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Research Article

Strategic load scheduling in smart home: Leveraging IOT and optimization algorithms for energy cost reduction

Ganesh SHIRSAT[1,*], Aniruddha MUKHERJEE[1], Ankit Kumar SHARMA[1]

[1]*University of Engineering & Management, Jaipur, Rajasthan, 303807, India*

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ABSTRACT

The exponential growth of electrical energy demand can be attributed to the increase in population and urbanization. A strategic approach required to tackle this pressing issue involves the integration of Internet of Things (IoT) technologies and intelligent devices within households, a key initiative being undertaken by smart cities. India has implemented Time of Day (ToD) tariffs for electricity consumption, particularly targeting industrial sectors. Nevertheless, a notable observation is the limited utilization of Time of Day (ToD) tariffs within the residential electricity sector, signaling an area with potential for improvement. To enhance the efficiency of the electricity market through responsive measures, it is crucial to expand the implementation of Time of Day (ToD) tariffs to include the residential sector as well, thereby promoting a more effective and equitable system. The core focus of the research paper centers on the optimization of load scheduling in intelligent residences, with the objective of mitigating energy expenses and diminishing peak power demand, while upholding user comfort and operational efficiency at uncompromised levels. The research investigates the comparison of various algorithms like Ant Colony Optimization Algorithm (ACO), Whale Optimization Algorithm (WOA), Particle Swarm Optimization Algorithm (PSO), and Genetic Algorithm (GA) within the framework of cost reduction using ToD tariffs, with GA emerging as the most effective in achieving savings and decreasing peak-to-average ratio (PAR). This strategic approach not only benefits residential consumers in terms of cost savings but also proves advantageous for utility providers in managing resources effectively.

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INTRODUCTION

Smart homes and IoT-enabled appliances are gaining immense importance due to their ability to revolutionize daily living and energy efficiency. With the IoT within smart homes, it is possible to design smart home systems with advanced features for appliances control remotely [1]. Moreover, the smart homes are resulting with evolution of wearables and ambient devices for motion as well as health sensing and security, to build sustainable and

***Corresponding author.**
*E-mail address: ganeshshirsat1234@gamail.com

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smart living environment [2]. Appliance load monitoring in smart homes is also an important factor for attaining energy efficiency, and methods such as intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) have very good impact in controlling its power consumption [3]. Integrating IoT functionalities into Home Energy Management Systems (HEMS) can also increase energy savings in that it can supply customers with feedback information and support control over on of the main energy consumers like white goods in a home, showing also the growing relevance of smart home and IoT appliances in contemporary residential environments [4].

Energy management is confronted with significant challenges arising from the uncertainties associated with load consumption patterns and the sporadic nature of renewable energy generation, which adversely affects the management of active resources [5]. In order to mitigate these challenges, the implementation of efficient load scheduling is imperative, as it optimizes the utilization of renewable resources such as solar energy and energy storage systems, all while striving to minimize both costs and carbon emissions [6], [7]. Moreover, load scheduling plays an essential role within demand response initiatives, in which the deliberate redistribution of loads during intervals of diminished pricing can result in cost reductions for end-users, although it may also lead to rebound peaks and user discontent [7]. The application of sophisticated algorithms such as Enhanced Differential Evolution (EDE) and Genetic Algorithm (GA) facilitates the automation of responses to demand signals, thereby optimizing load schedules to achieve reductions in energy expenditures, carbon emissions, and peak-to-average ratios, whilst simultaneously enhancing user comfort [7]. Consequently, the efficacy of load scheduling is paramount for achieving an equilibrium between supply and demand, curtailing costs, and promoting sustainability within energy management frameworks.

The phenomenon of elevated energy expenditures and suboptimal energy utilization within smart homes is attributed to the escalating energy requirements and the deficiency of efficacious strategies for managing energy consumption during peak hours. Urban environments characterized as smart cities are profoundly dependent on the provision of efficient energy services, with Time-of-Use pricing emerging as an effective policy mechanism for reconciling electricity consumption patterns and alleviating strain on the electrical grid [8]. Scholars underscore the significance of scheduling energy usage during off-peak periods as a means to diminish energy costs, which necessitates meticulous profiling of appliances and the implementation of real-time monitoring systems for effective peak load management [9]. The proliferation of Internet of Things (IoT)-enabled smart homes is associated with an increase in energy consumption, thereby necessitating the development of optimization strategies aimed at enhancing both energy efficiency and user comfort [10] . Additionally, the convergence of Artificial Intelligence (AI) with IoT technologies promotes energy-efficient communication within smart homes, with novel algorithms and frameworks being devised to optimize Quality-of-Service during video streaming, consequently decreasing energy usage and enhancing performance metrics [11]. It is imperative to address these complexities through the deployment of cutting-edge technologies and optimization methodologies to mitigate the effects of rising energy costs and to enhance energy efficiency in smart residences.

