PAR, for the benefit of utility, and hence, to further increase the end-user comfort level.

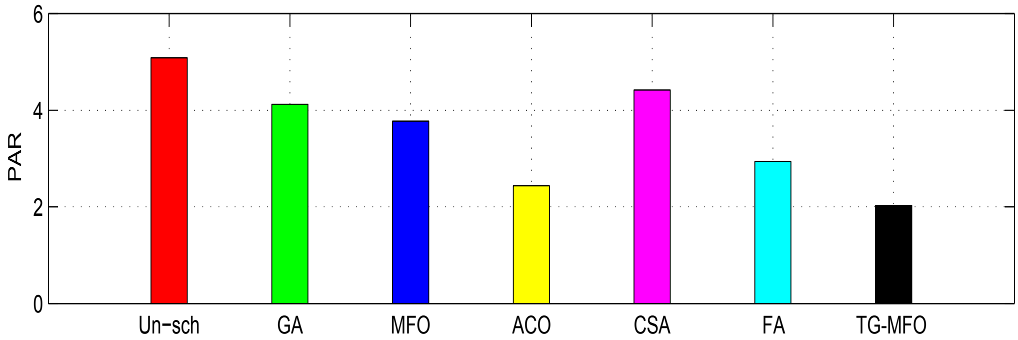

FIGURE 4.11: PAR for a single home for a single day.

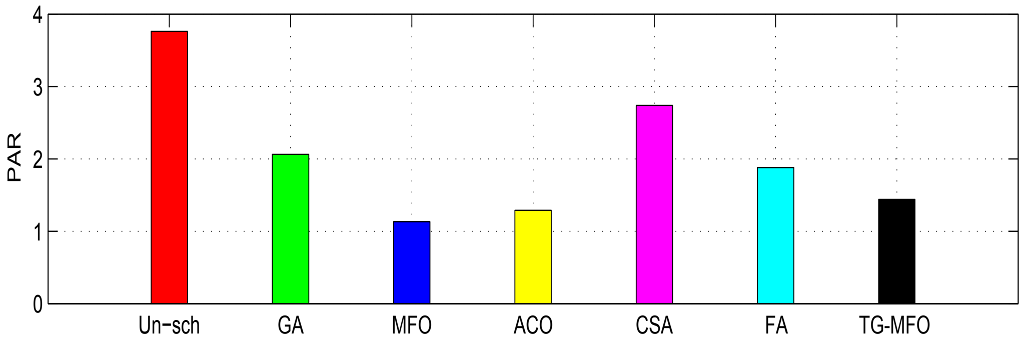

FIGURE 4.12: PAR for thirty homes for a single day.

4.3.7 Integration of RES and BSU

The use of renewable energy sources is a good practice for cost reduction in all three sectors of energy consumption. In order to minimize the consumed energy for further reduction of the total cost, RES and BSUs were integrated in homes. Figure 4.13 shows that the day-time load will be supported by RES, while extra energy will be stored in BSUs for running the load in peak hours. It drastically reduces the cost. The figure depicts that our proposed TG-MFO algorithm has intelligently not only shifted the load to day-time off-peak hours for cost minimization, but also reduced the PAR.

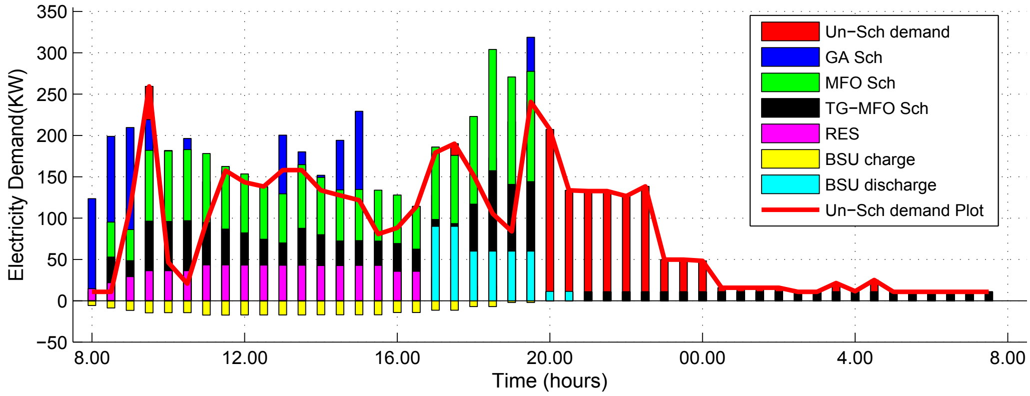

FIGURE 4.13: Energy demand curves of the scheduled and the un-scheduled load along with RES and BSUs.

A comparison of the proposed algorithm with state-of-the-art research works in the smart grid environment for energy optimization and end-user comfort is depicted in Table 4.2. Most of the existing techniques have used trade-offs between user comfort and bill minimization. Table 4.3 shows the run-time of the proposed

TABLE 4.2: Comparison of TG-MFO with the state-of-the-art work.

Techniques	**No. of Homes/Days**	**Cost Reduction**	**Waiting Time**
K. Ma et al. [97]		34%	1.76 h
Y. Peizhong et al. [92]	30 days	20%	7.64 h
TLGO [100] TLBO GA		33% 31.5% 31%	1.83 h 2.14 h 2.37 h
Ogunjuyigbe et al. [101]			9.6 (dis-satisfaction level) 20.2= 30.9=
Pilloni et al. [84]		33%	1.65 to 1.70 (Annoyance rate)
K. Muralitharan et al. [104]	10 Home appliances 11 12 13 14	38%	73.32 s 76.28 s 86.83 s 94.39 s 107.58 s
TG-MFO (Proposed)	1 home for 1 day 1 home for 30 days 30 homes for 1 day 30 homes for 30 days	32.25% 19.39% 43.98% 49.96%	0.62 h 0.48 h 0.38 h 0.26 h

algorithms using an Intel (R) Core (TM) i5 processor, with 4.00 GB of installed memory (RAM) and the 32-bit Windows 7 Operating system.

TABLE 4.3: Runtime of the proposed algorithm in four different scenarios.

Proposed Algorithm	**No. of Homes/Days**	**Run Time (s)**
TG-MFO	Single home for 1 day	47.65
	Single home for 30 days	123.02
	Thirty homes for 1 day	129.18
	Thirty homes for 30 days	841.65

Table 4.4 shows the performance of the proposed TG-MFO algorithm, compared to unscheduled load and scheduled with the GA, MFO, ACO, FA and CSA algorithms.

TABLE 4.4: Comparison of the un-scheduled load with GA, MFO, ACO, CSA, FA and TG-MFO.

Techniques	**No. of Homes/Days**	**Cost ($)**	**%Cost Reduction**	**Waiting Time (h)**	**PAR**	**% PAR Change**
Un-Schedule	Single home for 1 day	6.2	–	–	4.58	–
	Single home for 30 days	366	–	–	—	–
	30 homes for 1 day	582	–	–	3.84	–
	30 homes for 30 days	8476	–	–	—	–
GA Scheduled	Single home for 1 day	5.8	06.45%	1.75	4.19	8.5%
	Single home for 30 days	332	09.28%	7.41	—	—
	30 homes for 1 day	340	41.58%	1.45	2.13	44.5%
	30 homes for 30 days	4320	49.03%	6.76	—	—
MFO Scheduled	Single home for 1 day	4.2	32.26%	2.81	3.82	16.6%
	single home for 30 days	296	19.12%	4.62	—	—
	30 homes for 1 day	490	15.8%	4.67	1.21	68.5%
	30 homes for 30 days	4992	41.10%	4.61	—	—
TG-MFO Scheduled	Single home for 1 day	4.2	32.25%	0.62	2.02	49.8%
	single home for 30 days	295	19.39%	0.48	—	—
	30 homes for 1 day	326	43.98%	0.38	1.48	61.4%
	30 homes for 30 days	4241	49.96%	0.26	—	—
ACO Scheduled	Single home for 1 day	4.4	29.03%	2.74	2.34	48.9%
	Single home for 30 days	245	33.06%	5.02	—	—
	30 homes for 1 day	242	58.41%	1.48	1.37	64.3%
	30 homes for 30 days	3212	62.10%	1.39	—	—
CSA Scheduled	Single home for 1 day	4.38	29.35%	2.46	4.26	6.9%
	Single home for 30 days	336	08.19%	5.21	—	—
	30 homes for 1 day	239	58.93%	6.82	2.67	30.4%
	30 homes for 30 days	4295	49.32%	1.18	—	—
FA Scheduled	Single home for 1 day	5.2	16.12%	4.54	2.45	46.5%
	Single home for 30 days	338	07.65%	2.38	—	—
	30 homes for 1 day	398	31.61%	1.17	1.83	52.3%
	30 homes for 30 days	4852	42.75%	2.32	—	—

4.4 Summary

In chapter, we mapped GA, MFO and a new efficient and robust hybrid TG-MFO meta-heuristic bio-inspired algorithm for optimal scheduling of home appliances in the smart grid and compared their results with existing techniques of CSA, FA and ACO. We considered both, the single and multiple homes scenarios in a residential sector. In multiple homes, we took different LOTs and power ratings of appliances to make it more practical. Day-ahead RTP signaling was used for demand response in smart homes. The results show that there was a 6.45%–49.03%, 32.26%–41.10% and 32.25%–49.96% decrease in the total cost with GA, MFO and TG-MFO scheduling, respectively, for single and multiple users. RESs and BSUs were also integrated to obtain a further decrease in the total cost and end-user waiting time. In this work, we tried to not only reduce the total cost, but to achieve a high comfort level of the end-user by minimizing the waiting time of home appliances using the time constraints of a maximum average delay of 0.26–0.62 h. This algorithm can be applied to actual data when and where they are provided. It not only reduces the energy cost, but also increases the stability and reliability of the grid.

Future work includes exploration of more bio-inspired algorithms for intelligent and efficient energy optimization, and a multi-objective approach will be applied.

Chapter 5

Use of Bio-inspired Algorithms for an Efficient EMS in Commercial Applications

This chapter presents two bio-inspired energy optimization techniques; the grasshopper optimization algorithm (GOA) and bacterial foraging algorithm (BFA), for power scheduling in an office. We have also applied our proposed hybrid TG-MFO algorithm for comparison purpose in commercial application. Energy is one of the valuable resources in this biosphere. However, with the rapid increase of the population and increasing dependency on the daily use of energy due to smart technologies and the Internet of Things (IoT), the existing resources are becoming scarce. Therefore, to have an optimum usage of the existing energy resources on the consumer side, new techniques and algorithms are being discovered and used in the energy optimization process in the smart grid (SG). In SG, because of the possibility of bi-directional power flow and communication between the utility and consumers, an active and optimized energy scheduling technique is essential, which minimizes the end-user electricity bill, reduces the peak-to-average power ratio (PAR) and reduces the frequency of interruptions. Because of the varying nature of the power consumption patterns of consumers, optimized scheduling of energy consumption is a challenging task. For the maximum benefit of both the utility and consumers, to decide whether to store, buy or sale extra energy, such active environmental features must also be taken into consideration. It is clear from the simulation results that the consumer electricity bill and PAR can be reduced as compared to unscheduled energy consumption with the day-ahead pricing (DAP) scheme.

5.1 Introduction

With the increased use of modern technologies and smart appliances in every field of life, energy consumption is rapidly increasing. The rising electricity demand cannot be fulfilled by the traditional electric power grid. That is why the smart grid is becoming more popular to fulfil daily electricity demand. The smart grid (SG) is supposed to be the incorporation of information technologies (IT) in the existing power grids to increase their robustness and consistency. Smart meters (SM) are used for communication and energy monitoring purposes in SG. To schedule smart appliances in residential, commercial and industrial sectors, an energy management controller (EMC) is installed at the consumer premises. Demand side management (DSM) has many strategies that help to solve the energy optimization problem by peak clipping, load shifting, strategic conservation, flexible load shifting, strategic load growth and valley filling. By using these strategies, the load is shifted from high demand timings to low demand timings [137]. The two main functionalities of DSM are proper management of the load and demand response (DR) [138]. Consumer load management is also known as DSM. It is the process of shifting electricity demand from high-demand (on-peak) hours to low-demand(off-peak) hours to decrease the energy cost. DR is the consumer's response to variable pricing signals. There are two shapes of DR: in the form of energy price reduction or some incentives to consumers [139, 140].

The main objectives of the energy management system (EMS) are the reduction of the energy bill, PAR and consumer discomfort.

Many algorithms have been deigned to accomplish the aforementioned objectives. For cost and energy consumption minimization, mixed integer linear programming

(MILP), mixed integer nonlinear programming (MINLP), non-integer linear programming (NILP) and convex programming were used in [141]-[144]. However, these techniques are used for fewer appliances and have a large convergence time.

In order to overcome these deficiencies, researchers use meta-heuristic techniques to resolve the issue of energy optimization. For cost minimization, the genetic algorithm (GA) was proposed by the authors in [145, 146]. For cost minimization and aggregated power consumption, differential evolution (DE) and ant colony optimization (ACO) were used in [147, 148].

In this chapter, we apply meta-heuristic optimization algorithms in a single office using the DAP pricing signal. The simulation is performed in MATLAB, and we obtained the results of PAR, cost and average waiting time.

5.1.1 Proposed System Model Architecture

The efficient utilization of the existing energy resources is necessary in our daily life. The proposed system model architecture is depicted in Figure 5.1. It consists of a smart meter (SM), the energy management controller (EMC), automatically-operated appliances (AOAs) and advance distribution and communication systems. EMC receives the required energy consumption outline from all connected appliances, which schedule the energy consumption pattern according to the pricing signal. The utility sends the pricing signal to the smart meter, which is then forwarded to the EMC. At the same time, the SM receives the consumed electricity reading from EMC and transmits it to the utility.

5.1.2 Load Categorization

5.1.2.1 Fixed Load

As discussed in chapter 4, these are those regular appliances whose starting time remains fixed. That is, a consumer can start and stop these appliances any time.

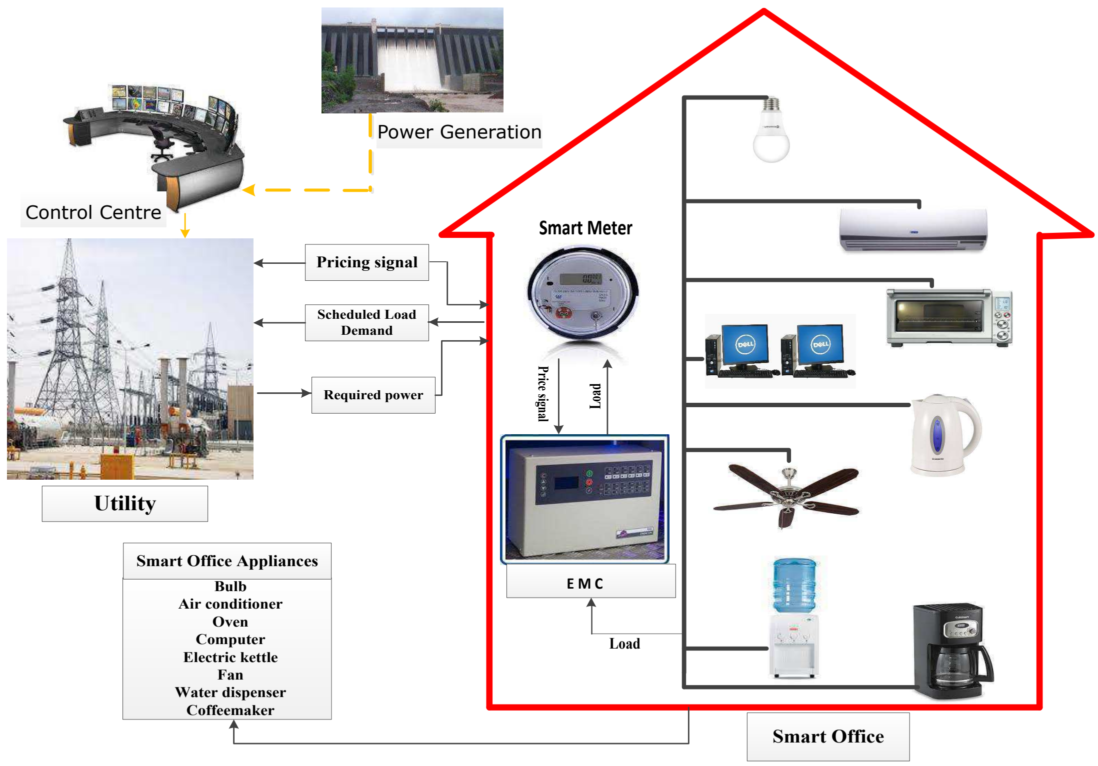

FIGURE 5.1: The proposed system model architecture

Here in the office, fans, lights, air conditioners and water dispenser are examples of Fixed Load (FL). In this work, we considered only a single office with eight appliances. In our case, the decision would be made after every 30 minutes, not 1 h, because we have divided 24 h into 48 time slots, each equal to 30 minutes. Here, we considered 48/2=24 time slots for offices because offices only consume energy during the daytime.

