Mini Project Report

on

Optimization and Scheduling Appliances Priority for Residential Buildings

Submitted by

Annamaneni Rohit - 20BCS019

Sai Tarun Parasa - 20BCS096

Venkata Sai Nikhil Vemprala - 20BCS135

Sowmya S - 20BDS053

Under the guidance of

Dr. Prakash Pawar

Assistant Professor,

DEPARTMENT OF ECE

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, DHARWAD

06/11/2023

Contents

List of Figures ii

List of Tables iii

1 Introduction 1

2 Related Work 2

3 Problem formulation 5

4 Objective function and constraints 7

5 Algorithms 10

5.1 Binary Particle Swarm Optimization 10

5.2 Differential Evolution 11

5.3 Harmonic Search Algorithm 12

6 Results and Discussions 13

7 Conclusion 17

References 18

List of Figures

1 Objective function flow diagram . . . 9
2 BPSO flow diagram . . . 10
3 Differential Evolution flow diagram . . . 11
4 HSA flow diagram . . . 12
5 Hourly curtailment comparison . . . 13
6 On time comparison . . . 14
7 Weighted cost comparison . . . 15

List of Tables

1 Appliance properties 5
2 Minimum hourly curtailment 6
3 Curtailment prioritization comparison 15
4 PAR comparison 16
5 Runtime comparison 16
6 Solution fitness comparison 16

1 Introduction

Over the past few years, economic growth has led to a drastic increase in the demand for electricity. This increased demand has proven that the traditional power grid (TPG) is inadequate to meet this escalating demand. In this regard, Smart Grids have been introduced to address the energy challenges.

Smart Grids are characterized by their bi-directional capabilities, facilitating the efficient exchange of information between utility providers and consumers. This flow of information empowers the optimization of energy consumption at the demand side, ensuring a more efficient and responsive electricity distribution system.

Through Demand Side Management (DSM) strategies, we manage power consumption as the utility gains insights into consumer electricity usage patterns. Managing power usage reduces electricity costs by shifting the load from peak hours (PHs) to off-peak hours (OPHs).

Two key components of DSM are Demand Response (DR) and Load Management. These elements are integral to achieving a more efficient and cost-effective electricity distribution system, ultimately benefiting both consumers and utility providers.

In parallel, the field of energy management has seen a growing reliance on advanced algorithms to tackle these challenges effectively. This report delves into the performance and efficacy of three distinct algorithms: Binary Particle Swarm Optimization (BPSO), Differential Evolution, and Harmony Search (HMS). These algorithms have been applied to address critical aspects of energy management and are subjected to a comprehensive analysis across multiple metrics, including curtailing energy comparison, on-time performance, weighted hourly cost, peak to average ratios, algorithm runtimes, and fitness comparison.

Our objective in this report is to provide a detailed comparison of the algorithms and offer insights into their respective strengths and weaknesses. By doing so, we aim to facilitate informed decision-making and the selection of the most suitable algorithm for specific energy optimization tasks.

The ensuing sections of this report will delve into related work, problem formulation, objective function and constraints, algorithms, results, and discussions. Through this structured approach, we aim to provide a thorough understanding of our methodology and findings, allowing for a more comprehensive assessment of the practical implications of these algorithms in the field of energy management.