The implementation of Time-of-Day (ToD) tariffs for the purpose of energy conservation presents numerous advantages, as substantiated by a variety of empirical research studies. ToD tariffs serve to incentivize consumers to realign their electricity consumption from peak demand periods to off-peak intervals, thereby mitigating peak load and fostering a more efficient utilization of energy resources. This behavioral modification not only contributes to energy conservation but also facilitates peak load shaving, which is essential for the preservation of grid stability and the diminishment of the necessity for costly grid expansions [12]. Moreover, the utilization of ToD tariffs has been empirically demonstrated to significantly lower power consumption while concurrently preserving benefits for both consumers and electricity providers, as evidenced by the application of genetic algorithms in the optimization of stepwise power tariffs [13]. In summary, the utilization of Time-of-Day (ToD) tariffs signifies a holistic approach designed to advance energy conservation, uphold grid reliability, and enhance economic efficiency, thereby rendering it as an exceptionally favorable framework for modern energy systems.

LITERATURE REVIEW

The practice of strategic load scheduling in smart homes equipped with IoT technology is imperative for curtailing energy costs and advancing energy management strategies. Several algorithms, notably the Whale Optimization Algorithm (WOA), Ant Colony Optimization Algorithm (ACO), Particle Swarm Optimization Algorithm (PSO), and Genetic Algorithm (GA), have been examined extensively for this purpose. Ant Colony Optimization (ACO) has been acknowledged as a proficient approach for enhancing energy management in smart residential contexts. By emulating the foraging behavior exhibited by ants, ACO algorithms are capable of efficiently scheduling domestic appliances to reduce energy expenses and peak demand [14]. ACO not only prioritizes cost reduction but also improves user comfort by ensuring that the scheduling of appliances is congruent with consumer requirements, thereby enhancing overall satisfaction [15]. ACO, renowned for its effectiveness in resolving combinatorial problems, has been adeptly employed in home energy management systems (HEMS) to enhance appliance scheduling while considering fluctuating pricing models and user comfort [16].

WOA, inspired by the social dynamics observed in cetacean populations, has demonstrated significant effectiveness in reducing energy expenditures and enhancing the peak-to-average ratio (PAR) through the optimal scheduling of domestic devices within sophisticated grid systems. PSO, recognized as a widely utilized heuristic optimization methodology, has found extensive application within home energy management systems (HEMS) to harmonize energy consumption and associated costs, capitalizing on its rapid convergence towards optimal solutions. Genetic Algorithms (GA), a prominent optimization methodology, has been rigorously applied in numerous research endeavors aimed at the creation of efficient Home Energy Management Systems (HEMS), specifically focusing on curtailing electricity expenditures and easing peak demand via the judicious scheduling of household devices [17]. These algorithms are customarily associated with advanced Internet of Things (IoT) technologies and real-time data analytics to bolster their operational efficacy. The fusion of GA with IoT-oriented controllers has revealed significant economic advantages and enhanced user gratification through the effective real-time optimization of load profiles [18].

In a similar vein, Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) have been employed in tandem with predictive modeling to anticipate energy consumption patterns and enhance scheduling in accordance with user preferences and environmental variables [19]. The efficacy of these algorithms is corroborated through both simulations and empirical data, thereby demonstrating their capacity to facilitate significant reductions in energy costs while simultaneously ensuring user satisfaction [20, 21]. In summary, the predominant corpus of literature underscores the vital importance of these optimization methodologies in the evolution of smart home energy management, thus delineating the need for sustained research and development to proficiently tackle future challenges and uncertainties [22].

Problem Formulation

The regulation of energy within intelligent residential settings has achieved increased prominence due to rising energy costs and the necessity for sustainable approaches. This study is focused on two primary objectives: the reduction of costs and the improvement of efficiency in energy management. Through the utilization of time-of-day pricing structures and diverse optimization algorithms, this research endeavors to formulate strategies that mitigate energy expenses and optimize efficiency, all while maintaining the comfort of the inhabitants.

The primary objectives of this research are:

- To establish strategies centered on cutting energy expenditure in intelligent home systems.
- To analyze the use of time-of-day tariffs to boost energy efficiency in non-peak periods ultimately lowering electricity expenses.
- To evaluate the efficacy of various optimization algorithms specifically ACO, WOA, PSO, and GA in achieving these objectives.

This research assesses the application of diverse optimization algorithms for effective load scheduling, crucial for cost minimization and efficiency enhancement in smart homes while developing viable load scheduling methodologies.