5.1.2.2 Shiftable Load

These are those appliances that can be fully managed, i.e., they can be shifted to any time slot and can also be interrupted at any time keeping in view the minimization of PAR and electricity bill [102]. These include: computers, electric kettles, coffee makers and Oven. The energy consumed by all shiftable appliances in the total time interval of 12 h with 24 time-slots can be found as:

$$E_T^N = \sum_{n=1}^{N} W_n \times X_n \tag{5.1}$$

where, W_n is the power of n^{th} appliance, N shows the total no of appliances, X_n is the ON-time in a time slot of n^{th} appliance and E_T^N is the total energy calculated for all appliances in a single time slot.

Now the total cost C_{Sch} for all scheduled appliances can be calculated by multiplying total energy $E_{T,m}^N$ calculated in m^{th} time slot with respective energy price ζ_m in that time slot.

$$C_{Sch} = \sum_{m=1}^{M} E_{T,m}^N \times \zeta_m \tag{5.2}$$

C_{unsch} is the total energy price for all slots of Unscheduled appliances calculated in the similar manner, then the normalized C_{Norm} of scheduled appliances can be calculated as:

$$C_{Norm} = \frac{C_{Sch}}{C_{Sch} + C_{unsch}} \tag{5.3}$$

In this work, we assumed a single office with different fixed and shiftable appliances, as tabulated in Table 5.1.

TABLE 5.1: Specifications of office automatically operating appliances (AOAs).

S. No.	AOAs	Category	Power rating (kW)	LOT	Time-Span (slots)
1	Air conditioner	Fixed	4.00	15	1–24
2	Fan	Fixed	3.5	12	1–24
3	Light	Fixed	2	17	1–24
7	Water dispenser	Fixed	2.5	22	1–24
4	Computer	shiftable	0.25	20	1–24
5	Electric kettle	shiftable	3.00	1	1–22
6	Coffee maker	shiftable	2.00	2	3–20
8	Oven	shiftable	5.00	2	3–20

In the proposed work, we formulate our problems of; (a) end-user high comfort level, (b) consumers' electricity bill minimization, and (c) minimization of PAR by optimization of energy consumption profiles of office appliances, using the MKP (multiple knapsack problem) scheduling technique, as discussed in chapter 4. Now, if E_T is the cumulative energy demand of the end-user and V_T is the maximum energy capacity in a particular interval of time, then,

$$E_T \leq V_T \tag{5.4}$$

MKP scheduling tells us to keep the total energy demand of end user less than or equal to this maximum energy capacity threshold.

Waiting time (τ_w) and PAR can be calculated as discussed in chapter 1, Figure 1.1, Equations 1.4 to 1.7

5.1.3 Objective Function

Our proposed objective function aims to reduce electricity cost, while maintaining higher end user comfort level by minimization of waiting time. The final expression for our objective function is given by:

$$min\Big((\lambda_1 \times C_{Norm}) + (\lambda_2 \times \tau_w)\Big) \tag{5.5}$$

λ_1 and λ_2 are multiplying factors of two portions of our objective function. Their values varies between '0' and '1' so that $\lambda_1 + \lambda_2$=1 . It reveals that either λ_1 and λ_2 could be 0 to 1. That is, if an end user does not want to participate in the load scheduling process, then his multiplying factors will be λ_1 =1 and λ_2 =0 in the objective function.

5.2 Results and Discussions

5.2.1 Consumer Scenarios

Different consumer scenarios are possible in commercial sector. For example, Offices, shopping malls, markets, street lights and parks. In this chapter, we have taken an office as a case study, and scheduled its appliances. A substantial simulation was performed to show the performance of different algorithms in terms of minimization of electricity cost by shifting appliances from on-peak hours to off-peak hours, minimization of PAR and minimization of end-user discomfort due to waiting time. In this chapter, eight appliances were selected, as shown in the Table 5.1. For comparison purpose, firefly algorithm (FA), cuckoo search algorithm (CSA) and ant colony optimization algorthm (ACO) are considered in the same scenario for thirty-days load scheduling.

5.2.2 Pricing Signal

Figure A-1 gives the day-ahead pricing (DAP) signal, taken from the daily report of the New York Independent System Operator (NYISO) [152]. The total time of 24 h was divided into 24 time slots. For an office, usually 8–12 h are used, so time was taken from 8:00–20:00.

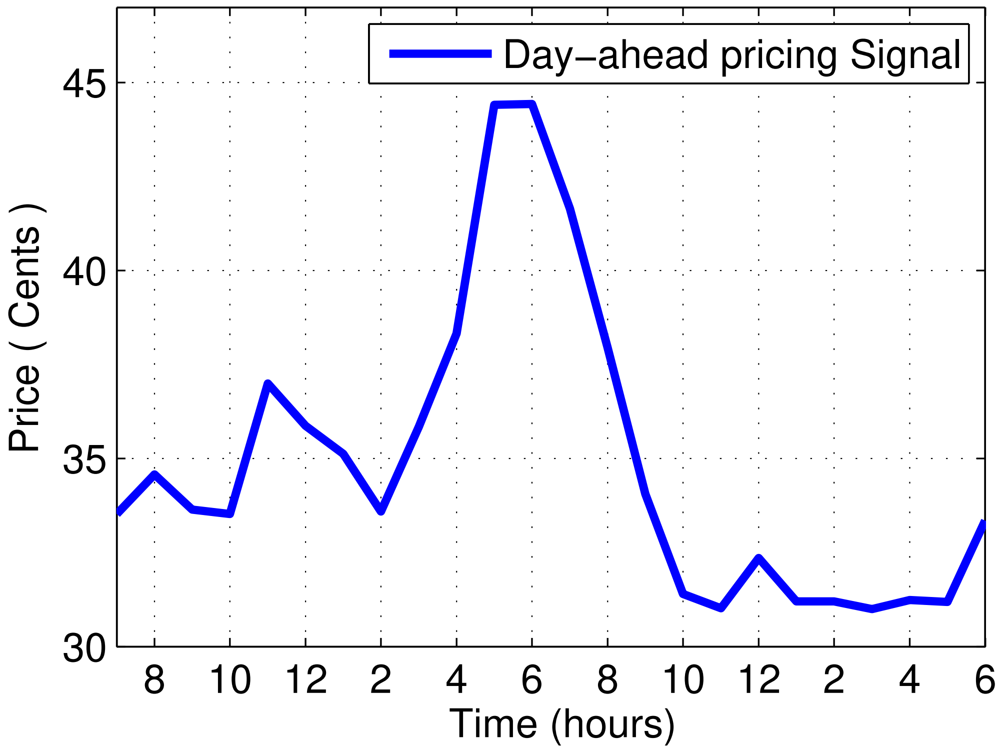

FIGURE 5.2: Day-ahead real time pricing signal [152]

5.2.3 Hourly Load

Figure 5.3 shows the daily unscheduled load and scheduled load with the Grasshopper optimization algorithm (GOA) and Bacterial Foraging Algorithm (BFA) algorithms. It delivers important information in terms of time dependent load. The figure shows that Grasshopper optimization algorithm (GOA) outperforms Bacterial Foraging Algorithm (BFA) algorithms by eliminating the peak in the unscheduled load.

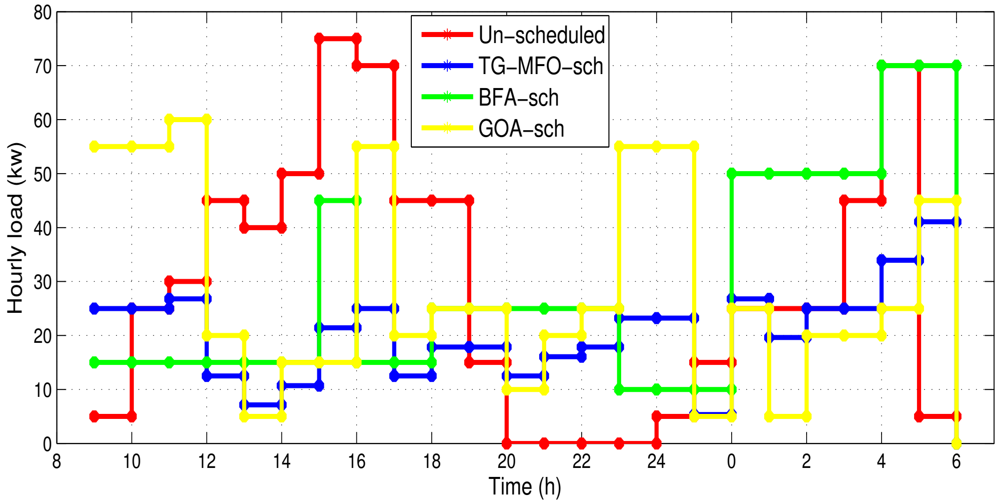

FIGURE 5.3: Hourly load for unscheduled load and scheduled load with the TG-MFO, GOA and BFA algorithms.

5.2.4 Hourly Cost

Figure 5.4 shows the hourly unscheduled (Un-sch) and scheduled cost with Grasshopper optimization algorithm (GOA) outperforms Bacterial Foraging Algorithm (BFA) algorithms cost. It is clear that the hourly cost is averaged compared to the unscheduled cost, especially the high cost in the on-peak hours due to shifting of the load from on-peak hours to off-peak hours.

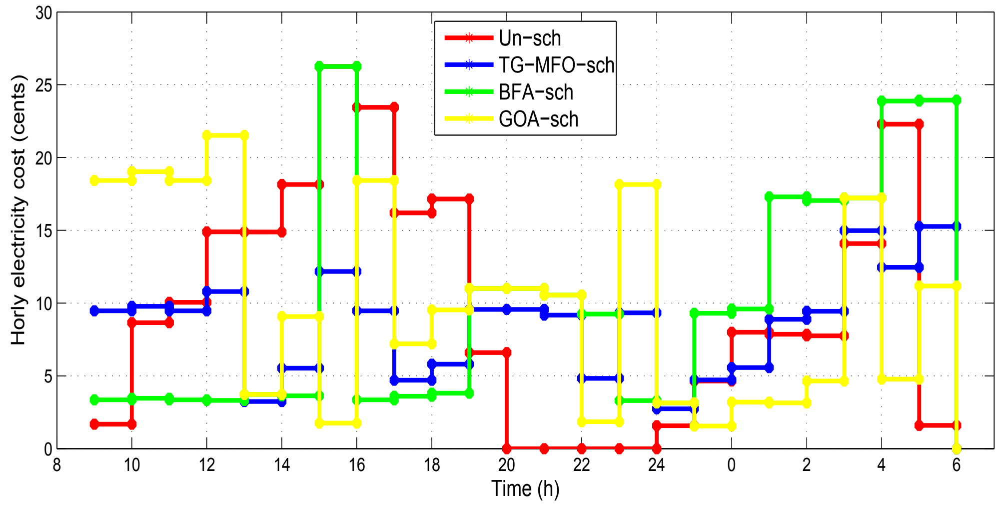

FIGURE 5.4: Hourly cost for unscheduled load and scheduled load with the TG-MFO, GOA and BFA algorithms.

5.2.5 The Total Electricity Cost

Figure 5.5 depicts the total monthly electricity cost in dollars. In the unscheduled case, we had a maximum cost of 267.45 $; when scheduled by GOA, it became 174.67 $ (34.69% reduction); and in the case of BFA, it became 161.23 $ (37.47% reduction). The comparison of these proposed algorithms with state-of-the-art algorithms for the same scenario is depicted in Table 5.3.

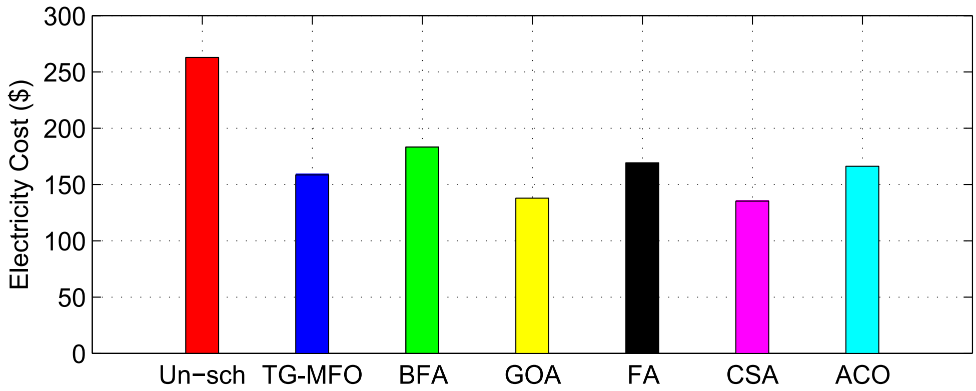

FIGURE 5.5: Total cost

5.2.6 Average Waiting Time

Figure 5.6 depicts the average waiting time. The waiting time in the case of GOA was 1.28 h, and BFA was 1.32 h. This shows that the waiting time of BFA was greater than GOA because it had reduced the total cost more than that reduced by BFA. Table 5.3 shows that, there is always a trade-off between energy cost and waiting time.

Figure 5.7 shows that the office monthly load was equal for all algorithms, as each algorithm had to reschedule the appliances only.

5.2.7 Peak to Average Power Ratio (PAR)

Figure 5.8 depicts the daily PAR. It is clear from the figure that our proposed schemes minimized the PAR. Before scheduling, the PAR value was 7.81, and after

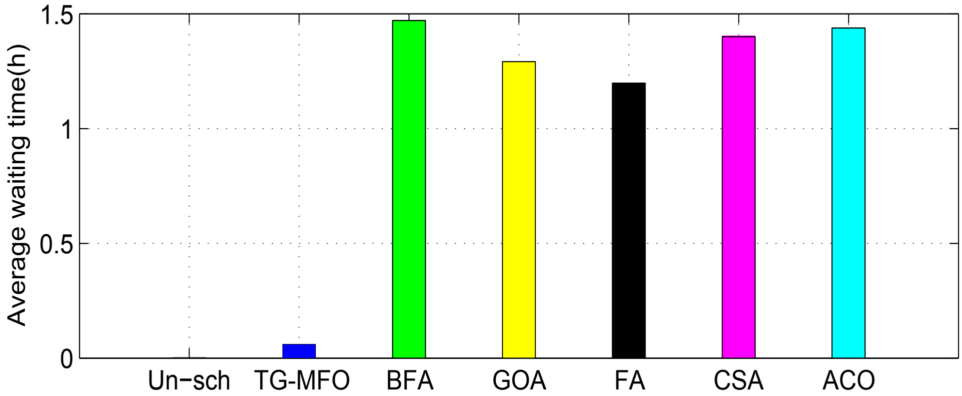

FIGURE 5.6: Average waiting time

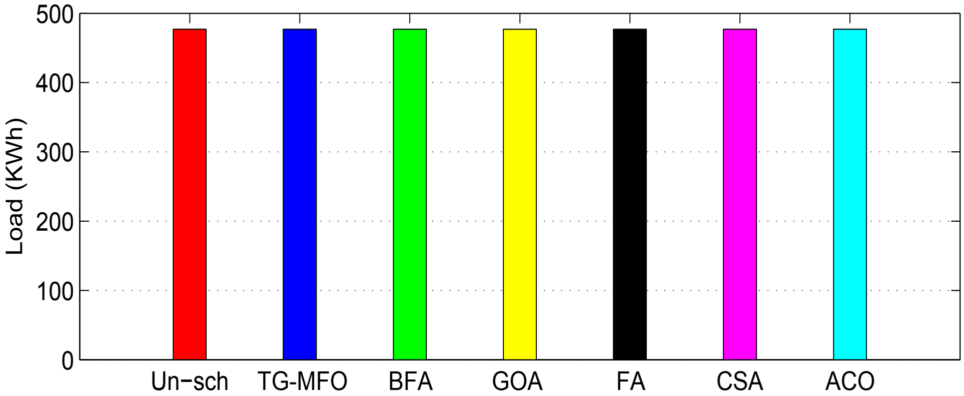

FIGURE 5.7: Total monthly load

scheduling with GOA and BFA, the PAR values became 3.42 (56.20% reduction) and 6.18 (20.87% reduction), respectively.