2 Related Work

Many researchers around the world work on energy optimization to optimally schedule smart appliances, balance the load, and efficiently manage energy consumption. In this regard, this section discusses some of the papers on Energy Management Systems (EMS), which encompass a wide range of energy optimization topics. In [5], authors discuss an approach for efficiently scheduling interruptible loads (ILs) to effectively manage peak-hour consumption and load reduction. This study employs Binary Particle Swarm Optimization (BPSO) as the primary algorithm. The fitness function in this method considers various constraints and objectives to improve IL scheduling. In a comparative analysis with fuzzy dynamic programming (FDP), BPSO emerges as a more effective approach. To enhance performance, the relevant paper introduces the concept of sub-swarms, enhancing the probability of finding optimal solutions. This insightful study offers valuable contributions to the field of energy optimization and can provide essential insights for our comparative analysis of algorithms. In [2], this paper explores the application of metaheuristic algorithms, specifically the Earthworm algorithm (EWA), Harmony search algorithm (HSA), and a hybrid approach combining EWA and HSA (EHSA), for the control and monitoring of appliances in single and multiple households. The model takes into account various types of appliances, including Interruptible and Non-interruptible ones. The EHSA combines EWA for generating new solutions with HSA for selecting good solutions from memory. The primary objectives of this study are to reduce Peak-to-Average Ratio (PAR) and electricity costs. This research presents a significant contribution to the field of energy optimization and offers valuable insights into the application of these metaheuristic algorithms for efficient appliance control and energy management. In [3], this paper explores the optimization of demand response systems with a focus on two main strategies: price-based and incentive-based approaches. The price-based system involves real-time pricing, time-of-use (TOU), and critical peak pricing (CPP). This study employs a teaching and learning-based optimization algorithm and Shuffled Frog Leaping (SFL) algorithm. The study classifies loads into shiftable, sheddable, and non-sheddable categories. When comparing the teaching and learning-based optimization (TLBO) algorithm and the Shuffled Frog Leaping (SFL) algorithm, TLBO outperforms SFL in producing more optimized results in terms of power consumption and cost savings across all tariff classes. This research provides valuable insights into the optimization of demand response systems, which can significantly impact electricity consumption and cost savings. In [10], the paper discusses the utilization of Binary Particle Swarm Optimization (PSO) for optimizing appliance usage, focusing on minimizing electricity costs. It discusses the categorization of domestic appliances and integrates time-of-use prices into the optimization process. Power matrix schemes are created for each appliance, aiming to minimize costs while considering time-of-use rates. The approach can be configured as single-objective or double-objective, focusing on reducing tariffs and power consumption, and promoting load shifting through nighttime operation of shiftable appliances. In [1], this paper explores energy management in residential areas, employing heuristic optimization techniques such as Binary Firefly Algorithm (BFA) and Grey Wolf Optimization (GWO). The primary focus is on achieving cost reduction and effective management of the peak-to-average ratio (PAR). Additionally, the study delves into the integration of renewable energy resources to enhance overall energy efficiency. In [9], the paper discusses a smart grid system characterized by inelastic demand, renewable energy sources, and energy storage batteries. The primary objective is to minimize short-term average electricity costs by considering four key decision variables: battery discharge, grid-based load supply, grid-based battery charging, and control of renewable energy usage. The optimization strategy revolves around the efficient use of energy storage, emphasizing charging the battery when electricity prices are low and discharging it when prices are high. This research provides valuable insights into the optimization of smart grids, particularly when dealing with inelastic demand and the integration of renewable energy sources and energy storage batteries. In [4], the paper introduces a novel approach - a gradient-based repair Particle Swarm Optimization (PSO) algorithm designed for home energy management systems. This innovative algorithm leverages gradient information to guide optimization towards feasible regions and possesses the versatility to be implemented in embedded devices, such as smart meters. The paper conducts a comparative analysis, pitting this algorithm against commercial software CPLEX and traditional PSO algorithms. The results indicate that this approach offers an efficient solution with low computational costs, making it a practical choice for implementation in embedded devices. This research contributes significantly to the field of home energy management and the development of optimized algorithms for smart grid applications. In [6], the proposed home energy management (HEM) method takes into account the operational priority of controllable appliances, primarily influenced by electricity price signals. The method involves the calculation of the value of lost load (VOLL) and formulates an optimization problem aimed at minimizing energy and reliability costs. The effectiveness of this method in the context of smart homes is rigorously tested through numerical studies and comparisons with other existing methods. However, it's worth noting that this approach may not be universally suitable for all households or appliances. It may require additional hardware or software installations, and its success could depend on customer participation in price-based demand response programs. This research offers valuable insights into the optimization of home energy management systems and the challenges associated with their implementation. In [7], The proposed solution uses a genetic algorithm to optimize energy sharing in a smart community grid system, addressing challenges like demand response, bidding, dynamic electricity tariffs, and prosumer handling. Validated using six prosumers' data sets, it significantly improves energy sharing loss without compromising user preferences. However, the solution is based on a genetic algorithm, which may not always guarantee optimal performance. Future work could explore incorporating individual preferences and goals for better decision-making. In [8], the paper introduces a novel approach for optimizing home energy management. It focuses on effectively scheduling the operation of appliances in smart homes to minimize electricity costs and manage Maximum Demand. The proposed method relies on Binary Particle Swarm Optimization (BPSO), a technique well-suited for handling binary variables, to achieve efficient load scheduling. The study also accounts for flexible and non-flexible loads, ensuring that the operation adheres to the constraints of Maximum Demand set by utility providers. This approach is particularly advantageous for homes with time-varying electricity tariffs and a need for load optimization. By utilizing BPSO, the algorithm searches for near-optimal solutions, efficiently allocating the operation of appliances throughout the day. This research makes a valuable contribution to the field of home energy management, providing an effective strategy to reduce electricity costs and optimize load scheduling under Maximum Demand constraints, as observed in the results.

3 Problem formulation

In this case, we consider a scenario with several appliances that can be scheduled for curtailment at various hours of the day. The problem at hand requires a solution which is a curtailment schedule. As an example problem we consider the problem used in [5].

We consider 19 appliances which are to be scheduled for curtailment through out 16 hours in a day. The solution is represented as a matrix of shape 16x19, Sch, representing the hours and the appliances. *Sch(t, i)* is equal to 1 if the ith appliance is being curtailed during the tth hour. Each of the appliances is given a capacity and a curtailment rate which is indicative of the cost incurred from curtailing the appliance. The appliances also have an associated maximum off duration and minimum on duration that they must adhere to. This is shown in Table 1. There also exists a minimum hourly curtailment requirement that must be fulfilled as shown in Table 2.

Appliance No	Capacity (kW)	Rate ($/kW)	Max off	Min on
1	320	23.8	4	2
2	200	25.7	4	2
3	80	16.9	4	2
4	84	16.9	4	2
5	100	19.2	4	2
6	160	23.6	4	2
7	100	19.2	3	1
8	60	16.9	3	1
9	200	25.7	3	1
10	40	16.9	4	1
11	40	16.9	3	1
12	72	16.9	3	3
13	140	21.4	4	3
14	80	16.9	3	3
15	40	25.7	3	3
16	180	25.7	3	3
17	180	25.7	4	2
18	160	23.6	4	2
19	60	16.9	4	2

Table 1
Appliance properties

Hour	Required curtailment (kW)
1	0
2	0
3	0
4	0
5	444
6	430
7	436
8	0
9	336
10	797
11	455
12	71
13	0
14	0
15	0
16	0

Table 2
Minimum hourly curtailment

Additionally, the appliances are divided into three priority levels. Each of the priority levels indicates how frequently the appliances can be curtailed with priorities ranging from 1 to 3.