SYSTEM MODEL

The utilization of metaheuristic algorithms within the Smart Home Energy Control (SHEC) system optimizes power consumption in smart devices by establishing efficient usage schedules. This integration aims to achieve cost reduction, decrease the Peak Average Ratio (PAR), and enhance user comfort (UC) through effective energy resource management. Through the proactive participation in demand response initiatives and the adjustment to fluctuating energy prices, the Smart Home Energy Controller (SHEC) system not only mitigates consumer energy

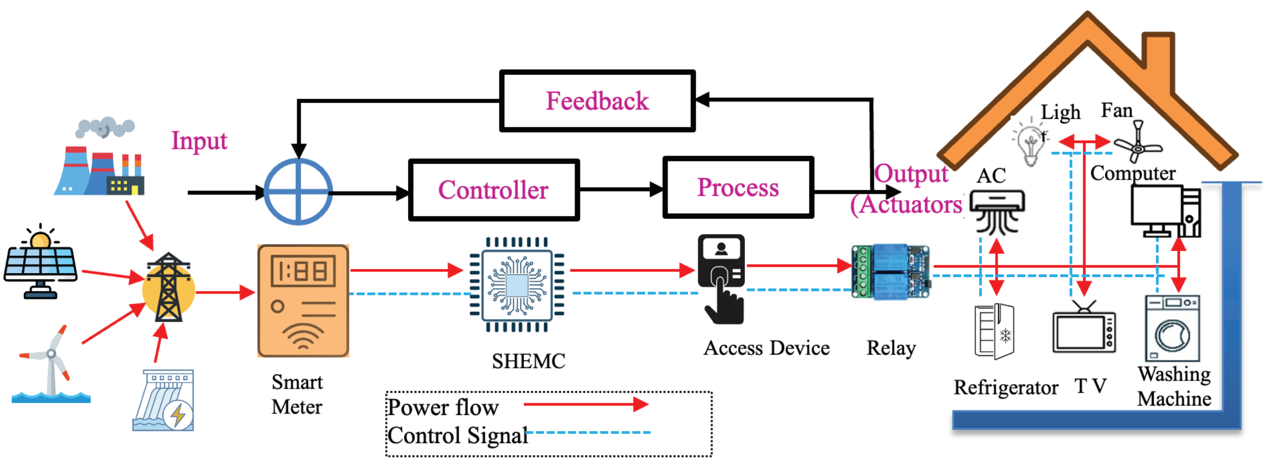


Figure 1. Workflow of Smart home energy management system.

expenditures but also enhances the overall efficiency and sustainability of Internet of Things (IoT)-integrated smart residences. Figure 1 delineates the proposed sequential workflow of the system, highlighting the procedural phases involved in the optimization of energy management.

Study Focus and Objectives

This study concentrates on optimizing energy management in a smart home environment using a set of ten commonly used appliances which are given in table 1. Each appliance is denoted by

n ϵ N = {1,2,3………10)

with energy management decisions made hourly across 24 time slots

s ϵ S = {0,1,2,3………23)

Energy Consumption and Cost Formulation

The total energy consumption of appliances within each time slot is calculated as:

$$AEC^S = \sum_{n=1}^{10} AEC_n \tag{1}$$

where AECn represents the energy consumption of appliance n.

The total energy consumption over 24 hours (AECT) is:

$$AEC_T = \sum_{n=1}^{24} AEC^S \tag{2}$$

Energy cost is determined by:

$$C = \sum_{s=1}^{24} (E_{rate} \times P_{rate}) \tag{3}$$

where E rate is the energy cost per hour and Prate is the power rating of connected appliances.

Optimization Objective

The objective function aims to minimize the total cost and reduce user discomfort due to waiting times $\omega_T = b - a$ before appliance operation.

It is formulated as:

$$min(\sum_{s=1}^{24} [\, \omega_1 \times \sum_{n=1}^{10} (AEC_T \times E_{rate}) + (\omega_2 \times \omega_T) \,]) \tag{4}$$

Here, ω1 and ω2 are weighting are weighting factors (either 0 or 1) balancing cost reduction and user comfort, with ω1+ω2=1.

Role of Smart Home Energy Controller (SHEC)

In residential environments integrated with the Internet of Things (IoT), the Smart Home Energy Controller (SHEC) plays a crucial role by responding to real-time demand signals and optimizing energy consumption with remarkable efficacy. It considers a multitude of factors, including price-driven demand response strategies, characteristics of appliances, operational timeframes, Time-of-Day (TOD) pricing structures, and the energy resources available from the grid to formulate optimal energy consumption schedules.

Pricing schemes

Many countries have implemented Time of Day (ToD) tariffs for electricity consumption, particularly targeting commercial and industrial sectors. In proposed ToD tariff three zone are considered based on load curve plotted by taking actual use of appliances from household consumer. These are Peak (6 to10 hrs. &18 to 22 hrs.), Valley (4 to 6 hrs.,10 to 12 hrs. & 16 to 18 hrs.) & Flat Zone (0 to 4 hrs., 12 to 16 hrs. & 22 to 23 hrs.). The primary goal of these tariffs is to encourage consumers to adjust their electricity usage to times of lower demand on the grid, ultimately aiding in load balancing. The increase in demand for electrical energy has grown significantly because of population growth and urban development. To address this issue, smart cities are utilizing Internet of Things (IoT) technology and smart devices within households.