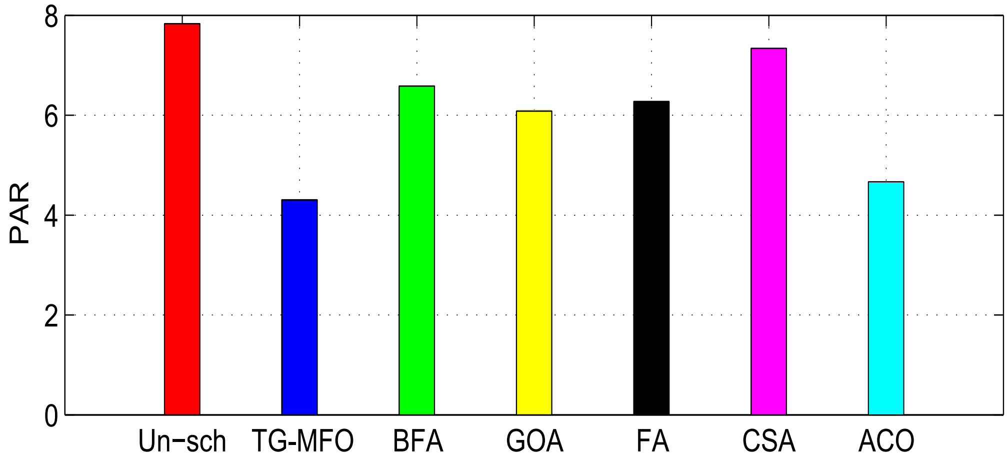

FIGURE 5.8: The peak-to-average power ratio (PAR)

Table 5.2 shows the run-time of the proposed algorithms using an Intel (R) Core (TM) i5 processor, with 4.00 GB of installed memory (RAM) and the 32-bit Windows 7 Operating system.

TABLE 5.2: Run-time of the proposed algorithms for 30 days of load scheduling.

Proposed Algorithm	**No. of Days**	**Run time (s)**
TG-MFO	30 days	15.173
GOA	30 days	11.695
BFA	30 days	13.171

Table 5.3 compares the performance of the proposed algorithms with unscheduled load and state-of-the-art algorithms like firefly algorithm (FA), cuckoo search algorithm (CSA) and ant colony optimization (ACO) with respect to three parameters; energy cost, waiting time and PAR.

TABLE 5.3: Comparison of the unscheduled load and scheduled load with the TG-MFO, BFA, GOA, FA, CSA and ACO algorithms.

Techniques	**Days**	**Cost ($)**	**Cost Reduction**	**Waiting Time (h)**	**PAR**	**PAR Change**
Un-schedule	30 days	267.45	–	–	7.86	–
TG-MFO-scheduled	30 days	161.92	39.45%	0.06	4.27	45.67%
BFA-scheduled	30 days	179.81	32.76%	1.46	6.69	14.88%
GOA-scheduled	30 days	138.54	37.47%	1.28	6.06	20.87%
FA-scheduled	30 days	169.89	48.19%	1.22	6.32	22.90%
CSA-scheduled	30 days	136.15	49.09%	1.39	7.23	08.01%
ACO-scheduled	30 days	168.71	36.92%	1.43	4.77	39.31%

5.3 Summary

In this chapter, we have proposed a novel technique of appliances' scheduling in an office. Different algorithms have been taken and applied to different scenarios of consumers for comparison purpose. In some circumstances, an algorithm performs good, but in some other situation, the same algorithm does not perform well. Therefore, as adoptive approach will give better results. Therefore, in this chapter, we used two more nature-inspired optimization algorithms, GOA and BFA and compared their performance with our proposed hybrid TG-MFO to achieve our objective functions of end-user electricity bill minimization along with a reduction of PAR and user discomfort due to appliance scheduling. We considered only eight appliances to check our proposed algorithms' performance. We compared our results with a few state-of-the-art nature-inspired algorithms in the literature like FA, CSA and ACO for the three mentioned fitness functions, i.e., minimization of the electricity bill, PAR and waiting time. Indeed, numerous countries in the world can fulfill electricity demand. However, keeping in view the minimization of the electricity bill, the reliability of the existing system and improvements towards smart grids to facilitate the customers, with increased dependency on electricity with automation, energy optimization is a big issue throughout the world. Furthermore, with increased electricity generation, carbon emission increases due to the use of different types of fuels, which pollute this biosphere day by day. Therefore, the advantage of these algorithms for energy optimization is not only to save money, but to reduce pollution, as well. The simulation results show that our proposed energy optimization scheme performed well in the case of minimization of PAR and cost. However, when energy cost is minimized, user waiting time will increase as a penalty. therefore our designed TG-MFO minimized the energy cost and PAR while keeping in view the high comfort level of consumers. In future, more nature-inspired algorithms will be used and analyzed for achieving good results.

Chapter 6

Use of Bio-inspired Algorithms for an Efficient EMS in Industries

6.1 Motivation

Industries are consuming more than 27% of the total generated energy in the world, out of which 50% is used by different machines for processing, producing, and assembling various goods. Energy shortage is a major issue of this biosphere. To overcome energy scarcity, a challenging task is to have optimal use of existing energy resources. An efficient and effective mechanism is essential to optimally schedule the load units to achieve three objectives: minimization of the consumed energy cost, peak-to-average power ratio, and consumer waiting time due to scheduling of the load. To achieve the aforementioned objectives, two bio-inspired heuristic techniques—Grasshopper-Optimization Algorithm (GOA) and Cuckoo Search Optimization Algorithm (CSOA) are analyzed and simulated for efficient energy use in an industry. Then we applied our proposed hybrid TG-MFO algorithm for comparison and testing purpose in such industrial applications. We considered a woolen mill as a case study, and applied our algorithms on its different load units according to their routine functionality. Then we scheduled these load units by proposing an efficient energy management system (EMS).

6.2 Introduction

According to the US Environmental Protection Agency, industries are responsible for about 27% of total consumed energy [153]. Meanwhile, there has been an exponential rise in energy demand worldwide due to rapid population expansion. On the other hand, the generation of electric power contributes to nearly 25% of green-house gases (GHGs) to the environment. The inadequacy of energy is a major issue in many countries of the world, directly affecting the economy, development, and environment. Therefore, the main focus is to preserve energy resources [154]. In such circumstances, the electricity requirement of different users cannot be fulfilled by traditional electric power grids. For this purpose, the concept of smart grid (SG) arises, which efficiently overcomes energy generation and use problems by using renewable energy sources (RES) and a distribution generation (DG) system. An efficient and effective energy management system (EMS) is now needed to not only integrate these RESs and DG systems into the existing network, but also optimally use the existing energy resources to reduce consumed electricity cost.

We are proposing two bio-inspired optimization algorithms for an optimal use of the existing resources. For this purpose, our proposed system model will consist of many smart agents in the premises of the industry like smart machines, smart meters (SMs), and energy management controllers (EMC) etc. SM is a communication agent between utility and consumers. Because it shares of the consumer load information, the energy supplier capacity is enhanced and it becomes able to solve energy problems. Demand-side management (DSM) is used for this purpose, to shift consumer load from high-demand hours to low-demand hours.

In this chapter, we have considered DSM, which helps in load balancing between users and utility [155], [156]. In DSM strategies, demand response (DR) is the mechanism in which utility tries to manage consumer demand with a condition, such that users must reduce their consumption at critical times [106]. Utilities give different incentives, in the form of reduced electricity pricing, to the user due to this load reduction at peak hours. Out of different pricing schemes, day-ahead pricing (DAP), critical peak pricing (CPP), time of use (TOU), and real-time pricing (RTP) schemes are used in DR [74].

The important matters which need to be addressed in distribution system are: minimization of cost, stability of SG and user comfort maximization. Nowadays power consumption is increasing due to increase in population. Traditional grid (TG) is can not fulfill the present energy requirements. In order to meet users demand, we must have to increase the power generation through thermal power plants, nuclear power plants and renewable energy sources like wind and solar etc. To handle this complexity of power resources integration, the concept of revolutionary technology of SG arises. SG is environmental friendly because it utilizes the available power resources efficiently among the users. To over come energy optimization problem, different optimization techniques are used in SG. In [152] through convex programming (CP) technique the cost of electricity is reduced but user comfort is compromised. The reduction of electricity is addressed by authors in [153]-[155] using optimization techniques i.e. MILP, ILP and NILP but RES and user comfort have not been considered. In [156] the authors have used MILP technique to minimize the electricity cost but considering RES and user comfort are ignored. The techniques which are discussed above are unable to handle a large number of machines or appliances. In order to surmount the flaw, researchers move towards probabilistic models. Different meta-heuristic models are proposed to solve the energy optimization problem. In this chapter we are taking two meta-heuristic population based algorithms i.e. GOA and CSA. In our work we are going to evaluate these techniques on the basis of different objectives which are cost minimization, PAR reduction and user comfort maximization. To apply our proposed algorithms on real world problems, we have considered a case study on industrial sector which comprise of different independent sections. Our proposed schemes performed well and efficiently conquer the aforementioned objectives.

Researchers all over the world have proposed numerous algorithms for optimal scheduling of the load in the industrial, commercial and residential sectors [75]-[111]. Most of these research works aim to reduce electricity bill and PAR. However, very few have considered end-user frustration due to scheduling of appliances.

With more than 90% energy blackout and interruptions, found in power distribution networks, the world moves towards the smart grid concept. Due to the rapid increase in the fuel cost, connected with failure of utility to increase its generation in parallel with the rising electricity demand, has speeded up the need to improve the distribution system by evolving new energy optimization techniques in DSM. In the beginning, automated meter reading (AMR) technology was introduced in SG, however, not too much successful due to its one-way communication towards utility. After the limitation in AMR, the utility companies moved towards advanced metering infrastructure (AMI) technology, which provides the two-way communication system. Through the AMI, utility not only can get instantaneous information about the consumer's load demand, but also impose its small hat on load consumption, in order to get low electricity cost.

In SG, different mathematical models such as LP (linear programming), ILP (integer-linear programming) and MILP (mixed integer linear programming) are used to resolve the issue of energy optimization. However, when appliances or machines are increased in number, these models are not much applicable. So the researchers moved towards meta-heuristic algorithms. In this chapter, we are focusing on the industrial sector, comprise of automatic operated machines (AOMs). The objectives of this work are; the reduction of the electricity cost, PAR and user discomfort due to scheduling of the machines. We have proposed three optimization techniques i.e GOA, CSA and TG-MFO to achieve our objectives.

6.2.1 Proposed System Model Architecture

The energy management system (EMS) in SG consists of two sides, DSM and SSM (supply-side management). We are considering DSM in an industry that consists of machines, EMC and SM. SM has AMI technology which helps in the two-way communication between consumers and utility. Different machines send their power consumption patterns to EMC. EMC then schedules the load according to the pricing signal received from utility. SM receives the pricing signal and forward it to EMC. Simultaneously, it receives power consumption pattern from

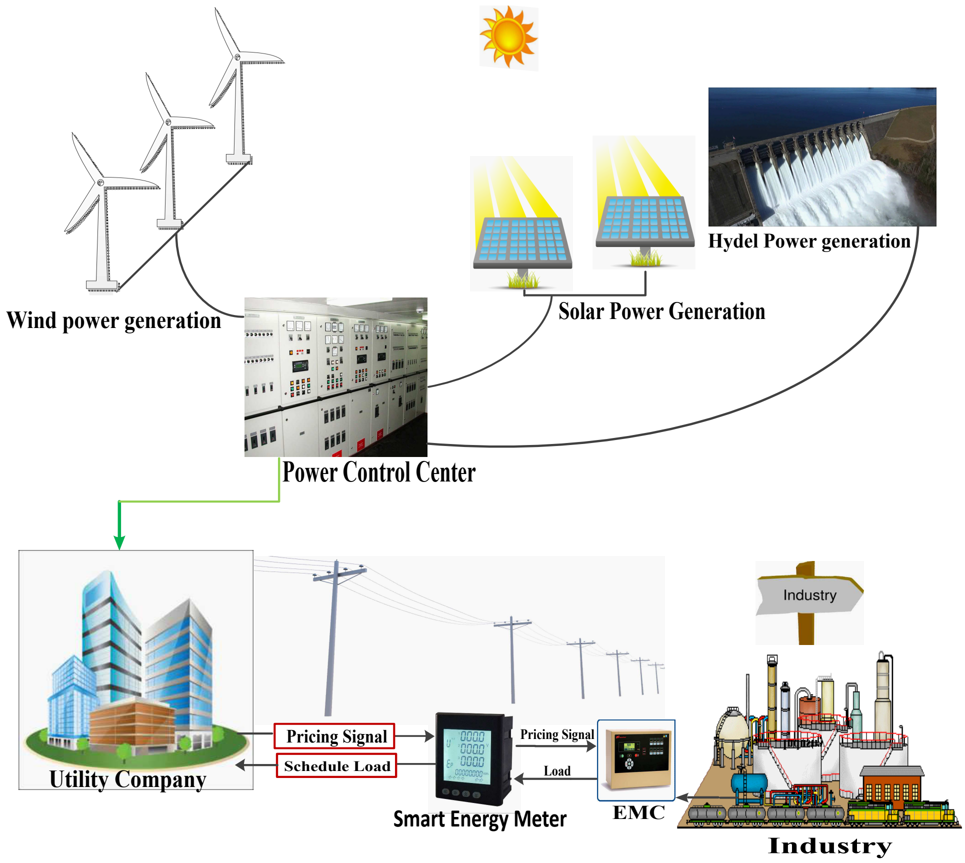

FIGURE 6.1: System Model Architecture

EMC and send it to utility. The communication between SM and utility is through different wireless networks i.e. Wi-Fi, GSM, ZigBee, Home Area Network (HAN) or wired medium like power line communication (PLC). In this chapter we are considering an industry (woolen-mills), that consists of six AOMs. The DAP pricing signal is used for electricity bill calculation and time horizon for load scheduling is considered as one hour. Figure 6.1 shows the system model architecture of the proposed scheme.

The Table 6.1 depicts the load units with their respective power ratings and the length of operational times (LOTs), while Figure 6.2 shows these load units in the block diagram form.