4 Objective function and constraints

We formulate a multi objective function to help the solutions adhere to several constraints using a single function. The function describes constraints pertaining to user comfort, reduction of cost associated to curtailment, prioritizing appliances and reduce under curtailment.
The first objective is to limit the cost incurred through curtailment. We take the sum of the costs for curtailment weighted by the priority as given below.

$weighted\_cost = \sum_t^T \sum_n^N Sch[t,n] * Rate[n] * Capacity[n] * (4 - Priority[n])$

The next objective is to reduce the amount of under-curtailment occurring from the solution. This is done by checking the amount of curtailment on an hourly basis and create a count of instances of under-curtailment wherever observed as follows.

$curtailment[t] = \sum_n^N Sch[t,n] * Capacity[n]$
$UC = \sum_t^T count(curtailment[t] < required\_curtailment[t])$

Another requirement is to account for the frequency of curtailment and penalize repeated curtailment of specific appliances. This is to ensure that the implemented algorithms do not converge on solutions that adhere to the constraints by frequently curtailing the same appliances.

$freq\_penalty = \sum_{t=2}^T 2^{t-2} * C_t$
C_t = count of appliances curtailed t times or more.

We must also account for the instances of violation of the maximum off duration and minimum on duration. This can be done by creating a penalty as follows.

$off\_penalty = \sum_n^N max\_off[n] - (\sum_t^T Sch[t,n])$
$on\_penalty = \sum_n^N (T - \sum_t^T Sch[t,n]) - min\_on[n]$

We also make use of the peak to average ratio. Minimization of this factor helps reduce the amount of excess curtailment created by the solution.

$PAR = \frac{Max\_load}{Avg\_load}$

These objectives are then combined together to produce a score for a given solution via a weighted sum as follows.

$Score = weighted\_cost + \alpha * UC + freq\_penalty + \beta * off\_penalty + \gamma * on\_penalty + \delta * PAR$

Based on empirical results, it was found that the following weights provide the best representation of solution fitness ($\alpha = 1000, \beta = 100000, \gamma = 100000, \delta = 10000$). The implementation of the objective function is shown in figure 1