In India, Maharashtra MSEDCL applies energy rates for consumer based on power consumption. The different energy rates are applied for different consumers based on Total energy Consumption (0-100,100-300,300-500,500

Table 1. Smart home Appliances and its rating

Sr. No	Appliances	Power Rating [Prate] (Watts)	Total Usage hrs. [Li]	Time Slots
1	Air Conditioner	1500	6	10–21
2	Computer	250	8	9–23
3	Electric kettle	1000	1	4–20
4	Coffee maker	1000	1	5–21
5	Water Dispenser	300	9	0-23
6	Oven	1000	2	4–21
7	Fan	500	5	0–23
8	Light	150	7	0–23
9	Washing Machine	1000	2	5-21
10	TV	100	6	0-23

onwards). Proposed ToD Method in which Energy rates are applied based on peak, Valley & flat zones of load curve.

In this study for Cost minimization of Smart Homes Two Methods were adopted

Case I: Cost minimization by saving the KW power consumption & using ToD tariff for power consumption

Case II: Cost minimization by only adopting ToD tariff for power consumption.

METHODOLOGY

In this study, we use two main approaches to optimize energy usage in smart homes: Single Interval Programming (SIP) and Multi-Interval Programming (MIP).These strategies are designated according to two distinct temporal phases in dispatch planning and pricing, referred to as pre-dispatch and real-time [23]. SIP comes into play when we have set electricity prices ready to go for the whole day! The single interval program runs once each day to figure out the best schedule that fits user's preferences. Multi interval programming (MIP) works throughout each interval to find the ideal scheduling based on hourly real-time pricing conditions.

In particular circumstances, Single Interval Programming (SIP) is frequently preferred over Multi-Interval Programming (MIP) due to its various notable advantages. To begin with, SIP showcases computational clarity and heightened efficiency, targeting the optimization of energy usage during specific time intervals, which enables rapid calculations and on-the-fly adaptability. This characteristic renders SIP particularly suitable for prompt energy management decisions and scenarios necessitating swift modifications. Secondly, SIP necessitates a reduced volume of data in comparison to MIP, thereby rendering it advantageous in situations where extensive data across multiple intervals is either inaccessible or prohibitively expensive to obtain.

Numerous scholarly investigations have examined the challenge of optimal scheduling of domestic appliances via the utilization of diverse algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Harmony Search Algorithm (HSA), Water Distribution Optimization (WDO), and Hybrid Genetic Harmony Search Algorithm (GHSA), among others [24-26].

In this paper a comparative performance of ACO, WOA, PSO and GA is given.

Ant Colony Optimization (ACO)

This research introduces an Ant Colony Optimization (ACO) strategy aimed at refining energy consumption schedules for residences within the framework of Time-of-Day (TOD) pricing. The Ant Colony Optimization (ACO) algorithm initiates its process with a collection of artificial ants, each of which constructs a potential energy consumption timetable by incrementally selecting hours for each appliance, informed by pheromone trails and heuristic information. The pheromone matrix experiences real-time updates based on the efficacy of the solutions generated, thus reflecting the attractiveness of each hour for the activation of appliances. This approach achieves a harmonious equilibrium between exploration (via stochastic selections influenced by pheromone concentration) and exploitation (by focusing on advantageous solutions identified throughout the algorithm's execution).

The technique incorporates various constraints within the optimization framework. These constraints include maintaining appliances within designated time frames and adhering to maximum usage limits. Furthermore, the objective function incorporates variable electricity pricing across different temporal intervals (peak, off-peak, and flat rates), aiming to discern schedules that minimize total expenditures while possibly considering idle periods for appliance usage. The optimization process is executed through numerous generations of ant solutions, employing mechanisms for pheromone evaporation and updates that promote convergence toward an optimal or near-optimal solution throughout successive iterations.

Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) constitutes an advanced metaheuristic optimization approach that is predicated upon the social behaviors demonstrated by humpback whales, particularly highlighting their bubble-net feeding strategy. This algorithm is characterized by its proficiency in global search capabilities and its necessity for a limited quantity of control parameters, thus making it efficacious across a diverse array of optimization problems [27]. This investigation describes an optimization approach directed at the scheduling of electrical loads within a domestic setting, leveraging the WOA as a core methodology. The algorithm systematically improves the schedules via iterative processes, adeptly harmonizing the dual aims of exploration and exploitation to identify the optimal solution. Throughout this process, constraints are rigorously applied to guarantee that the schedules maintain their feasibility. The findings presented in this study provide robust support for the effectiveness and practicality of the aforementioned approach, particularly in relation to its capacity to facilitate substantial reductions in operational costs while simultaneously improving overall energy efficiency metrics, thereby further solidifying and amplifying the primary aim of demand-side management strategies as they pertain to the optimization of intelligent residential systems designed to enhance user experience and sustainability.