In the industry system model with load units, shown in the Figure 6.2, scoring section takes 150 kw power and consists of only one type of motors, that are induction motors of 10 hp each. Carding section takes 50 kw power and consists

TABLE 6.1: Specification of industry Automatically Oerated Machines (AOMs)

AOMs	PR(kw)	LOT	AOMs	PR(kw)	LOT
Scoring Section	150	8	Temperature control load	100	9
Carding Section	50	12	Packing Section	100	10
Spinning Section	200	7	Weaving Section	250	6

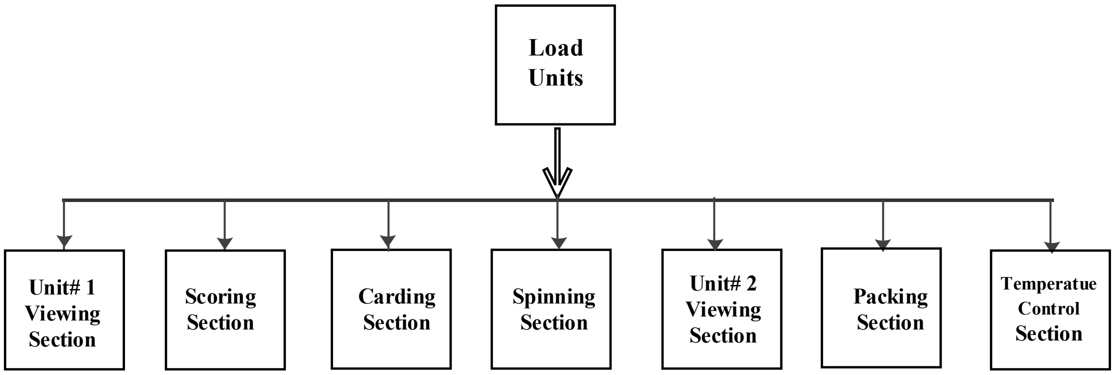

FIGURE 6.2: Industry load units

of two types of motors, induction motors of 10 hp and slip ring motors of 50 hp. Spinning section takes 200 kw power and consists of one type of induction motors of 100 hp each. Weaving section takes power of 250 kw and consists of three types of motors; stepper motors of 0.5 hp, induction motors of 10 hp and induction motors of 2.5 hp. Packing section takes power of 100 kw and comprise of induction motors of 5 hp and slip ring motors of 10 hp. The Temperature control section takes 100 kw of power. It is just like an AC plant. The connected load is 900 kw from utility and the running load is 400 kw to 550 kw.

Average load of the mill is 400 kw, which show that at a time, 3 to 4 machines are in running position. Maximum demand indicator (MDI) is considered as 500 kw. The machines in the industry stop working on the basis of production, because it follows demand and supply mechanism.

6.2.2 Problem Formulation

The important matters which need to be addressed in the distribution system are minimization of cost, stability of SG by reduction of PAR and user comfort maximization. Nowadays power consumption is increasing due to increase in population. Traditional grid (TG) can not fulfill the present energy requirements. In order to meet users demand, we must have to increase the power generation through thermal power plants, nuclear power plants and renewable energy sources like wind and solar. To handle this complexity of power resources integration, the concept of revolutionary technology of SG arises. SG is environmental friendly because it utilizes the available power resources efficiently among users. To over come energy optimization problem, different optimization techniques are used in SG. In [158], through the convex programming (CP) technique the cost of electricity is reduced, but user comfort is compromised.

The reduction of electricity bill is addressed by authors in [143, 144] using optimization techniques, i.e., MILP, ILP and MILP but RES and user comfort have not been considered. In [159] the authors have used MILP technique to minimize the electricity cost, however, considering RES and user comfort are ignored. The techniques which are discussed above are unable to handle a large number of machines or appliances. In order to surmount the flaw, researchers move towards probabilistic models. Different meta-heuristic models are proposed to solve the energy optimization problem. In this chapter we are taking the two meta-heuristic population based algorithms i.e. GOA and CSA. In our work, we are going to evaluate these techniques on the basis of different objectives like reduction of electricity bill, PAR and user frustration. To apply our proposed algorithms on real world problems, we have considered a case study of a textile industry, that comprises of different independent sections (i.e. load units).

The design of the power system, which is perfect and confident, must begin with user needs and comfort. In this chapter, we have to tackle the aforementioned problems, using the following objective function:

$$min\Big((\lambda_1 \times C_{Norm}) + (\lambda_2 \times \tau_w)\Big) \tag{6.1}$$

λ_1 and λ_2 are multiplying factors of two portions of our objective function. Their values varies between '0' and '1' so that $\lambda_1 + \lambda_2$=1 . It reveals that either λ_1 and

λ_2 could be 0 to 1. That is, if an end user does not want to participate in the load scheduling process, then his multiplying factors will be λ_1 =1 and λ_2 =0 in the objective function.

6.2.3 User's Waiting Time (τ_w)

As discussed in chapter 1 in details, that user's comfort in terms of waiting time is important for end-users. Waiting time must be minimized to have a high comfort level so that the end-user's frustration can be avoided. It is that interval of time when a consumer wants to switch-ON an appliance, however, due to the scheduling limitations of the system, consumer has to wait for starting its operation. As we have defined the starting time α and the latest ending time β of a load unit in the mills, then another parameter η will be the operational starting time of the same switched-ON machine in a load unit. This is shown diagrammatically in Figure 1.1 in chapter 1. Where, β - α is the time span, defined by the consumer. The figure shows that a consumer's maximum waiting time could be up to η_{max}. Since length of operational time (LOT) is already defined by the consumer, so at η_{max}, the algorithm will have to start the machine to complete its operation up to the final time β. As shown in Figure 1.1 in chapter 1, appliances' normalized waiting time (τ_w) can be calculated as:

$$\tau_w = \frac{\eta - \alpha}{\eta_{max} - \alpha} \tag{6.2}$$

This shows that the normalized waiting time can be from "0" (when $\eta = \alpha$) to "1" (when $(\beta - LOT) = \eta$).

In the proposed work, we formulate our problems of; (a) end-user high comfort level, (b) consumers' electricity bill minimization, and (c) minimization of PAR by optimization of energy consumption profiles of office appliances, using the MKP (multiple knapsack problem) scheduling technique, as discussed in chapter 4. Now, if E_T is the cumulative energy demand of the end-user and V_T is the maximum energy capacity in a particular interval of time available from the utility grid, then the following condition must be satisfied.

$$E_T \leq V_T \tag{6.3}$$

MKP scheduling tells us to keep the total energy demand of end user less than or equal to this maximum energy capacity threshold.

6.3 Results and Discussions

Different industries like steel mills, wooden industries, medicine, flour mills and textile industries are available at consumer side. In this section, results and simulations work are explained in detail. To show legitimacy and benefits of our proposed work, we have considered a MATLAB computing environment for simulations. For the solution of the energy optimization problem, simulation of our proposed scheduling schemes are performed. To check out the performance of our algorithms i.e., GOA and CSA, we are considering different parameters such as total energy consumption, PAR, consumed energy expenditure and user comfort. Moreover, in the industrial sector, automatic operating machines(AOMs) are being used as they can work independently and could be turned ON/OFF any time during 24 h.

6.3.1 Pricing Signal

The day-ahead pricing (DAP) signal, shown in Figure 6.3 issued by the utility [152](Accessed on 29/08/2020), is reproduced in Figure 6.4 and is used for the manipulation of consumed energy bill.

6.3.2 Hourly Power Consumption

Figure 6.5 shows the graph of hourly power consumption. The consumption pattern shows that in unscheduled cases, more power is consumed in high demand

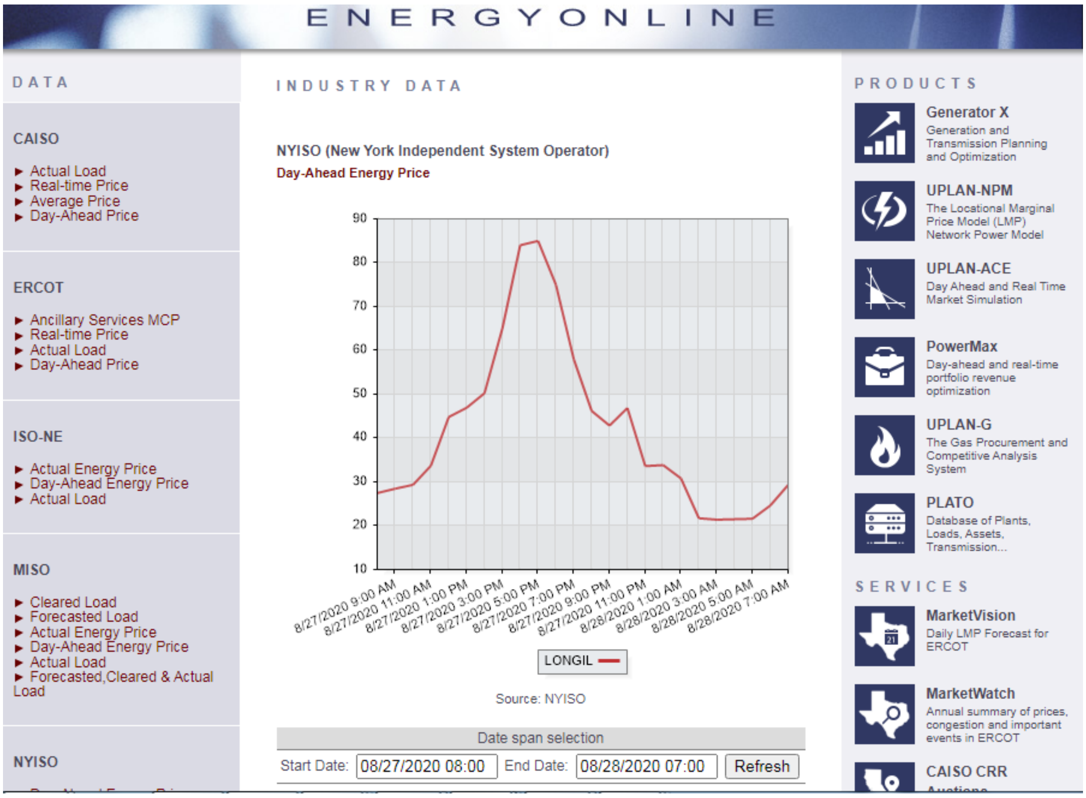

FIGURE 6.3: Day-ahead pricing (DAP) signal [152]

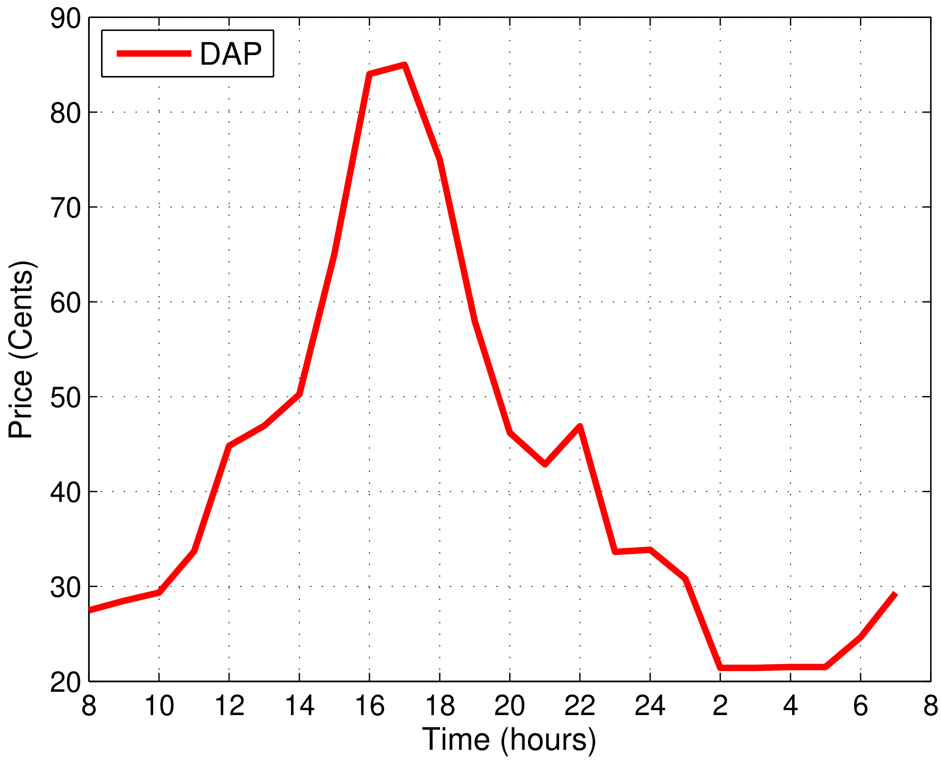

FIGURE 6.4: (Day-ahead pricing (DAP) signal (Reproduced).

time and thus creates the peak load. After the scheduling of the load through algorithms, power consumption in high demand time is shifted to low-demand hours. From the graph it is clear that a TG-MFO-scheduled load pattern is a bit uniform and is low during the highest price from 16.00 to 18.00 hrs as per the DAP signal shown in the Figure 6.4. Figure 6.5 depicts that CSA, GOA and ACO-scheduled-load pattern show a bit variable response. Although the load is not totally shifted from the first high price between 6.00 and 8.00 hr, during highest price at 18.00 hr, TG-MFO gives tremendous reduction in load pattern.

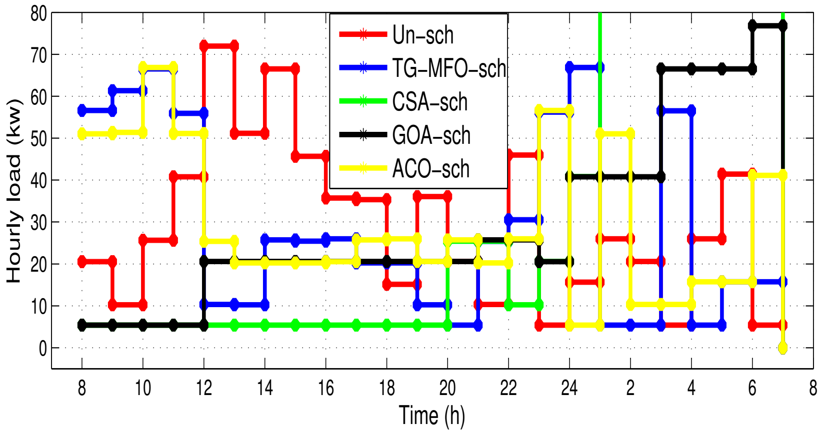

FIGURE 6.5: Hourly load

6.3.3 The Hourly Consumed Energy Price

Figure 6.6 elaborates the graph of per-hour consumed energy price. The result illustrates that in unscheduled cases, the company must pay higher cost because the peak load is created in on-peak hours. However, in the scheduled-load case, the load is shifted from timing of high load demand to low-demand hours and thus reduces the cost per hour. TG-MFO-scheduled load-per-hour cost is again a bit uniform due to its load pattern, and gives reduced total cost as is shown in Figure 6.7. However, due to the variable nature of the CSA, GOA and ACO-scheduled-load pattern, its total cost is a bit more than the TG-MFO-scheduled load cost, but still it is less than unscheduled-load cost.

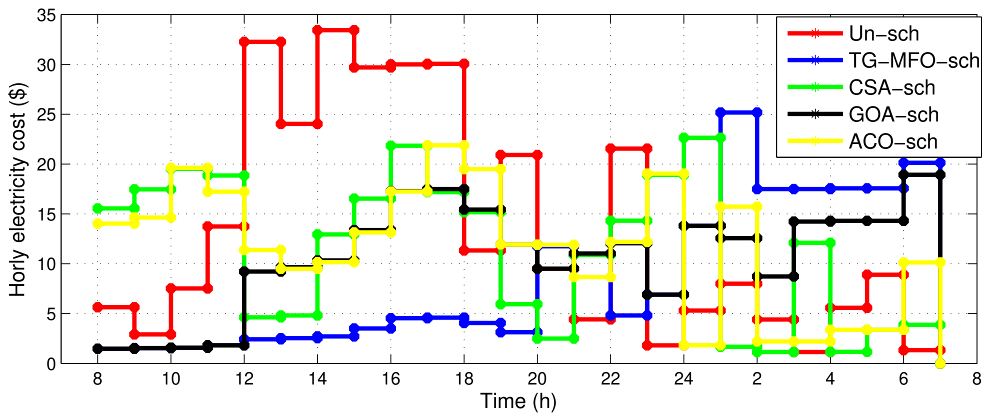

FIGURE 6.6: Hourly electricity cost

6.3.4 Total Daily Average Cost

Figure 6.7 shows the total daily average cost in case of unscheduled load compared to load scheduled using different algorithms. The figure depicts that the unscheduled-load total daily cost is 211.831\$. However, after scheduling, the total daily cost for TG-MFO-scheduled load is 112.277 \$, CSA-scheduled load is 146.318\$, for GOA it is 119.291\$ and for ACO it is 168.383\$per day. These results show that by using optimization algorithms, we can reduce our total cost. TG-MFO gives better results in reducing per-day energy cost compared to other scheduling algorithms. The figure also depicts a comparison of the proposed algorithms with the most modernistic optimization algorithms such as ant-colony optimization (ACO).