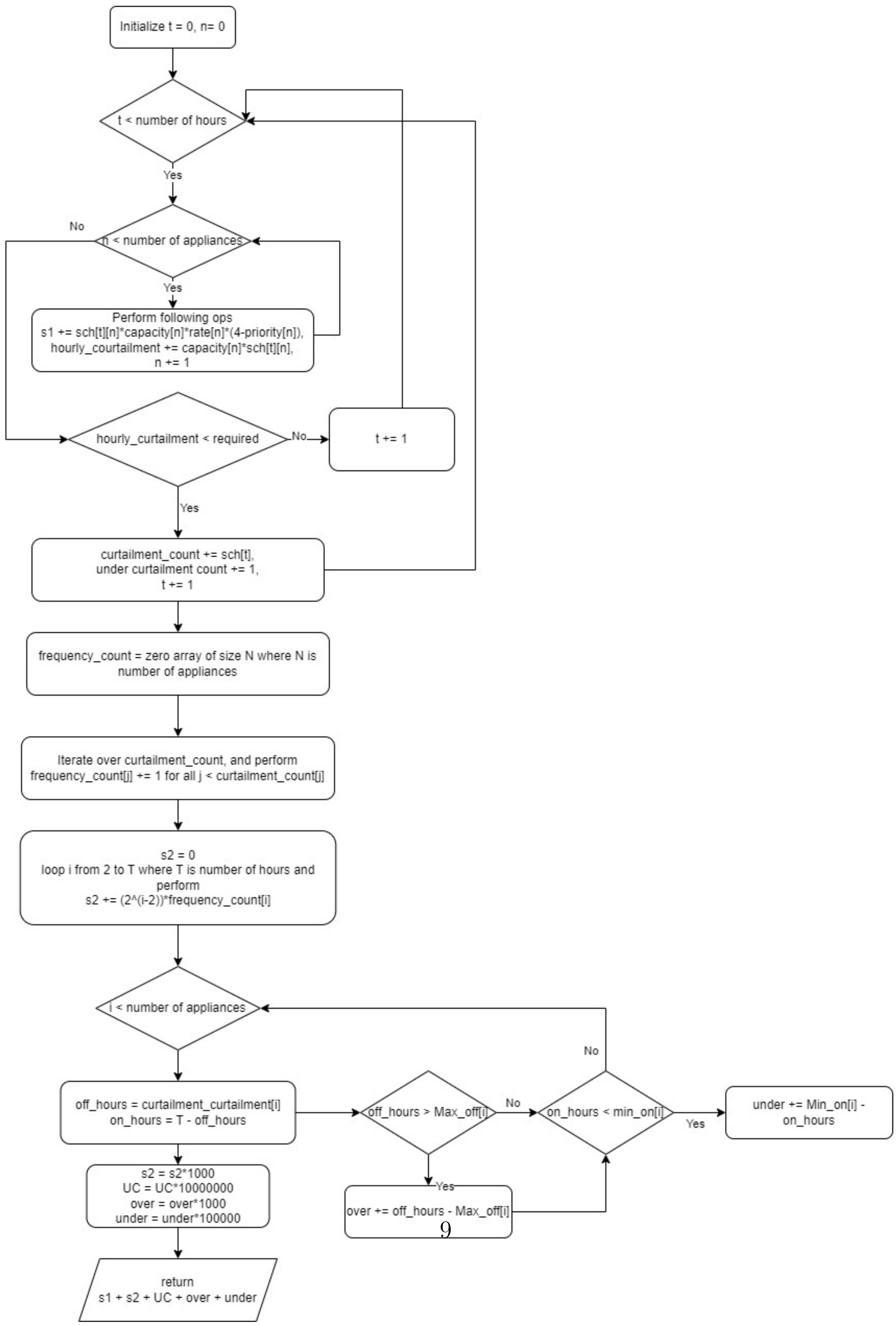

Figure 1. Objective function flow diagram

5 Algorithms

We make use of the proposed objective function to implement three optimization algorithms following which we evaluate the algorithms on various objectives such as user comfort, curtailment cost, appliance prioritization, etc.

5.1 Binary Particle Swarm Optimization

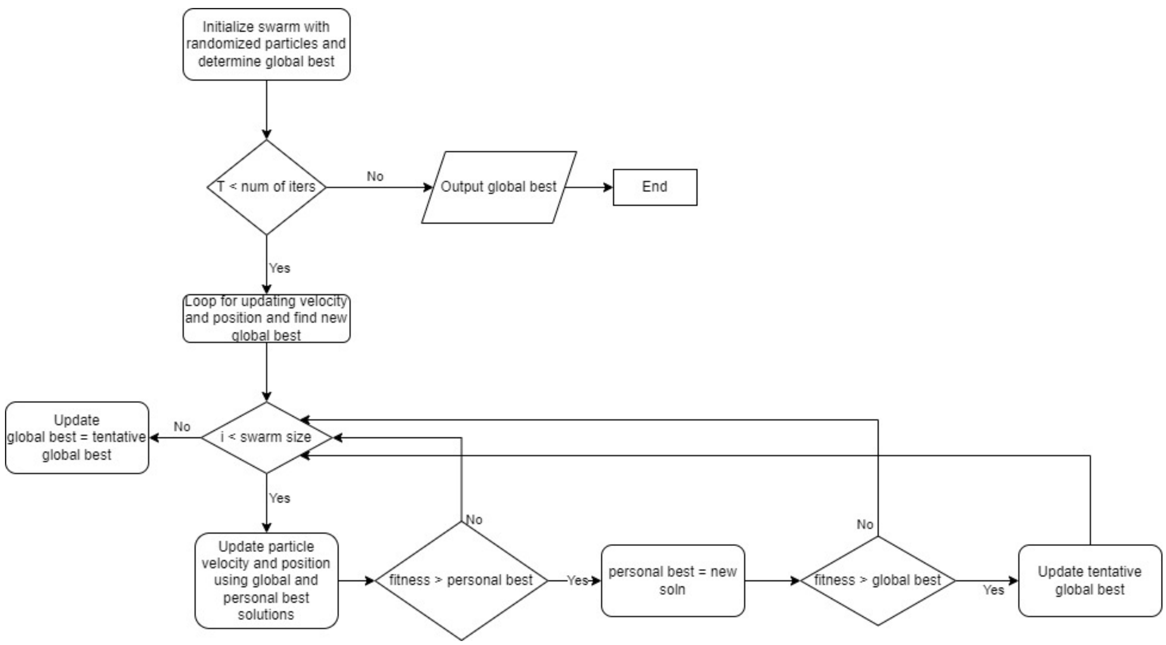

Figure 2. BPSO flow diagram

The BPSO algorithm is a variant of the PSO algorithm used in cases of binary representation of solutions. Here, we make use of a swarm of particles, each representing a schedule. Each of the particles state is represented by its position and velocity. The particles also maintain their personal best solution and the swarm maintains the overall global best solution. The velocities and positions are updated based on the global and personal best solutions.

$$v_{t,n} = v_{t,n} + \phi_1 * U(0,1) * P_{best}[t,n] + \phi_2 * U(0,1) * G_{best}$$

v=velocity
ϕ_1=cognitive coeff
ϕ_2=social coeff
$U(0,1)$ is a uniform distribution in the range of 0 to 1.

The position is updated by making use of the sigmoid of the velocity.

$$x_{t,n} = \begin{cases} 0 & \text{if } \sigma(v_{t,n}) < U(0,1) \\ 1 & \text{if } \sigma(v_{t,n}) \geq U(0,1) \end{cases} \text{ where } \sigma(v_{t,n}) = \frac{1}{1+e^{-v_{t,n}}}$$

The algorithm deals with iterating over the particles to update velocity and positions while determining the personal and global bests. The algorithm flow is described in Figure 2.