Particle Swarm Optimization (PSO)

The PSO algorithm is a technique for stochastic optimization based on population dynamics, draws inspiration from the collective behaviors observed in bird flocking and fish schooling [28]. PSO consists of particles representing potential solutions distributed randomly. Each particle's position and velocity are updated based on personal best and global best. The algorithm starts with initializing particles' positions and velocities, followed by evaluating fitness function [29]. Particles adjust velocities and positions using a rule incorporating personal best and global best [30].

The proposed PSO framework initializes a swarm of particles, each representing a potential schedule. The evaluation of each particle's fitness is conducted according to the objective function, which takes into account the TOD rates and load constraints. The particles systematically revise their positional coordinates through a process informed by their individual prior experiences alongside the globally optimal solution identified by the swarm, influenced by cognitive and social factors. In order to ensure feasibility, additional constraints such as peak power limits and specified operational timeframes are enforced upon the scheduling framework of each particle. The algorithm efficiently converges towards an optimal or nearly optimal solution, thereby showcasing its proficiency in balancing cost minimization with adherence to constraints.

Genetic Algorithm (GA)

The Genetic Algorithm (GA) functions as an optimization methodology grounded in principles of natural selection and genetic theory, wherein essential elements facilitate the evolution of solutions to intricate challenges [31]. Entities within a population are representative potential solutions that are encoded in the form of chromosomes [32]. Parental entities are selected according to fitness levels and undergo crossover to generate novel offspring. The mutation mechanism enhances genetic diversity and expands the search parameter space, thereby reducing the likelihood of convergence to local optima. This repetitive sequence of selection, crossover, and mutation defines a singular generation, with the objective of advancing the quality of solutions through subsequent generations [31,33].

To enhance the effectiveness of optimizing residential electrical consumption while factoring in peak load management and time-of-use pricing, we have devised an innovative genetic algorithm (GA). Our methodology tackles the challenge by adaptively scheduling household appliances in alignment with variable electricity tariffs and temporal constraints. The algorithm is initialized utilizing pre-established appliance schedules and imposes limitations such as operational hours and maximum load thresholds. The objective function is designed to balance the reduction of electricity expenses with the comfort of consumers, wherein weighting coefficients are finely tuned to correspond to either overall consumption metrics or time-variable pricing rates. Implementing iterative processes of selection, crossover, and mutation, the genetic algorithm steadily optimizes schedules, consequently ensuring alignment with

Table 2. Comparison of Algorithms based on strength and weakness

Algorithm	Strength	Weakness
ACO	-Exhibits effectiveness in addressing combinatorial optimization challenges. -Demonstrates expertise in traversing extensive search landscapes. -Displays an aptitude for modification within shifting contextual paradigms.	-The incidence of premature convergence might ensue when pheromone trails reveal excessive potency. -The convergence speed is regularly recognized to be diminished when engaging with elaborate problems. -The process of parameter optimization can introduce considerable intricacies.
WOA	-Encourages rapid convergence without compromising the critical exploratory facets. -Mimics authentic behavioral patterns evident in the foraging methodologies of humpback whales.	- There exists a relative scarcity of research and a lack of established methodologies in comparison to alternative approaches. - The performance outcomes may fluctuate contingent upon the specific parameter configurations employed. - There may be difficulties encountered in highly multimodal landscapes.
PSO	-Rapid convergence, particularly in the context of unimodal optimization challenges - Straightforward execution and comprehensible interpretation - Effective in addressing dynamic optimization scenarios	-Challenges may arise when endeavoring to perform global exploration within complex landscapes. - The methodology is significantly sensitive to the configuration of parameters, which may profoundly influence performance indicators. - A proclivity for premature convergence may become apparent in certain circumstances.
GA	- Maintains diversity through genetic operations - Robust to different types of problems	- Convergence may be comparatively slower than that observed in Particle Swarm Optimization (PSO). - It necessitates meticulous calibration of population size, mutation rates, and crossover rates. -The degree of complexity related to implementation can vary greatly based on the specific genetic representation chosen.

peak power regulations and boosting overall efficiency in energy consumption. The empirical observations affirm the success of our methodology in diminishing electricity costs and enhancing consumption dynamics across a range of household environments.

A comparative examination of Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) delineating their respective advantages and limitations is presented in Table 2 within the framework of optimization challenges. By comprehensively understanding their distinct attributes, one can more effectively evaluate their appropriateness for particular applications, especially in contexts where efficient energy management and load scheduling are of paramount importance.

Genetic Algorithms (GA) excel in intricate optimization tasks, especially with multimodal functions featuring several optimal solutions. Their maintenance of genetic diversity via crossover and mutation mitigates premature convergence, facilitating exploration of varied solution regions. Furthermore, GAs exhibit high adaptability, rendering them suitable for problems characterized by evolving environments or dynamic constraints, including scheduling and resource allocation.