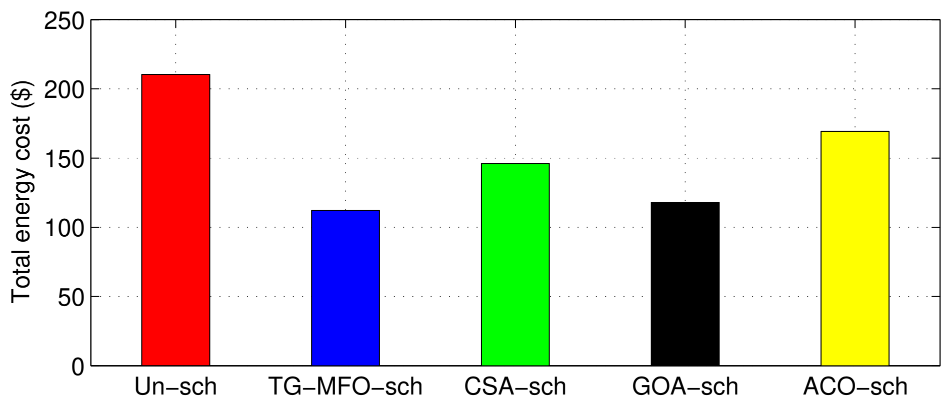

FIGURE 6.7: Total daily cost

6.3.5 Machines Average Waiting Time

Figure 6.8 shows the average waiting time of machines for each technique. It is that time interval, when a consumer switches on a machine, but due to scheduling for reduction of cost, the machine does not start operation. Therefore, the consumer must wait for a specific amount of time τ_w. The figure shows that the waiting time of TG-MFO is almost zero, which is the main contribution of this work, to reduce cost, while keeping higher end user comfort level.

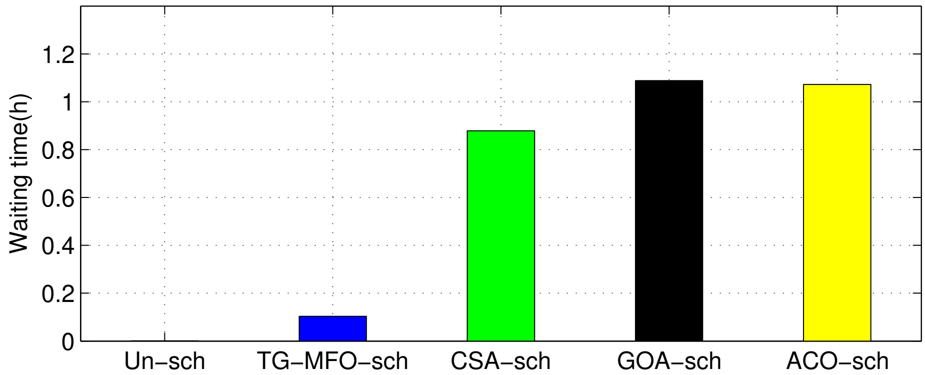

FIGURE 6.8: Average waiting time

6.3.6 Peak to Average Power Ratio (PAR)

Figure 6.9 shows PAR results, which tells the stability of a grid. When the PAR value increases or decreases, it affects the stability of a grid. Due to the more reduction in the cost, usually PAR is not reduced. however, TG-MFO showed good results due to its hybrid nature. The figure also depicts a comparison of the proposed algorithms PAR with the most modernistic optimization algorithms such as CSA, GOa and ACO algorithms PARs.

6.3.7 The Total Daily Average Load

Figure 6.10 shows that the total daily load is same in the case of unscheduled and scheduled with different algorithms. It is clear from the figure that, irrespective

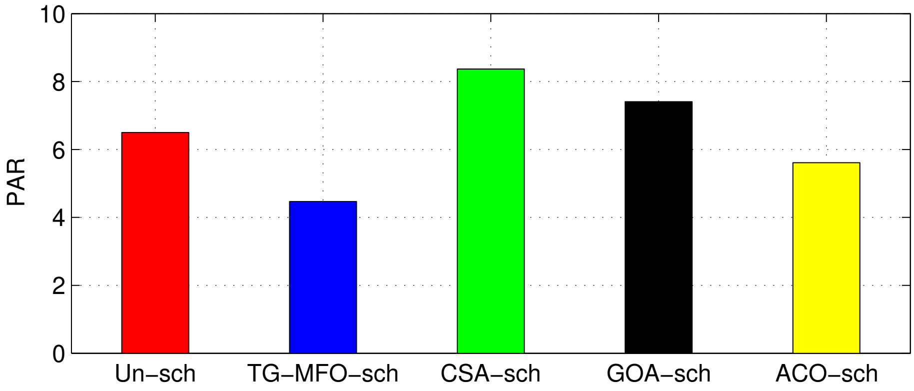

FIGURE 6.9: Peak to average power ratio (PAR)

of the scheduling algorithms, the total daily load remains the same. Scheduling algorithms only shift the load to low cost or low demand hours; however, they do not reduce the total daily load run by the industry.

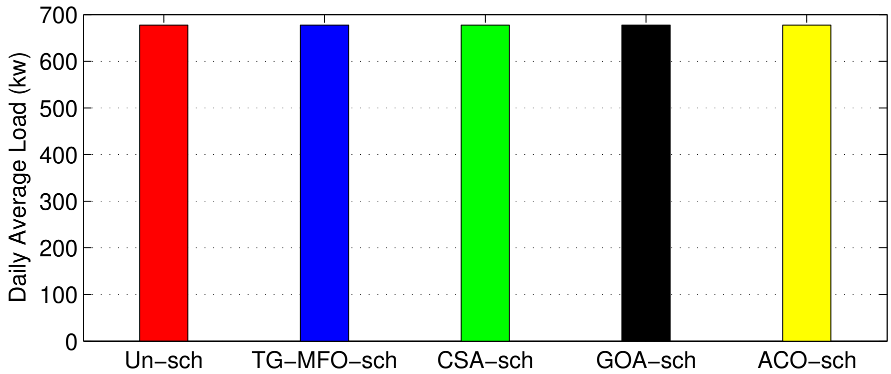

FIGURE 6.10: The total daily average load.

6.3.8 Feasible Regions

A feasible region is a set of all possible points. Due to the scheduling of load, using different algorithms, cost minimization is decided on the bases of the pricing signal issued by the utility. We have considered DAP signal for our calculations. Figure 6.11 shows the feasible region for TG-MFO algorithm. Point $P_1(5.41, 115.8)$ gives the minimum load with minimum cost and point $P_2(5.41, 250)$ gives the minimum load with maximum cost in any interval of time. It usually happens when minimum load is running in peak hrs with high energy cost. Similarly, point $P_3(71.96, 3226)$

gives maximum load with maximum cost in the case of un-scheduled load. Point $P_4(71.96, 1363)$ gives the maximum load during off peak hrs with minimum cost. $P_5(45.7, 2063)$ puts a threshold on the maximum cost after scheduling with GOA. It continues until point $P_6(71.96, 1363)$ reaches, which gives a point of maximum load with reduced cost. Figure 6.12 shows all these points for CSA scheduling and Figure 6.13 depicts theses points for GOA. It is clear from these figures that our proposed hybrid TG-MFO algorithm performs better as compared to CSA and GOA in the case of cost minimization.

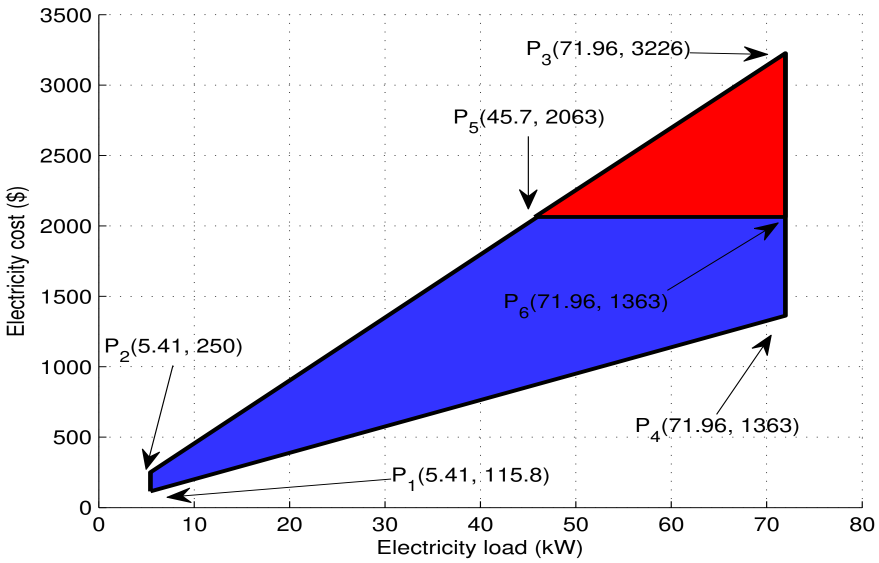

FIGURE 6.11: Feasible region for TG-MFO-scheduled load.

Table 6.2 depicts a comparison of the proposed algorithms with the unscheduled load in terms of minimization of consumed energy price, PAR and user average time of waiting. A comparison of the proposed algorithms with recently applied algorithms such as the ACO,FA and MFO algorithms is also shown in the table.

TABLE 6.2: A comparison of the proposed TG-MFO algorithm with other algorithms for appliances scheduling in terms of unscheduled load and scheduled load with GOA, CSA, ACO, FA and MFO algorithms.

Mechanisms	Price ($)	Price Reduction	PAR	PAR Changes	Waiting Time (h)
Unscheduled	211.831	–	6.38	–	–
TG-MFO-scheuled	112.277	46.99%	4.27	−33.07%	0.103
CSA-scheduled	146.318	30.92%	8.34	+30.72%	0.872
GOA-scheduled	119.291	43.68%	7.39	+15.83%	1.089
ACO-scheduled	168.383	20.51%	5.53	−13.32%	1.076

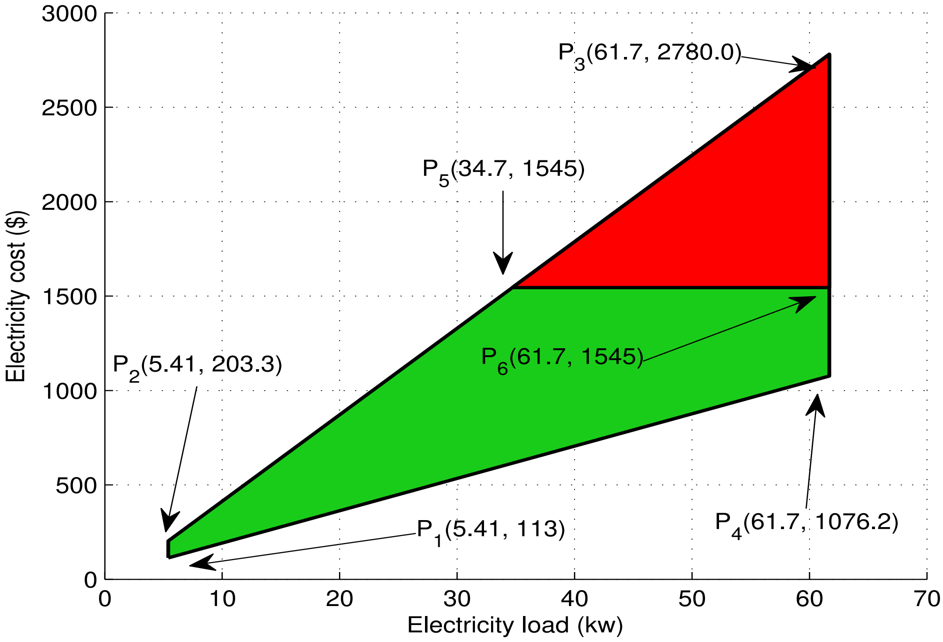

FIGURE 6.12: Feasible region for CSA-scheduled load.

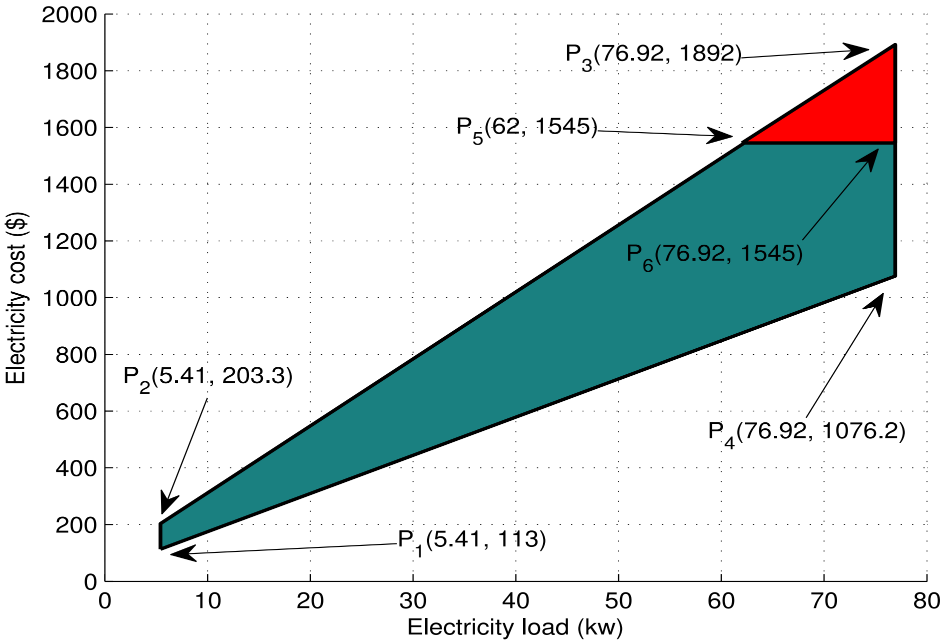

FIGURE 6.13: Feasible region for GOA-scheduled load.

Table 6.3 depicts the run-time of GOA and CSA algorithms using an Intel (R) Core (TM) i5 processor, with 4.00 GB of installed memory (RAM) and the 32-bit Windows 7 Operating system.

Table 6.3: Run-time of the GOA and CSA algorithms for one day.

Proposed Algorithm	**No. of Days**	**Run-Time (s)**
TG-MFO	one day	12.937
CSA	one day	9.152
GOA	one day	8.702

6.4 Summary

In this chapter, we have illustrated a DSM strategy for the energy optimization problem. We have divided industrial load into different load units. We have proposed and practically applied two bio-inspired optimization schemes; GOA and CSA in comparison with TG-MFO to these load units for scheduling the automatic operated machines according to the day-ahead pricing signal. We checked out the performance of our proposed hybrid TG-MFO algorithm based on total consumed energy, reduction of PAR, cost and user comfort in terms of waiting time, compared to unscheduled load. We also tested and compared the performance of our proposed algorithms with state-of-the-art algorithm ACO. Simulation results show that by applying bio-inspired techniques, we can minimize the consumed energy price by shifting some load to low-demand load hours, without disturbing its operation. Because of this, the burden on utility is reduced in the form of PAR and maximized user comfort.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

In this work, we have proposed a new hybrid TG-MFO bio-inspired algorithm. We have applied some of the bio-inspired meta-heuristic algorithms, like, ACO, ALO, BFA, CSOA, FA, GA, GOA, MFO and TG-MFO, for energy optimization problem in smart grid and compared their results. We considered three sectors of energy consumption, residential, commercial and industrial.