5.2 Differential Evolution

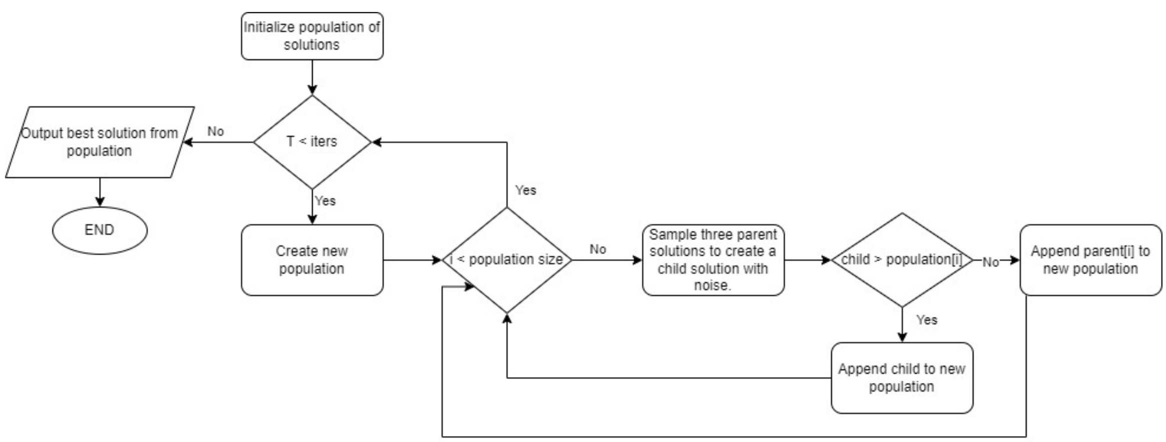

Figure 3. Differential Evolution flow diagram

Differential evolution is an optimization algorithm that iteratively improves upon a population of solutions. We begin with an initial population of random solutions. At each iteration, we create a new population. We fill the new population by iterating through the previous population. Three solutions from the previous population are then sampled to create a trial solution as follows.

$trial\_soln = x_1 + F * (x_2 + x_3)$
where x_1, x_2 and x_3 are sampled solutions and F is a scaling factor.

The trial solution and the solution from the previous population are compared and the better of the two is added to the new population. Once all the iterations are completed, we find the best candidate from the final population to be our solution.

5.3 Harmonic Search Algorithm

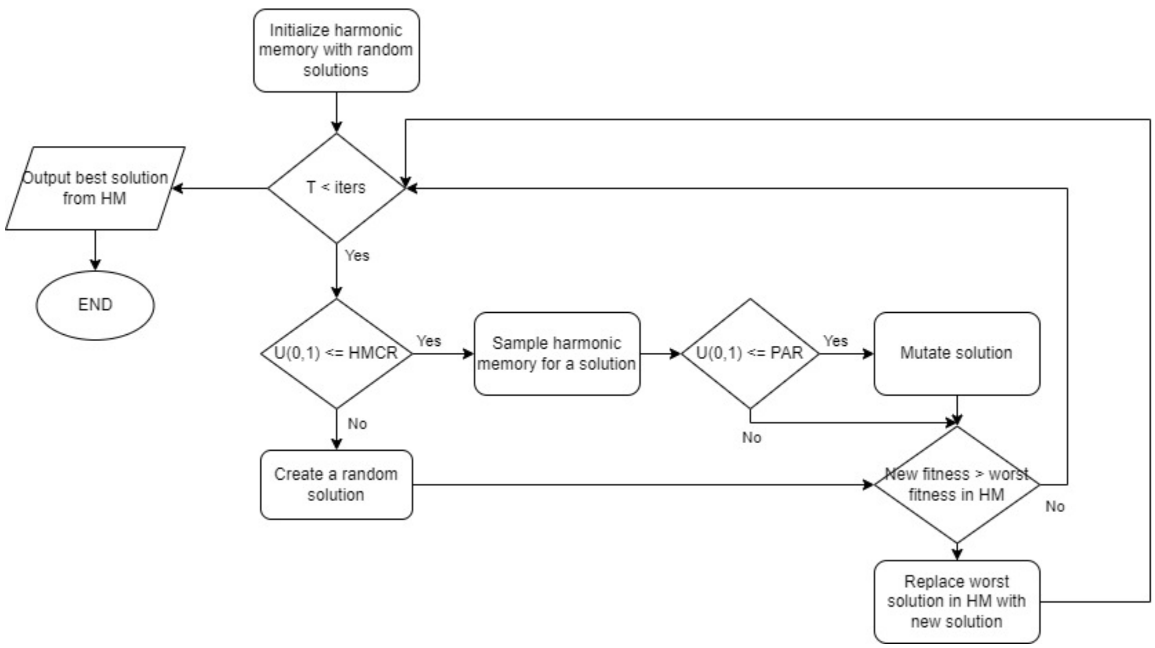

Figure 4. HSA flow diagram

Harmonic search is an optimization algorithm that maintains a memory of the best found solutions over all the iterations. The algorithm makes use of harmonic memory consideration rate (HMCR) and pitch adjustment rate (PAR). The HMCR parameter determines if the solution for the iteration is to be sampled from the harmonic memory or a completely new solution is to be generated. The PAR value determines the changes made in the sampled solution. At the end of each iteration, the worst solution in the harmonic memory is replaced with the new solution if it has a better fitness. This is done to ensure that the harmonic memory maintains the best set of solutions found. At the end of all the iterations, the best candidate from the harmonic memory is considered the solution.

6 Results and Discussions

We compare the algorithm implementations based on various objectives such as user comfort, cost of curtailment and operational duration of appliances.