RESULTS AND ANALYSIS

The focus of this study is the reduction of electricity expenses for residential consumers while ensuring user comfort. Simultaneously, the aim is to decrease the PAR ratio. In this study comparative results are obtained for both cases fixed charges as per current scenario & after applying the TOD tariff in Table 3 and Table 4. In this case, we have two cost rates first Based on MSEDCL power consumption (KW) slabs (i.e KW Slab) and second ToD tariff rates (i.e ToD rates). The initial energy consumption & Energy cost curve for a day is shown in Fig. 2.

In Proposed ToD Method in Energy rates are applied based on peak, Valley & flat zones of load curve. Initial Power consumption without appliances scheduling for KW

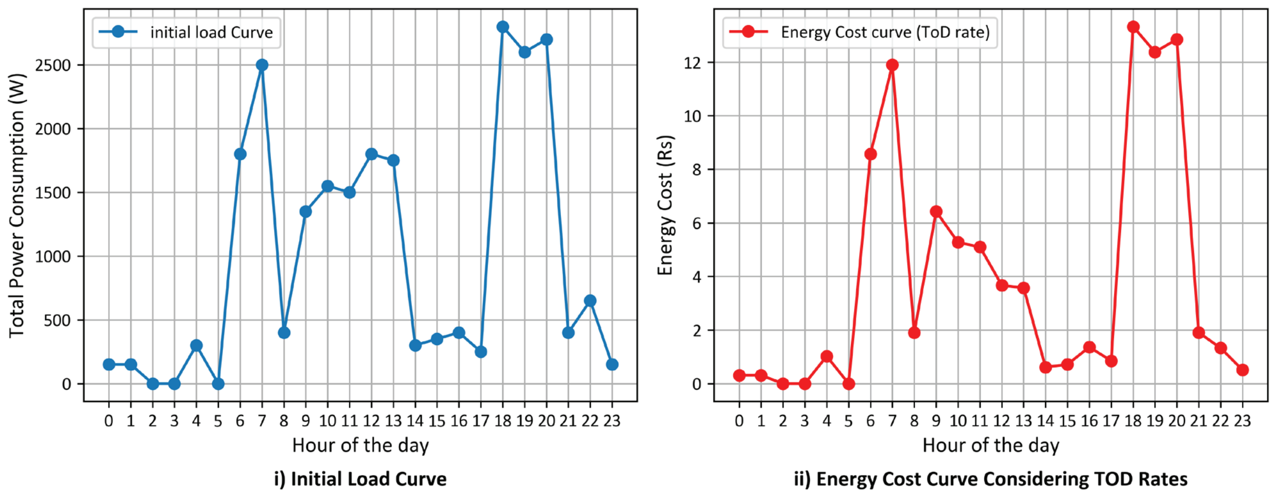


Figure 2. Energy Consumption and Cost Curve of smart home.

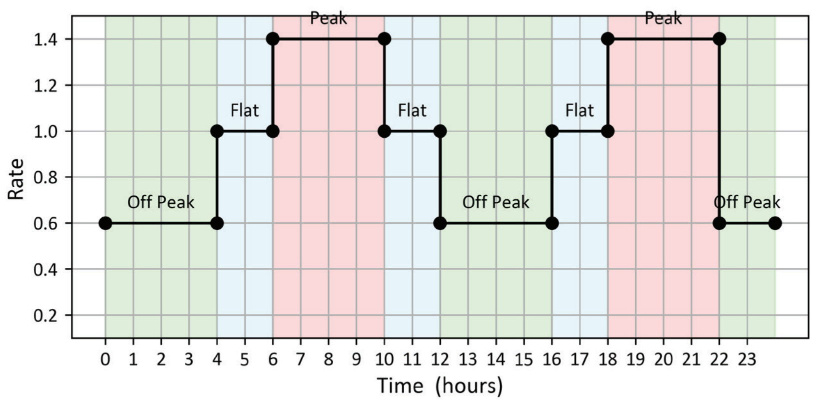


Figure 3. Consumer ToD tariff rates with respect to Slab rate.

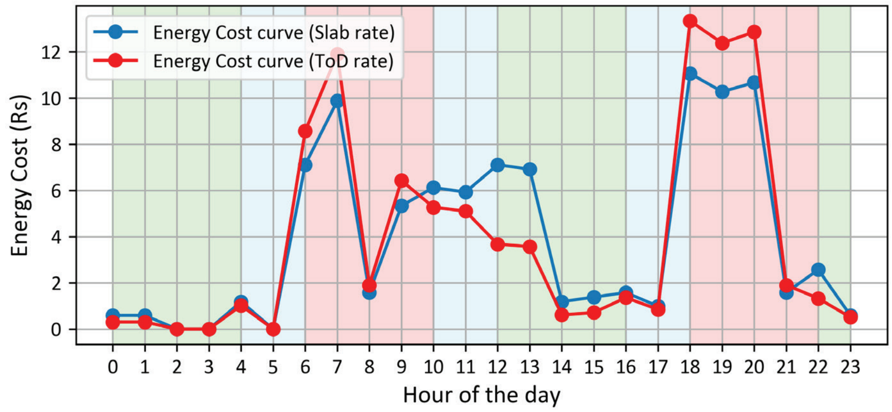


Figure 4. Comparison of Energy cost by Slab rate & ToD tariff.