In residential sector, we considered a single- and multiple home scenarios. In multiple homes, we took different length of operational time intervals and power ratings of appliances to make it more practical. Day-ahead RTP signaling was used for demand response in smart homes. The results show that there was a 6.45%–49.03%, 32.26%–41.10% and 32.25%–49.96% decrease in the total cost with GA, MFO and TG-MFO scheduling, respectively, for single and multiple users. Renewable energy sources and battery storage units were also integrated to obtain a further decrease in the total cost and end-user waiting time. In this work, we tried to not only reduce the total cost, but to achieve a high comfort level of the end-user by minimizing the waiting time of home appliances using the time constraints. Using bio-inspired algorithms, not only reduces the energy cost, but also increases the stability and reliability of the grid.

In commercial application, we have proposed a novel technique of appliances' scheduling in an office. We used two new bio-inspired optimization algorithms, grasshopper optimization algorithm and bacterial foraging algorithm, to achieve our objective functions of end-user electricity bill minimization along with a reduction of PAR and user discomfort due to appliance scheduling. We considered only eight appliances to check our proposed algorithms' performance. We compared our results with a few state-of-the-art bio-inspired algorithms in the literature like GA, FA, CSA and ACO for the three mentioned fitness functions, i.e., minimization of the electricity bill, PAR and waiting time. The simulation results show that our proposed energy optimization schemes performed well in the case of minimization of PAR and cost. However, when energy cost is minimized, user waiting time will increase as a penalty.

In industrial applications, we have illustrated a demand side management strategy of energy optimization problem. We considered different types of automatic operated machines in the industrial sector. We have proposed different optimization schemes to schedule automatic operated machines according to the utility provided real time pricing signal. We checked out the performance of these bio-inspired algorithms on the basis of energy consumption, PAR reduction, cost reduction and user comfort in term of waiting time, compared to un-scheduled load. Simulation results show that by applying bio-inspired techniques, we can reduce the electricity bill by shifting some load to off-peak hrs, without disturbing its operation. Because of this, burden on utility is reduced in the form of PAR reduction and maximize user comfort.

7.2 Future Work

Exploration of more bio-inspired algorithms with adoptive nature for intelligent and efficient energy optimization, and a multi-objective approach will be applied. As some consumers prefer to reduce their consumed energy cost, while compromise on their comfort in terms of their waiting time. On the other side, those consumers who have little tolerance for their waiting time, will prefer to slightly reduce their energy cost. Therefore, bio-inspired algorithms with adoptive nature will be explored, having the capability of not only use in different load scenarios, but also, give option to end user for either cost or waiting time reduction. In industrial consumers, some running machines cannot be interrupted during their operations, so the future algorithms should be smart enough to decide on LOT, not on low price time slots only. Renewable energy sources will be accommodated for further reduction of cost and PAR, while keeping in view high user comfort level. Also, for comparison purpose, another software, i.e., CPLEX will be applied/used.

Bibliography

[1] O. Jacob, K. Mhenr, A. Shelly, “African buffalo optimization, A swarm-intelligence technique,” *Procedia Computer Science*, Vol. 76, no. 2, pp. 443-448, 2015.

[2] M. Dorigo, “Learning and natural algorithms,” *Ph. D. Thesis, Politecnico di Milano, Italy*, 1992.

[3] S. Mirjalili, “The Ant Lion Optimizer,” *Advances in Engineering Software*, Vol. 83, pp. 80-98, 2015.

[4] D. Karaboga and B. Basturk. “A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm,” *Journal of global optimization*, Vol. 39, no. 3, pp.459–471, 2007.

[5] G. Yan and Z. Hao. “A novel optimization algorithm based on atmosphere clouds model,” *International Journal of Computational Intelligence and Applications,* 2013.

[6] D. Simon, “Biogeography-based optimization”. *IEEE Transactions on Evolutionary Computation* , Vol. 12, no.6, pp. 702–713, 2008.

[7] Y. Shi, “An optimization algorithm based on brainstorming process,” *International Journal of Swarm Intelligence Research (IJSIR)*, Vol. 2, no. 4, pp. 35–62, 2011.

[8] K. Passino, “Biomimicry of bacterial foraging for dis-tributed optimization and control,” *IEEE Control Systems*, Vol. 22, no. 3, pp. 52–67, 2002.

[9] T. Chen, P. Tsai, S. Chu, and J. Pan, "A novel optimization approach: bacterial-ga foraging," *In Innovative Computing, Information and Control, 2007. ICI-CIC'07. Second International Conference* , pp. 391–391, 2007.

[10] X. Yang, "A new metaheuristic bat-inspired algorithm. Nature Inspired Cooperative Strategies for Optimization ," *NICSO 2010)*, pp. 65–74, 2010.

[11] S. Mirjalili, S. Mirjalili, X. Yang, "Binary bat algorithm," *Neural Computing and Applications,* Vol. 25 no. 4, pp. 663-681, 2014.

[12] D. Teodorovic and M. DellOrco, "Bee colony optimization a cooperative learning approach to complex transportation problems. In Advanced OR and AI Methods in Transportation," *Proceedings of 16th Mini–EURO Conference and 10th Meeting of EWGT (13-16 September 2005).–Poznan: Publishing House of the Polish Operational and System Research*, pp. 51–60, 2005.

[13] P. Lucic and D. Teodorovic, " Bee system: modeling combinatorial optimization transportation engineering problems by swarm intelligence," *In Preprints of the TRISTAN IV triennial symposium on transportation analysis,* pp. 441–445, 2001.

[14] H. Wedde, M. Farooq, and Y. Beehive, "An efficient fault-tolerant routing algorithm inspired by honey bee behavior," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinfor-matics), 3172 LNCS,* pp. 83–94, 2004.

[15] D. Pham, A. Ghanbarzadeh, E. Koc, and M Zaidi, "The bees algorithm-a novel tool for complex optimi-sation problems," *In Proceedings of the 2nd Virtual International Conference on Intelligent Production Machines and Systems (IPROMS 2006),* pp. 454–459, 2006.

[16] H. Drias, S. Sadeg, and S. Yahi, "Cooperative bees swarm for solving the maximum weighted satisfiability problem," *In Computational Intelligence and Bioinspired Systems, Springer*, pp. 318–325, 2005.

[17] F. Padr o, J. Navarro , “Bumblebees: a multiagent combinatorial optimization algorithm inspired by social insect behaviour.,” 2011.

[18] S. Chu, P. Tsai, and J.S. Pan, “Cat swarm optimization,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bio-informatics), 4099 LNAI*, pp. 854–858, 2006.

[19] A. Gandomi and X. Yang, “Chaotic bat algorithm,” *Journal of Computational Science*, Vol. 5 no. 4, pp. 224-232, 2014.

[20] G. Wang, S. Deb, and A. Gandomi, “ Chaotic cuckoo search,” *Soft Computing* Vol. 20(9) 3349, 2016.

[21] G. Wang, L. Guo, A. Gandomi, G. Hao and H. Wang, “ Chaotic Krill Herd algorithm,” *Information Sciences,*Vol. 274 no. 2, pp. 17-34, 2014.

[22] X. Meng, Y. Liu , X. Gao and H. Zhang, “ A new bio-inspired algorithm: Chicken swarm optimization,” *In Advances in Swarm Intelligence. ICSI, Lecture Notes in Computer Science, Springer* Vol. 8794. pp. 86-94, 2014.

[23] S. Iordache , “Consultant-guided search, a new metaheuristic for combinatorial optimization problems,” *In Proceedings of the 12th annual conference on Genetic and evolutionary computation,* pp. 225–232. ACM, 2010.

[24] X. Yang and S. Deb, “Cuckoo search via l’evy flights ,” *In Nature & Biologically Inspired Computing, NaBIC 2009. World Congress on,* pp. 210–214, 2009.

[25] R. Storn and K. Price, “ Differential evolution a simple and efficient heuristic for global optimization over continuous spaces,” *Journal of global optimization,* Vol. 11 no. 4, pp.341–359, 1997.

[26] S. Mirjalili, “ Dragonfly Algorithm,” *Neural Computing and Applications,* Vol. 27 no. 3, pp. 1053-1073, 2016.

[27] A. Kaveh and N. Farhoudi, “A new optimization method: Dolphin echolocation,” *Advances in Engineering Software,* Vol. 59(10), pp.53–70, 2013.

[28] X. Yang and S. Deb, “Eagle strategy using levy walk and firefly algorithms for stochastic optimization,” *In Nature Inspired Cooperative Strategies for Optimization (NICSO2010), Springer,* pp. 101–111, 2010.

[29] R.S. Parpinelli and H.S. Lopes, “ An eco-inspired evolutionary algorithm applied to numerical optimization,” *In Nature and Biologically Inspired Computing (NaBIC), 2011 Third World Congress on,* pp. 466–471, 2011.

[30] C. Sur, S. Sharma, and A. Shukla, “ Egyptian vulture optimization algorithm–a new nature inspired meta-heuristics for knapsack problem,” *In The 9th International Con-ference on Computing and InformationTechnology (IC2IT2013), Springer,* pp. 227–237, 2013.

[31] S. Deb, S. Fong and Z. Tian, “Elephant Search Algorithm for optimization problems,” *2015 Tenth International Conference on Digital Information Management (ICDIM), Jeju*, pp. 249-255, 2015.

[32] F. Neto, A. Lins, A. Nascimento and M. Lima, “ A novel search algorithm based on fish school behavior,” *In Systems, Man and Cybernetics, 2008. SMC 2008. IEEE International Conference on,* pp. 2646–2651, 2008.

[33] C. Filho, F. Neto and A. Lins, “ Ant onio IS Nascimento, and Marılia P Lima. Fish school search,” *In Nature-Inspired Algorithms for Optimisa-tion, Springer,* pp. 261–277, 2009.

[34] X. Yang, “ Flower pollination algorithm for global optimiza-tion,” *Unconventional Computation and Natural Computation,* Vol. 10 no. 2 pp. 240–249, 2012.

[35] X. Yang, M. Karamanoglu, and Xingshi He, “ Multi-objective flower algorithm for optimization,” *Procedia Computer Science,* Vol. 18 no. 2, pp.861–868, 2013.

[36] Y. Chu, H. Mi, H. Liao, Z. Ji, and Q.H. Wu, “ A fast bacterial swarming algorithm for high-dimensional function opti-mization ,” *In Evolutionary*

Computation, 2008. CEC 2008.(IEEE World Congress on Computational Intelligence). IEEE Congress on, pp. 3135–3140. 2008.

[37] X. Yang, " Firefly algorithm, stochastic test functions and design optimisation," *International Journal of Bio-Inspired Computation,* Vol. 2, no. 2, pp.78–84, 2010.

[38] X. Li, Z. Shao, and J. Qian, " Optimizing method based on autonomous animats: Fish-swarm algorithm. Xitong Gongcheng Lilun yu Shijian/," *System Engineering Theory and Practice,* Vol. 22, no. 11, 32, 2002.

[39] S. Su, J. Wang, W. Fan, and X. Yin, " Good lattice swarm algorithm for constrained engineering design optimization," *In Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on,* pp. 6421–6424, 2007.

[40] K. Krishnanand and D. Ghose, " Detection of multiple source locations using a glowworm metaphor with applications to collective robotics," *In Swarm Intelligence Symposium, 2005. SIS 2005. Proceedings 2005 IEEE,* pp. 84–91, 2005.

[41] K. Krishnanand and D. Ghose, " Glowworm swarm optimisation: a new method for optimising multi-modal functions," *International Journal of Computational Intelligence Studies,* Vol. 1, no. 1, pp.93–119, 2009.

[42] C. Ferreira, " Gene expression programming: a new adaptive algorithm for solving problems," *arXiv preprint cs/0102027,* 2001.

[43] S. Saremi, S. Mirjalili, and A. Lewis," *Advances in Engineering Software,* Vol. 105, pp. 30-47, 2017.

[44] S. Mirjalili, S.M. Mirjalili, A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw,* Vol. 69, no. 3, pp. 46-61, 2014.

[45] A. Mozaffari, A. Fathi, and S. Behzadipour, " The great salmon run: a novel bio–inspired algorithm for artificial system design and optimisation," *International Journal of Bio-Inspired Computation,* Vol. 4, no. 5, pp.286–301, 2012.

[46] S. He, Q. Wu, and J. Saunders, " Group search optimizer: an optimization algorithm inspired by animal searching behavior," *Evolutionary Computation, IEEE Transactions on,* Vol. 13, no. 5, pp. 973–990, 2009.

[47] L. Zhang, C. Dahlmann, and Y. Zhang, " Human-inspired algorithms for continuous function optimization," *In Intelligent Computing and Intelligent Systems, 2009. ICIS 2009. IEEE International Conference on,* Vol. 1, pp. 318–321, 2009.

[48] H. Chen, Y. Zhu, K. Hu, and X. He, " Hierarchical swarm model: a new approach to optimization," *Discrete Dynamics in Nature and Society,* 2010.

[49] A. Mehrabian and C. Lucas, " A novel numerical optimization algorithm inspired from weed colonization ," *Ecological Informatics,* Vol. 1, no. 4, pp. 355–366, 2006.

[50] H. Hernandez and C. Blum, " Distributed graphcoloring: an approach based on the calling behavior of japanese tree frogs," *Swarm Intelligence,* Vol. 6, no. 2, pp. 117–150, 2012.

[51] A. Gandomi and A. Alavi and K. herd, " a new bio-inspired optimization algorithm," *Communications in Nonlinear Science and Numerical Simulation,* 2012.

[52] B. Rajakumar. The lion's algorithm, "A new nature-inspired search algorithm," *Procedia Technology,* Vol. 6, pp. 126-135, 2012.

[53] H. Abbass, "Marriage in honey bees optimization-a haplometrosis polygynous swarming approach," *In Evolutionary Computation, 2001. Proceedings of the 2001 Congress on,* Vol. 1, pp. 207–214, 2001.

[54] A. Mucherino and O. Seref, " Monkey search: a novel metaheuristic search for global optimization," *In Data Mining, Systems Analysis and Optimization in Biomedicine,* Vol. 953, pp. 162–173, 2007.

[55] S. Mirjalili, "Moth-flame optimization algorithm," *Knowledge-Based Systems,* Vol. 89, pp. 228-249, 2015.

[56] S. Mirjalili, S. Saremi, S. Mirjalili and L. Coelho, " ," *Expert Systems with Applications,* Vol. 47, pp. 106-119, 2016.

[57] R. Maia, L. Castro, and W. Caminhas, " Bee colonies as model for multimodal continuous optimization," *The optbees algorithm. InEvolutionary Computation (CEC), 2012 IEEE Congress on,* pp. 1–8, 2012.

[58] U. Premaratne, J. Samarabandu, and T. Sidhu, " A new biologically inspired optimization algorithm," *InIndustrial and Information Systems (ICIIS), 2009 International Conference on*, pp. 279–284, , 2009.

[59] J. Kennedy and R. Eberhart. Particle swarm optimiza-tion," *In Neural Networks, 1995. Proceedings, IEEE International Conference on,* Vol. 4, pp. 1942–1948, 1995.

[60] Sung Hoon Jung, " Queen-bee evolution for genetic algorithms," *Electronics letters,* Vol. 39, no. 6, pp. 575–576, 2003.

[61] T. Havens, C. Spain, N. Salmon, and J. Keller, " Roach infestation optimization," *In Swarm Intelligence Symposium, SIS 2008*, pp. 1–7, 2008.

[62] S. Mirjalili, A. Gandomi, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," *Advances in Engineering Software,* Vol. 114, pp. 163-191, 2017.

[63] M.M. Eusuff and K.E. Lansey, " Optimization of water distribution network design using the shuffled frog leaping algorithm," *Journal of Water Resources Planning and Management,* Vol. 129, no.3, pp.210–225, 2003.