A plot of the hourly curtailment as shown in figure 5 shows that all three algorithms meet the minimum required hourly curtailment criteria. However, only BPSO and DE reduce the amount of excess curtailment with BPSO showing consistently lower excess curtailment. The

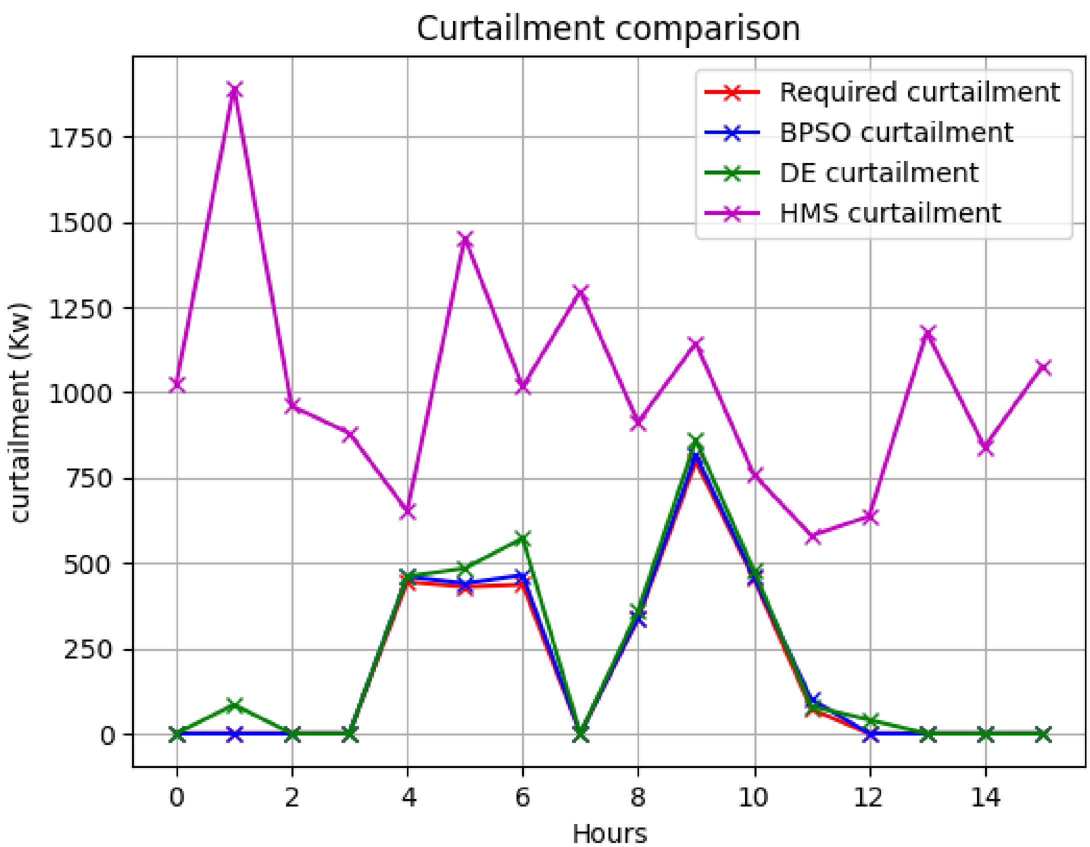

Figure 5. Hourly curtailment comparison

results from plotting the on time as shown in figure 6 show that all three algorithms generate solutions that meet the requirement of the minimum on time while only BPSO and DE meet the requirements criteria for maximum off time. Moreover, all three algorithms generate solutions where fitness is not achieved through repeated curtailment of specific appliances. This concludes that all three algorithms produce solutions that favour user comfort. It can be concluded from