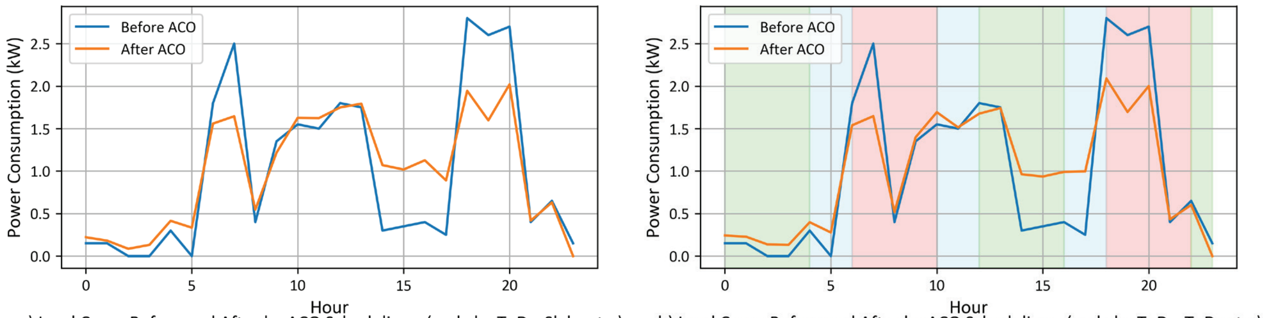
Table 3. Comparative results for cost minimization by kw saving & ToD tariff saving

Algorithm	Pricing		Result	KW saving	Cost Saving	% KW saving	% Cost Saving	PAR Redu.	% PAR Redu.
ACO	KW Slab	Scheduled KW	20.72	3.13		13.12		0.19	6.73
		Scheduled Cost	193.76		35.24		15.39		
	ToD	Scheduled KW	20.78	3.07		12.87		0.17	6.02
		Scheduled Cost	183.97		40.1		17.9		
	Total Saving			3.07	45.03	12.87	19.66	0.17	6.02
WOA	KW Slab	Scheduled KW	12.99	10.86		45.53		-1.6	-57.8
		Scheduled Cost	106.84		122.2		53.34		
	ToD	Scheduled KW	13.22	10.63		44.57		-1.6	-54.96
		Scheduled Cost	108.9		115.2		51.4		
	Total Saving			10.63	120.1	44.57	52.45	-1.6	-54.96
PSO	KW Slab	Scheduled KW	15.07	8.78		36.81		-0.6	-19.5
		Scheduled Cost	130.22		98.78		43.14		
	ToD	Scheduled KW	14.91	8.94		37.48		-0.5	-18.09
		Scheduled Cost	121.32		102.8		45.86		
	Total Saving			8.94	107.7	37.48	47.02	-0.5	-18.09
GA	KW Slab	Scheduled KW	21.25	2.6		10.9		0.28	9.92
		Scheduled Cost	199.8		29.2		12.75		
	ToD	Scheduled KW	21.36	2.49		10.44		0.28	9.92
		Scheduled Cost	156.54		68.27		30.37		
	Total Saving			2.49	72.46	10.44	31.64	0.28	9.92

slab rate is 23.85 Kw (Unscheduled KW) and cost is 229 Rs (Unscheduled cost). Initial Power consumption without appliances scheduling for ToD rate is 23.85 Kw (Unscheduled KW) and cost is 224.07 Rs (Unscheduled cost). So cost saving by ToD tariff is 05 Rs (2%) which is also observed in Fig. 3. Initial PAR without scheduling is 2.82.