[64] Y. Jjo, Li Vok, " A social spider algorithm for global optimization," *Applied Soft Computing,* Vol. 30, pp. 614-627, 2015.

[65] J. Bansal , H. Sharma," Spider monkey optimization algorithm for numerical optimization," *Memetic Computing,* Vol. 6, no. 1, pp. 31-47, 2014.

[66] R. Hedayatzadeh, F. Akhavan Salmassi, M. Kesht-gari, " Termite colony optimiza-tion: A novel approach for optimizing continuous problems ," *In*

Electrical Engineering (ICEE), 2010 18th Iranian Conference on, pp. 553–558, 2010.

[67] . Yang, J. Lees, and C. T Morley, " Application of virtual ant algorithms in the optimization of cfrp shear strengthened precracked structures," *In Computational Science–ICCS 2006, Springer*, pp. 834–837, 2006.

[68] X.. Yang, "Engineering optimizations via nature-inspired virtual bee algorithms.," Vol. 3562, pp. 317–323, 2005.

[69] T. Ting, K. Man, and K. Wan, " Weightless swarm algorithm (wsa) for dynamic optimization problems," *In Network and Parallel Computing, Springer*, pp. 508–515, 2012.

[70] S. Mirjalili, A. Lewis, "The Whale Optimization Algorithm," *Advances in Engineering Software*, Vol. 95, pp.51-67, 2016.

[71] R. Tang, S. Fong, " Wolf search algorithm with ephemeral memory," *In Digital Information Management (ICDIM), 2012 Seventh International Conference on,* pp. 165–172, 2012.

[72] D. Zhang, " Economic and environmental scheduling of smart homes with microgrid: DER operation and electrical tasks," *Energy Convers. Manag.* Vol. 110, pp. 113–124, 2016.

[73] C. Monteiro, T. Santos, " Short-Term Power Forecasting Model for Photovoltaic Plants based on Historical Similarity," *Energies* Vol.6, pp. 2624–2643, 2013.

[74] M. AboGaleela, M. El-Marsafawy, " A two level optimal DSM load shifting formulation using genetics algorithm case study: Residential loads," *IEEE Power and Energy Society Conference and Exposition in Africa: Intelligent Grid Integration of Renewable Energy Resources (PowerAfrica), Johannesburg*, pp. 1–7, 2102.

[75] O. Sianaki, O. Hussian, " A Knapsack Problem Approach for Achieving Efficient Energy Consumption in Smart Grid for End-user Life Style," *In*

Proceedings of the IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply Waltham, MA, USA, pp. 159–164, 2010.

[76] N. Kumaraguruparan, S. Sapatnekar, " Residential task scheduling under dynamic pricing using the multiple knapsack method ," *In Proceedings of the International Conference on, Innovative Smart Grid Technologies, Washington, DC, USA,* pp. 1–6, 2012.

[77] Y. Huang, L. Wang, " Chance Constrained Optimization in a Home Energy Management System," *IEEE Trans. Smart Grid*, Vol. 9, pp. 252–260, 2018.

[78] S. Khuri, T. Back, " The Zero/One Multiple Knapsack Problem and GA ," *In Proceedings of the 1994 ACM Symposium on Applied Computing, Phoenix, AZ, USA,* pp. 188–193, 2011.

[79] C. Ogwumike, M. Short, M. Denai, " Near-Optimal Scheduling of Residential SH Appliances using Heuristic Approach," *In Proceedings of the 2015 IEEE International Conference on Industrial Technolog, Seville, Spain,* pp. 3128–3133, 2015.

[80] K. Kusakana, " Energy management of a grid-connected hydrokinetic system under ToU tariff," *Energy* Vol. 101, pp. 1325–1333, 2017.

[81] C. Bharathi, D. Rekha, V. Vijayakumar, " Genetic Algorithm Based Demand Side Management for Smart Grid," *Wirel. Pers. Commun.* Vol. 93, pp. 481–502, 2017.

[82] M. Muratori, G. Rizzoni, Residential demand response, "Dynamic energy management and time-varying electricity pricing," *IEEE Trans. Power Syst.* Vol. 31, pp. 1108–1117, 2016.

[83] T. Logenthiran, D. Srinivasan, T.Z. Shun, "Demand Side Management in Smart Grid Using Heuristic Optimization," *IEEE Trans. Smart Grid*, Vol. 3, pp.1244–1252, 2012.

[84] V. Pilloni, A. Floris, A. Meloni, L. Atzori, "Smart Home Energy Management

Including Renewable Sources: A QoE-driven Approach," *IEEE Trans. Smart Grid*, 2016.

[85] E. Shirazi, S. Jadid, " Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS," *Energy Build.*, Vol. 93, pp. 40–49, 2015.

[86] C.O. Adika, L. Wang, " Smart charging and appliance scheduling approaches to DSM ," *Int. J. Electr. Power Energy Syst.*, Vol. 57, pp. 232–240, 2014.

[87] Y. Huang, L. Wang, W. Guo, Q. Kang, Q. Wu, " Chance Constrained Optimization in a Home Energy Management System," *IEEE Trans. Smart Grid*, Vol. 9, pp. 252–260, 2018.

[88] K. Ma, S. Hu, J. Yang, X. Xu, X. Guan, " Appliances scheduling via cooperative multi-swarm PSO under day-ahead prices and photovoltaic generation," *Appl. Soft Comput.*, Vol. 62, pp. 504–513, 2018.

[89] U. Asgher; B. Rasheed, A. Saad, A. Rahman, A. Alamri, " Smart Energy Optimization Using Heuristic Algorithm in Smart Grid with Integration of Solar Energy Sources," *Energies*, Vol. 11, 3494, 2018.

[90] C. Bharathi, D. Rekha, V. Vijayakumar, "Genetic Algorithm Based Demand Side Management for Smart Grid," *Wirel. Pers. Commun.* Vol. 93, pp. 481–502.

[91] Z.A. Khan, A. Zafar, S. Javaid, "Hybrid meta-heuristic optimization based home energy management system in smart grid," *J Ambient Intell. Human Computing* (2019). https://doi.org/10.1007/s12652-018-01169-y.

[92] P. Yi; X. Dong; A. Iwayemi; C. Zhou, S. Li, " Real-time opportunistic scheduling for residential demand response," *IEEE Trans. Smart Grid*, Vol. 4, pp. 227–234, 2013.

[93] C. Li, X. Yu, W. Yu, G. Chen, J. Wang, " Efficient computation for sparse load shifting in demand side management," *IEEE Trans. Smart Grid*, Vol. 8, pp. 250–261, 2017.

[94] K. Wang, H. Li, S. Maharjan, Y. Zhang, S. Guo, " Green Energy Scheduling for Demand Side Management in the Smart Grid," *IEEE Trans. Green Commun. Netw.*, Vol. 2, pp. 596–611, 2018.

[95] R. Gao, J. Wu, W. Hu, Y. Zhang, " An improved ABC algorithm for energy management of microgrid," *Int. J. Comput. Commun. Control* Vol. 13, 477–491, 2018.

[96] K. Shi, D. Li, T. Gong, M. Dong, F. Gong, Y. Sun, " Smart Community Energy Cost Optimization Taking User Comfort Level and Renewable Energy Consumption Rate into Consideration," *Processes*, Vol. 7, 63, 2019.

[97] K. Ma, H. Shubing, Y. Jie, X. Xia, G. Xinping, " Appliances scheduling via cooperative multi-swarm PSO under day-ahead prices and photovoltaic generation," *Appl. Soft Comput.*, Vol. 62, pp. 504–513, 2018.

[98] N. Javaid, S.M. Hussain, I. Ullah, M.A. Noor, W. Abdul," Demand Side Management in Nearly Zero Energy Buildings Using Heuristic Optimizations," *Energies*, Vol. 10, pp. 1131–1159, 2017.

[99] N. Javaid, F. Ahmed, I. Ullah, " Towards Cost and Comfort Based Hybrid Optimization for Residential Load Scheduling in a Smart Grid," *Energies*, Vol. 10, 1546, 2017.

[100] A. Manzoor, N. Javaid, I. Ullah, W. Abdul, " An Intelligent Hybrid Heuristic Scheme for Smart Metering based Demand Side Management in Smart Homes," *Energies*, vol. 10, 1258, 2017.

[101] A.S.O. Ogunjuyigbe, T.R. Ayodele, O.A. Akinola, " User satisfaction-induced demand side load management in residential buildings with user budget constraint," *Appl. Energy*, Vol. 187, pp. 352–366, 2017.

[102] S. Rahim, N. Javaid, A. Ahmad, " Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources," *Energy Build.*, Vol. 129, pp. 452–470, 2016.

[103] A. Ahmad, A. Khan, N. Javaid, " An Optimized Home Energy Management System with Integrated Renewable Energy and Storage Resources ," *Energies*, Vol. 10, 549, 2017.

[104] K. Muralitharan, R. Sakthivel, Y. Shi," Multiobjective optimization technique for demand side management with load balancing approach in smart grid," *Neurocomputing*, Vol. 177, pp. 110–119, 2016.

[105] S. Moon, J.W. Lee, "Multi-Residential Demand Response Scheduling with Multi-Class Appliances in Smart Grid," *IEEE Trans. Smart Grid* Vol. 9, 2518–2528, 2018.

[106] A. Khalid, N. Javaid, A. Mateen, B. Khalid, Z.A. Khan, U. Qasim, " Demand Side Management using Hybrid Bacterial Foraging and Genetic Algorithm Optimization Techniques," *In Proceedings of the 10th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS)*, Fukuoka, Japan, pp. 494–502, 2016.

[107] I. Ullah, S. Hussain, " Time-Constrained Nature-Inspired Optimization Algorithms for an Efficient Energy Management System in Smart Homes and Buildings," *Appl. Sci.*, Vol. 9, no. 792, 2019.

[108] S. Aslam, R. Bukhsh, A. Khalid, N. Javaid, I. Ullah, I. Fatima, " An Efficient Home Energy Management Scheme Using Cuckoo Search," *In Proceedings of the International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, Taichung, Taiwan,* pp. 167–178, 2018.

[109] X.S. Yang, D. Suash, " Cuckoo search via Lévy flights," *In Proceedings of the 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), Coimbatore, India,* pp. 210–214, 2009.

[110] A. Manzoor, N. Javaid, I. Ullah, W. Abdul, A. Almogren, A. Alamri, " An Intelligent Hybrid Heuristic Scheme for Smart Metering based Demand Side Management in Smart Homes," *Energies*, Vol. 10, 1258, 2017.

[111] N. Javaid, S.M. Hussain, I. Ullah, M.A. Noor, W. Abdul, " Demand Side Management in Nearly Zero Energy Buildings Using Heuristic Optimizations," *Energies*, Vol. 10, 1131–1159, 2017.

[112] M. B. Rasheed, N. Javaid, M. S. Arshad Malik, M. Asif, M. K. Hanif and M. H. Chaudary, "Intelligent Multi-Agent Based Multilayered Control System for Opportunistic Load Scheduling in Smart Buildings," *in IEEE Access,* Vol. 7, pp. 23990-24006, 2019.

[113] U. Latif, N. Javaid, S. S. Zarin, M. Naz, A. Jamal and A. Mateen, "Cost Optimization in Home Energy Management System Using Genetic Algorithm, Bat Algorithm and Hybrid Bat Genetic Algorithm," *2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA), Krakow,* pp. 667-677, 2018.

[114] F. Javeed, N. Arshad, " On the Use of Linear Programming in Optimizing Energy Costs," *In Procedings of the International Workshop on Self-Organizing Systems, Vienna, Austria,* pp. 305–310, 2018.

[115] S. Mirjalili, "The ant lion optimizer," *Advances in Engineering Software,* Vol. 83, pp. 80–98, 2015.

[116] K.M. Passino, " Biomimicry of bacterial foraging for distributed optimization and control ," *IEEE Control Syst.*, Vol. 22, 52–67, 2012.

[117] X.S. Yang, S. Deb, " Cuckoo search via Lévy flights ," *Proceedings of the World Congress on Nature & Biologically Inspired Computing, Coimbatore, India,* pp. 210–214, 2009.

[118] S. Mirjalili, "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems," *Neural Computing and Applications* , vol. 27, no. 4 : pp. 1053-1073, 2016.

[119] M. Wikelski, D. Moskowitz, S.A. James, J. Cochran, S. David, " *Wilcove, and Michael L. May. "Simple rules guide dragonfly migration." Biology letters,* Vol. 2, no. 3, pp. 325-329, 2006.

[120] Russell, W. Robert, L. Michael, May, L. Kenneth, Soltesz, and W. John, " Fitzpatrick. "Massive swarm migrations of dragonflies (Odonata) in eastern North America," *The American Midland Naturalist*, Vol. 140, no. 2, pp. 325-343, 1998.

[121] X.S. Yang, " Firefly algorithms for multimodal optimization, in Stochastic Algorithms: Foundations and Applications," *Lect. Notes Comput. Sci.* Vol. 5792, pp. 169–178, 2009.

[122] S. Mardle, S. Pascoe, " An overview of Genetic Algorithms for the Solution of Optimization Problems," *CHEER*, Vol. 13, pp. 16–20, 1999.

[123] S. Aslam, Z. Iqbal, N. Javaid, "Towards Efficient Energy Management of Smart Buildings Exploiting Heuristic Optimization with Real Time and Critical Peak Pricing Schemes," *Energies*, Vol. 10, 2065, 2017.

[124] S. Saremi, S. Mirjalili, A. Lewis, " Grasshopper optimization algorithm: Theory and application," *Adv. Eng. Softw.*, Vol. 105, pp. 30–47, 2017.

[125] S.J. Simpson, A. McCaffery, B.F. HAeGELE, " A behavioural analysis of phase change in the desert locust," *Biol. Rev.*, Vol. 74, 461–480, 1999.

[126] S.M. Rogers, T. Matheson, E. Despland, T. Dodgson, M. Burrows, S.J. Simpson, " Mechanistically-induced behavioural gregarization in the desert ," *locust Schistocerca gregaria,* Vol. 206, pp. 3991–4002, 2003.

[127] C.M. Topaz, A.J. Bernoff, S. Logan, W. Toolson, " A model for rolling swarms of locusts," *Eur. Phys. J. Spec. Top.*, Vol. 157, pp. 93–109, 2008.

[128] S. Mirjalili, " Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," *Knowl.-Based Syst.*, vol. 89, pp. 228–249, 2015.

[129] M.M. Sesana, G. Salvalai, " Overview on life cycle methodologies and economic feasibility for nZEBs," *Build. Environ.*, Vol. 67, pp. 211–216, 2013.

[130] C.H. Lo, N. Ansari," The progressive smart grid system from both power and communications aspects," *IEEE Commun. Surv. Tutor*, Vol.14, pp. 799–821, 2012.

[131] Y. Huang, H. Tian, L. Wang, “ Demand response for home energy management system,” *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 448–455, 2015.

[132] K. Ma, T. Yao, Y. Yang, X. Guan, “ Residential power scheduling for demand response in smart grid,” *Int. J. Electr. Power Energy Syst.*, Vol. 78, pp. 320–325, 2106.

[133] P.K. Naraharisetti, I.A. Karimi, A. Anand, D. Lee, “A linear diversity constraint application to scheduling in microgrids,” *Energy*, Vol. 36, 4235–4243, 2011.

[134] D. Fuselli, F.D. Angelis, M. Boaro, S. Squartini, Q. Wei, “Action dependent heuristic dynamic programming for home energy resource scheduling,” *Int. J. Elect. Power Energy Syst.*, Vol. 48, pp. 148–160, 2013.

[135] M.M. Albu, M. Snduleac, C. Stnescu, “ Syncretic use of smart meters for power quality monitoring in emerging networks,” *IEEE Trans. Smart Grid*, Vol. 8, pp. pp. 485–492, 2017.

[136] N. Saxena, S. Grijalva, “ Dynamic secrets and secret keys based scheme for securing last mile smart grid wireless communication,” *IEEE Trans. Ind. Inform.*, Vol. 13, pp. 1482–1491, 2017.