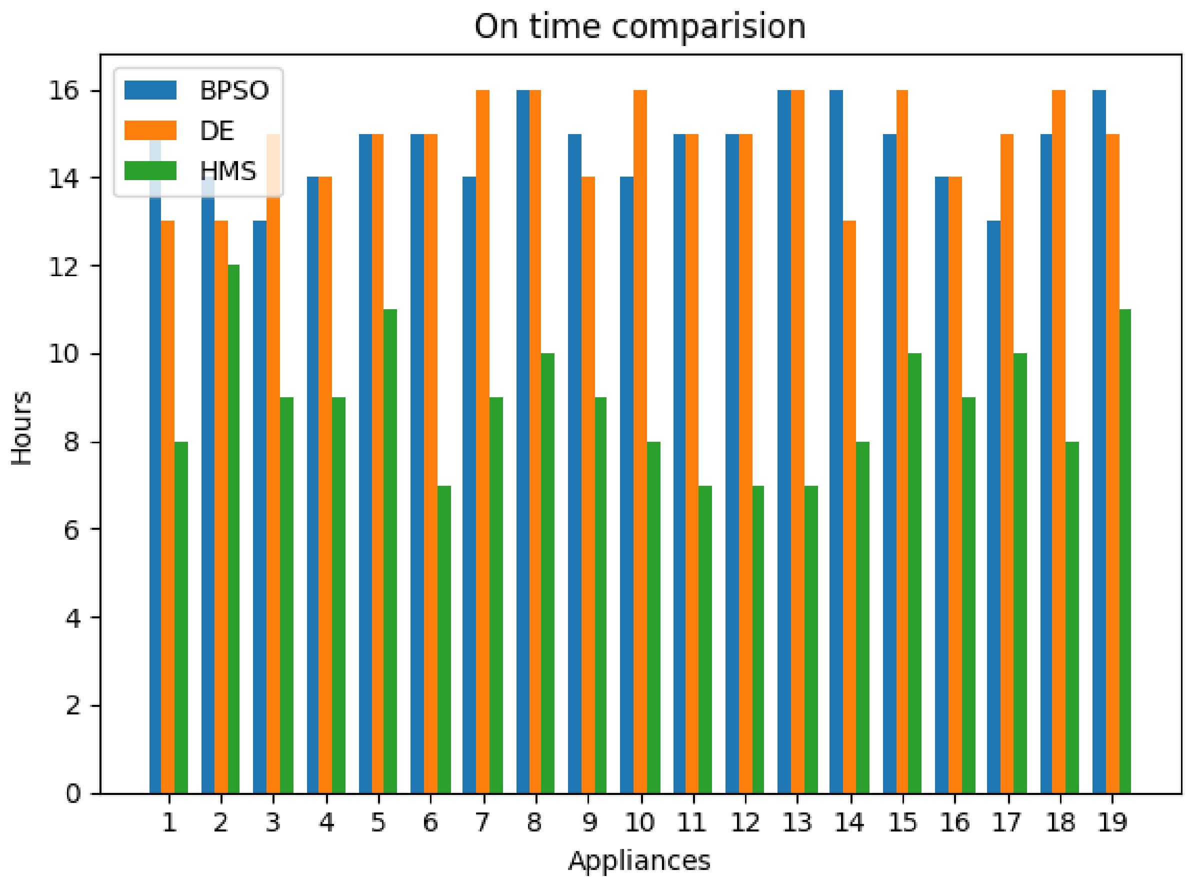

Figure 6. On time comparison

the plots of the weighted costs as shown in figure 7 that BPSO results in the least cost incurred based on the curtailment schedule in comparison to DE while HSA produces heavy cost.

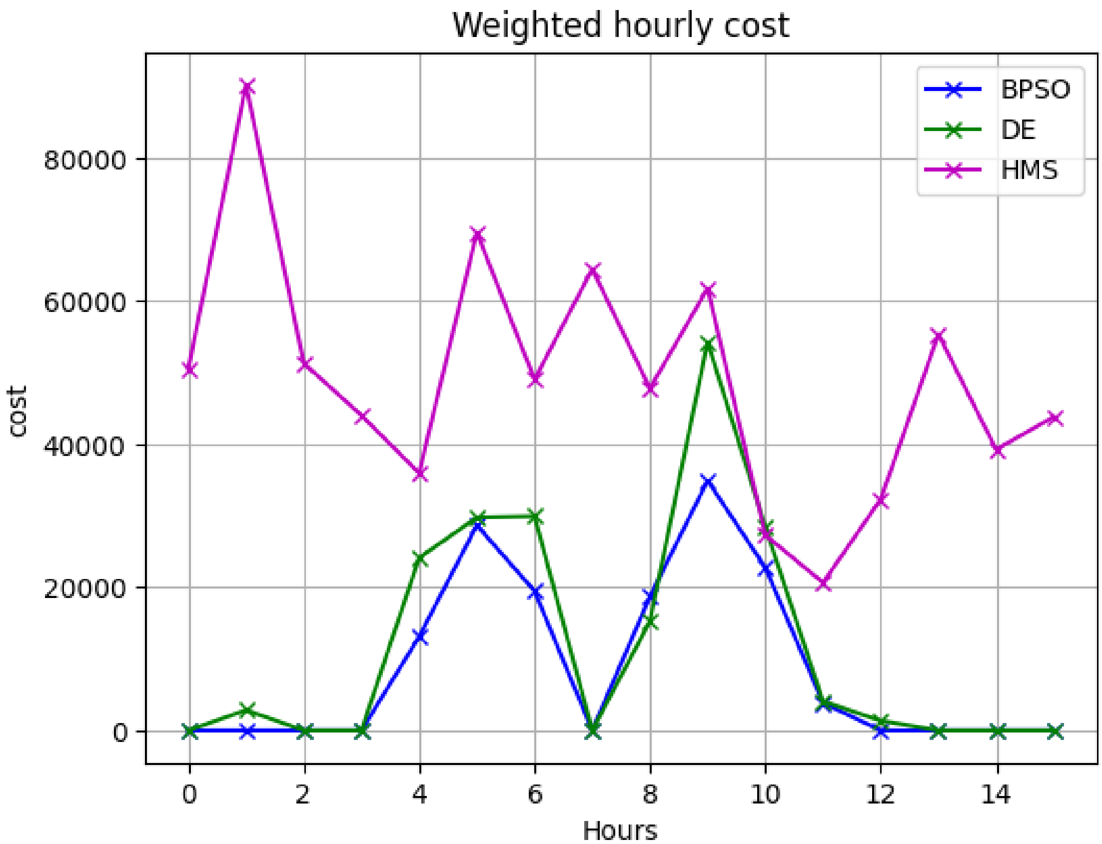

Figure 7. Weighted cost comparison

It was also found that BPSO best prioritizes curtailment of appliances followed by DE while HSA fails at prioritizing curtailment. These results are shown in table 3

Algorithm	Priority 1	Priority 2	Priority 3
BPSO	3	11	10
Differential Evolution	4	10	8
Harmonic search	54	42	39

Table 3
Curtailment prioritization comparison

Table 4 shows that BPSO and DE give similar PAR ratio while it is slightly higher in the case of HSA which could explain the excess curtailment in the case of HSA.

Algorithm	Peak to Average Ratio
BPSO	1.090
Differential Evolution	1.102
Harmonic search	1.342

Table 4
PAR comparison

The average runtime for each iteration is calculated for the algorithms as shown in table 5. While BPSO achieves the best results, it has a longer runtime as compared to DE and HSA.

Algorithm	Average iteration runtime
BPSO	0.401 secs
Differential Evolution	0.099 secs
Harmonic search	0.015 secs

Table 5
Runtime comparison

The average fitness values for the solutions from the three algorithms are found as shown in 6. It is noticed that BPSO consistently provides better fitness than DE while the solutions generated by HSA have very poor fitness.

Algorithm	Fitness
BPSO	152366.0
Differential Evolution	201868.0
Harmonic search	9456108.8

Table 6
Solution fitness comparison

7 Conclusion

BPSO seems to be the most balanced and effective optimization algorithm among the three, offering good user comfort, lower costs, better appliance prioritization, and competitive PAR ratios. Differential Evolution also performs well in many aspects, but BPSO appears to be the preferable choice for this specific problem domain. Harmonic Search, on the other hand, lags behind in several key areas, resulting in solutions with high costs and poor fitness. and also include objective function which is used in above data.

The choice of optimization algorithm is pivotal in achieving the objectives outlined in the objective function. The objective function, consisting of weighted cost, user comfort (UC), frequency penalty, off-time penalty, on-time penalty, and Peak to Average Ratio (PAR), serves as the guiding framework for evaluating and improving solutions.

Considering the data provided, there are ample opportunities for research and development in the realm of electricity consumption management. The impressive performance of BPSO accentuates the room for improving and tailoring algorithms for specific applications. Further investigations can delve into the refinement of parameters, the pursuit of multi-faceted optimization, the integration of machine learning, practical field implementations, incorporation into smart grid systems, utilization of energy storage methods, the incorporation of user input, environmental awareness, and adaptability to manage the changing dynamics of sustainable energy management.

References

[1] CH Anwar ul Hassan, Muhammad Sufyan Khan, Asad Ghafar, Syeda Aimal, Sikandar Asif, and Nadeem Javaid. Energy optimization in smart grid using grey wolf optimization algorithm and bacterial foraging algorithm. pages 166–177, 2018.

[2] Ch Anwar Ul Hassan, Jawaid Iqbal, Nasir Ayub, Saddam Hussain, Roobaea Alroobaea, and Syed Sajid Ullah. Smart grid energy optimization and scheduling appliances priority for residential buildings through meta-heuristic hybrid approaches. *Energies*, 15:1752, 02 2022. doi: 10.3390/en15051752.

[3] Ghasem Derakhshan, Heidarali Shayanfar, and Ahad Kazemi. The optimization of demand response programs in smart grids. *Energy Policy*, 94:295–306, 07 2016. doi: 10.1016/j.enpol.2016.04.009.

[4] Yantai Huang, Hongjun Tian, and Lei Wang. Demand response for home energy management system. *International Journal of Electrical Power and Energy Systems*, 73: 448–455, 2015. ISSN 0142-0615. doi: https://doi.org/10.1016/j.ijepes.2015.05.032. URL `https://www.sciencedirect.com/science/article/pii/S0142061515002379`.

[5] Michael Pedrasa, Ted Spooner, and Iain Macgill. Scheduling of demand side resources using binary particle swarm optimization. *Power Systems, IEEE Transactions on*, 24:1173 – 1181, 09 2009. doi: 10.1109/TPWRS.2009.2021219.

[6] Mohammad Rastegar, Mahmoud Fotuhi-Firuzabad, and Hamidreza Zareipour. Home energy management incorporating operational priority of appliances. *International Journal of Electrical Power and Energy Systems*, 74:286–292, 08 2016. doi: 10.1016/j.ijepes.2015.07.035.

[7] Zia Rehman, Mulika Fatima, Ahmad Khan, Sajid Shah, Raja Ahmad, Ahmad Din, and Attiqa Rehman. Energy optimization in a smart community grid system using genetic algorithm. *International Journal of Communication Systems*, 36:e4265, 11 2019. doi: 10.1002/dac.4265.

[8] Remani T., Jasmin E.A., and Imthias Ahamed T.P. Load scheduling with maximum demand using binary particle swarm optimization. In *2015 International Conference on*

Technological Advancements in Power and Energy (TAP Energy), pages 294–298, 2015. doi: 10.1109/TAPENERGY.2015.7229634.

[9] FatimaZahra Zahraoui, Houssam Eddine Chakir, Mehdi Et-Taoussi, and Hamid Ouadi. Smart grid cost optimization: Comparing bellman and genetic algorithms. pages 1–6, 2021. doi: 10.1109/IRSEC53969.2021.9741131.

[10] Yimin Zhou, Yanfeng Chen, Guoqing Xu, Qi Zhang, and Ludovic Krundel. Home energy management with pso in smart grid. pages 1666–1670, 2014. doi: 10.1109/ISIE.2014.6864865.