[137] L. Cirocco, M. Belusko, F. Bruno, “Optimization of Storage for Concentrated Solar Power Plants,” *Challenges* , Vol. 5, pp. 473–503, 2014.

[138] M. Hashmi, S. Hnninen, K. Mki, “ Survey of smart grid concepts, architectures, and technological demonstrations worldwide,” *In Proceedings of the IEEE PES Conference on Innovative Smart Grid Technologies (ISGT Latin America), Medellin, Colombia,* pp. 1–7, 2011.

[139] F. Rahimi, A. Ipakchi, “ Demand response as a market resource under the smart grid paradigm,” *IEEE Trans. Smart Grid*, Vol. 1, pp. 82–88, 2010.

[140] A. Ahmed, A. Manzoor, A. Khan, A. Zeb, H. Ahmad, “Performance Measurement of Energy Management Controller Using Heuristic Techniques,” *In*

Proceedings of the Conference on Complex, Intelligent, and Software Intensive Systems, Turin, Italy, pp. 181–188, 2017.

[141] Y. Ozturk, D. Senthilkumar, S. Kumar, G. Lee, " An intelligent home energy management system to improve demand response," *IEEE Trans. Smart Grid*, Vol. 4, pp. 694–701, 2013.

[142] G. Mavrotas, M. Karmellos, " Multi-objective optimization and comparison framework for the design of Distributed Energy Systems," *Energy Convers. Manag.*, Vol. 180, pp. 473–495, 2019.

[143] T. Sousa, H. Morais, Z. Vale, P. Faria, J. Soares, " Intelligent energy resource management considering vehicle-to-grid: A simulated annealing approach," *IEEE Trans. Smart Grid*, Vol. 3, pp. 535–542, 2012.

[144] J. Soares, T. Sousa, H. Morais, Z. Vale, P. Faria, " An optimal scheduling problem in distribution networks considering V2G," *In Proceedings of the IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), Paris, France,* pp. 1–8, 2011.

[145] K.M. Tsui, S.C. Chan, " Demand response optimization for smart home scheduling under real-time pricing," *IEEE Trans. Smart Grid*, Vol. 3, pp. 1812–1821, 2012.

[146] Z. Zhao, W.C. Lee, Y. Shin, K.B. Song, " An optimal power scheduling method for demand response in home energy management system," *IEEE Trans. Smart Grid*, Vol. 4, pp. 1391–1400, 2013.

[147] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M.S. Fadali, Y. Baghzouz, " Genetic-algorithm-based optimization approach for energy management ," *IEEE Trans. Power Deliv.*, Vol. 28, pp. 162–170, 2013.

[148] L. Tang, Y. Zhao, J. Liu, " An improved differential evolution algorithm for practical dynamic scheduling in steelmaking-continuous casting production," *IEEE Trans. Evol. Comput.*, Vol. 18, pp. 209–225, 2014.

[149] B. Liu, J. Kang, N. Jiang, Y. Jing, " Cost control of the transmission congestion management in electricity systems based on ant colony algorithm," *Energy Power Eng.*, Vol. 3, no. 17, 2011.

[150] Y. Liu, C. Yuen, S. Huang, " Peak-to-Average Ratio Constrained Demand-Side Management with Consumer's Preference in Residential Smart Grid," *IEEE J. Sel. Top. Signal Process.*, Vol. 8, pp. 1084–1097, 2014.

[151] X. Yang, " Firefly algorithms for multimodal optimization, in Stochastic Algorithms: Foundations and Applications," *Lect. Notes Comput. Sci.*, vol. 5792, pp. 169–178, 2009.

[152] Day-Ahead Pricing (DAP). NYISO (New York Independent System Operator). Available online: (accessed on 5th Jan. 2019 and 25 Oct. 2019).

[153] https://www.epa.gov/energy/electricity-customers (Accessed 02/20/2019)

[154] M. Hashmi, S. Hnninen, K. Mki, " Survey of smart grid concepts, architectures, and technological demonstrations worldwide," *In Innovative Smart Grid Technologies* (2011)

[155] F. Rahimi, A. Ipakchi, " Demand response as a market resource under the smart grid paradigm," *IEEE Transactions on Smart Grid* (2010)

[156] Irshad, Aamir, Ibrar, N. Khan and M. Riaz, "Reliable and Secure Advanced Metering Infrastructure for Smart Grid Network," *2018 International Conference on Computing, Electronic and Electrical Engineering (ICE Cube), Quetta,* pp. 1-6, 2018.

[157] R. Entriken, R. Hu, R. Skorupski, Y. Ye, " A mathematical Formulation for Optimal Load Shifting of Electricity Demand," *IEEE Trans. Smart Grid*, pp. 1-46, 2015.

[158] A. Molderink, V. Bakker, M.G. Bosman, J.L. Hurink, G.J. Smit, "Domestic energy management methodology for optimizing efficiency in smart grids," *In PowerTech, 2009 IEEE Bucharest* (2009).

[159] C. Feisst, D. Schlesinger, and W. Frye, "Smart Grid, The Role of Electricity Infrastructure in Reducing Greenhouse Gas Emissions", *Cisco internet business solution group, white paper,* (2008).

Appendix A

Table A-1 gives the specifications of different appliances in an home and their running time constraints used in chapter 4.

TABLE A-1: Home appliances and their running time constraints [72].

S. No.	Appliance	Category	Power Rating ρ (KW)	Starting Time (α)	Ending Time (β)	Time-Span ($\beta - \alpha$) (h)	LOT (h)
1	Fridge-1	Fixed	0.3	00	24	24	24
2	Interior Lighting-1	Fixed	0.84	18	24	06	6.0
3	Dish Washer-1	shiftable	2.0	09	17	08	2.0
4	Washing Machine-1	shiftable	0.6	09	12	03	1.5
5	Spin Dryer-1	shiftable	2.5	13	18	05	1.0
6	Cook Top-1	shiftable	3.0	08	09	01	0.5
7	Oven-1	shiftable	5.0	18	19	01	0.5
8	Microwave-1	shiftable	1.7	08	09	01	0.5
9	Laptop-1	shiftable	0.1	18	24	06	2.0
10	Desktop-1	shiftable	0.3	18	24	06	3.0
11	Vacuum Cleaner-1	shiftable	1.2	09	17	08	0.5
12	Electrical Car-1	shiftable	3.5	18	08	14	3.0
1	Fridge-2	Fixed	0.25	00	24	24	24
2	Interior Lighting-2	Fixed	0.9	19	24	07	7.0
3	Dish Washer-2	shiftable	1.9	11	15	04	2.0
4	Washing Machine-2	shiftable	0.5	10	14	04	2.0
5	Spin Dryer-2	shiftable	2.0	10	16	06	2.0
6	Cook Top-2	shiftable	3.5	09	10	01	0.5
7	Oven-2	shiftable	5.4	17	20	03	1.5
8	Microwave-2	shiftable	1.9	07	09	02	0.8
9	Laptop-2	shiftable	0.09	16	23	07	3.0
10	Desktop-2	shiftable	0.28	14	20	06	2.0
11	Vacuum Cleaner-2	shiftable	1.4	10	16	06	1.5
12	Electrical Car-2	shiftable	3.3	16	09	17	4.0
1	Fridge-3	Fixed	0.5	00	24	24	20
2	Interior Lighting-3	Fixed	0.62	17	06	13	13
3	Dish Washer-3	shiftable	2.5	10	16	06	2.5
4	Washing Machine-3	shiftable	0.8	08	14	06	1.8
5	Spin Dryer-3	shiftable	2.5	13	19	06	1.0
6	Cook Top-3	shiftable	3.2	07	09	02	0.5
7	Oven-3	shiftable	5.3	16	18	02	1.5
8	Microwave-3	shiftable	1.9	10	14	04	1.0
9	Laptop-3	shiftable	0.2	16	24	08	2.5
10	Desktop-3	shiftable	0.4	18	20	02	1.0
11	Vacuum Cleaner-3	shiftable	1.3	11	12	01	0.5
12	Electrical Car-3	shiftable	3.4	16	07	11	5.0
1	Fridge-4	Fixed	0.4	00	24	24	18
2	Interior Lighting-4	Fixed	0.7	19	08	13	13
3	Dish Washer-4	shiftable	2.3	08	19	11	4.0
4	Washing Machine-4	shiftable	0.9	11	14	03	1.0
5	Spin Dryer-4	shiftable	2.0	14	20	06	1.0
6	Cook Top-4	shiftable	3.5	10	12	02	1.2
7	Oven-4	shiftable	5.5	10	11	01	0.8
8	Microwave-4	shiftable	1.9	10	14	04	1.5
9	Laptop-4	shiftable	0.15	11	23	12	4.0
10	Desktop-4	shiftable	0.4	09	24	15	6.0
11	Vacuum Cleaner-4	shiftable	1.5	11	16	05	1.2
12	Electrical Car-4	shiftable	4.0	10	22	12	4.0

Table A-2 gives the specifications of different appliances in an office used in chapter 5.

Table A-2: Specifications of office automatically operating appliances (AOAs).

S. No.	AOAs	Category	Power rating (kW)	LOT	Time-Span (slots)
1	Air conditioner	Fixed	4.00	15	1–24
2	Fan	Fixed	3.5	12	1–24
3	Light	Fixed	2	17	1–24
7	Water dispenser	Fixed	2.5	22	1–24
4	Computer	shiftable	0.25	20	1–24
5	Electric kettle	shiftable	3.00	1	1–22
6	Coffee maker	shiftable	2.00	2	3–20
8	Oven	shiftable	5.00	2	3–20

The Table A-3 depicts the load units with their respective power ratings and the length of operational times (LOTs) used in chapter 6.

Table A-3: Specification of industry Automatically Oerated Machines (AOMs)

AOMs	PR(kw)	LOT	AOMs	PR(kw)	LOT
Scoring Section	150	8	Temperature control load	100	9
Carding Section	50	12	Packing Section	100	10
Spinning Section	200	7	Weaving Section	250	6

The day-ahead pricing (DAP) signal, shown in Figure A-1 issued by the utility [152] used in chapters 4 and 5, while Figure A-2(Accessed on 29/08/2020), is reproduced in Figure A-3 and is used for the manipulation of consumed energy bill in chapter 6.

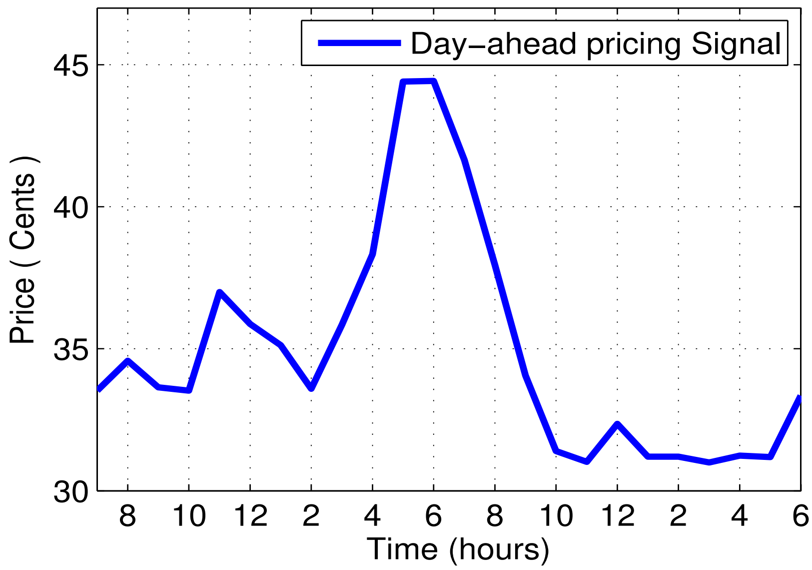

FIGURE A-1: Day-ahead real time pricing signal [152]

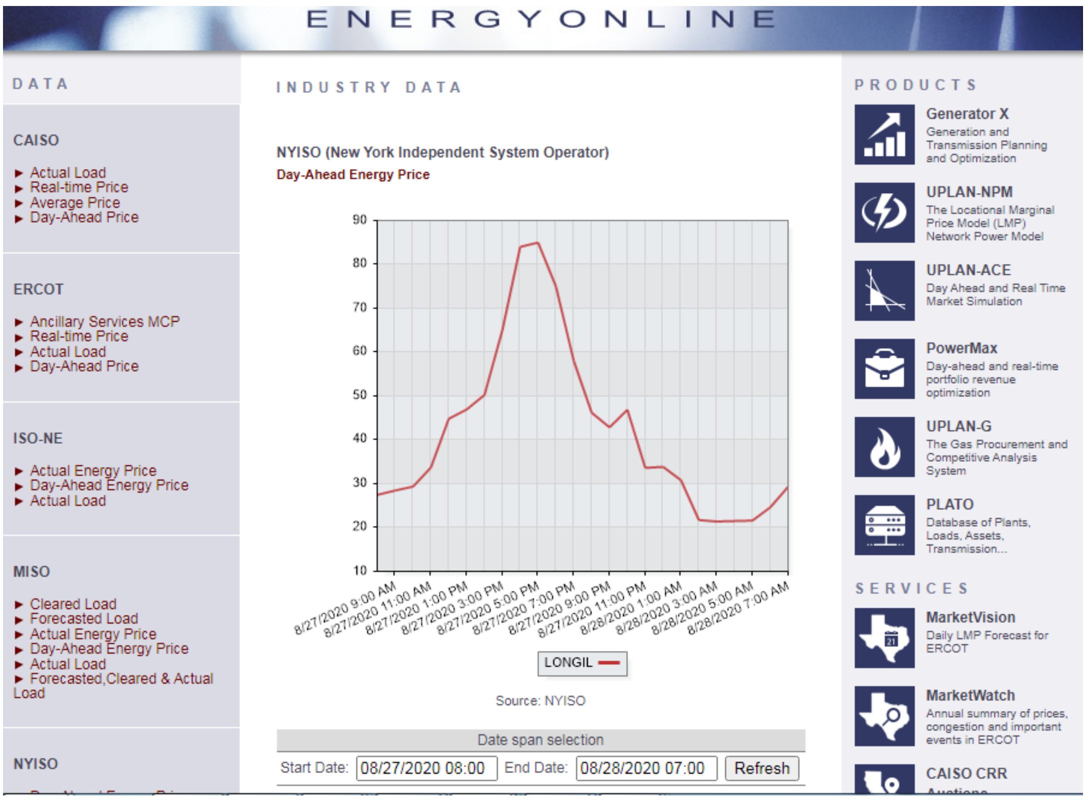

FIGURE A-2: Day-ahead pricing (DAP) signal [152]

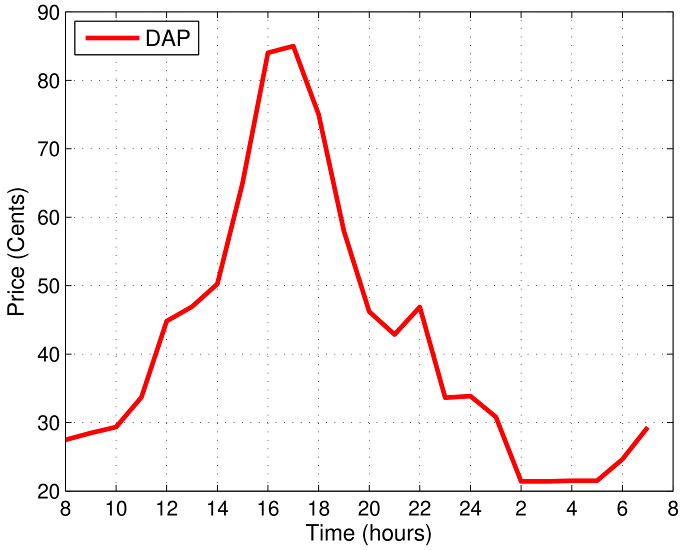

FIGURE A-3: (Day-ahead pricing (DAP) signal (Reproduced).