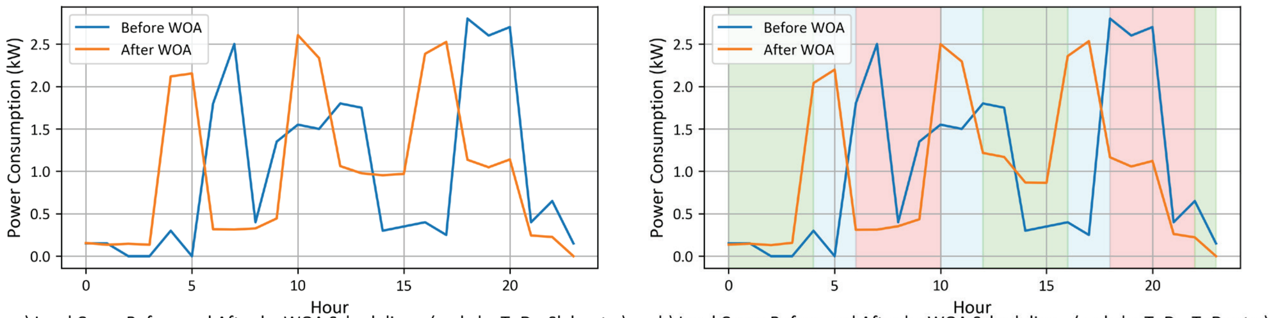
Computational Results for Case-I

The outcomes for case-I, where a flat rate tariff and Time of Day (ToD) tariff pricing are implemented are shown in Table 3. The table provides a comparative analysis of the electricity cost associated with the efficient scheduling of household appliances. This examination is conducted through SIP techniques employing in ACO, WOA, PSO, and GA algorithms. The load curve of Smart home before & after scheduling the appliances for each algorithm in case I is shown in Fig. 5, Fig. 6, Fig. 7 & Fig. 8. It is observed that some loads are not active for same day therefore there is saving in cost but due to this consumer comfort is disturbed because of unviability of specific load at important



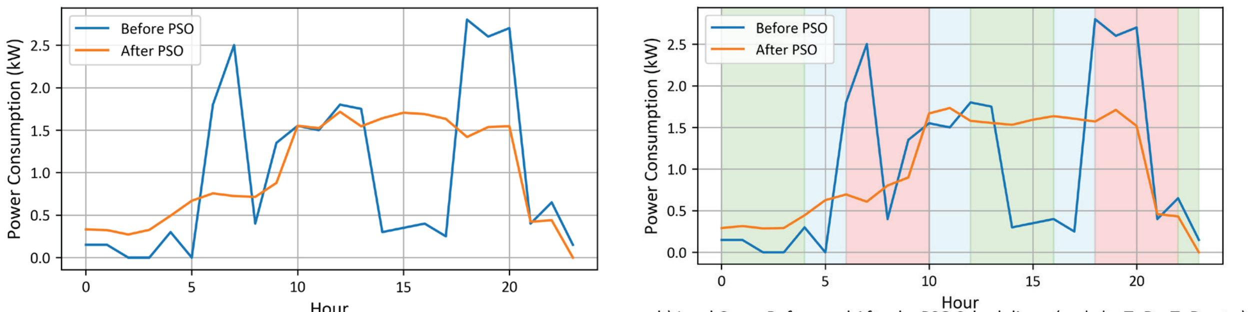
a) Load Curve Before and After by ACO Scheduling --(only by ToD --Slab rate) b) Load Curve Before and After by ACO Scheduling --(only by ToD --ToD rate)

Figure 5. Load curve Before and After Scheduling load by ACO a) Slab rate b) ToD rate.



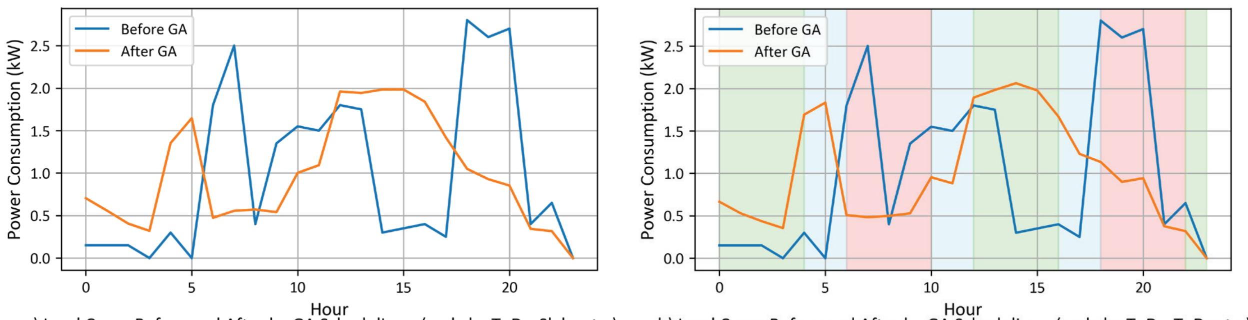
a) Load Curve Before and After by WOA Scheduling --(only by ToD --Slab rate) b) Load Curve Before and After by WOA Scheduling --(only by ToD --ToD rate)

Figure 6. Load curve Before and After Scheduling load by WOA a) Slab rate b) ToD rate.



a) Load Curve Before and After by PSO Scheduling --(only by ToD --Slab rate) b) Load Curve Before and After by PSO Scheduling --(only by ToD --ToD rate)

Figure 7. Load curve Before and After Scheduling load by PSO a) Slab rate b) ToD rate.



a) Load Curve Before and After by GA Scheduling --(only by ToD --Slab rate) b) Load Curve Before and After by GA Scheduling --(only by ToD --ToD rate)

Figure 8. Load curve Before and After Scheduling load by GA a) Slab rate b) ToD rate.

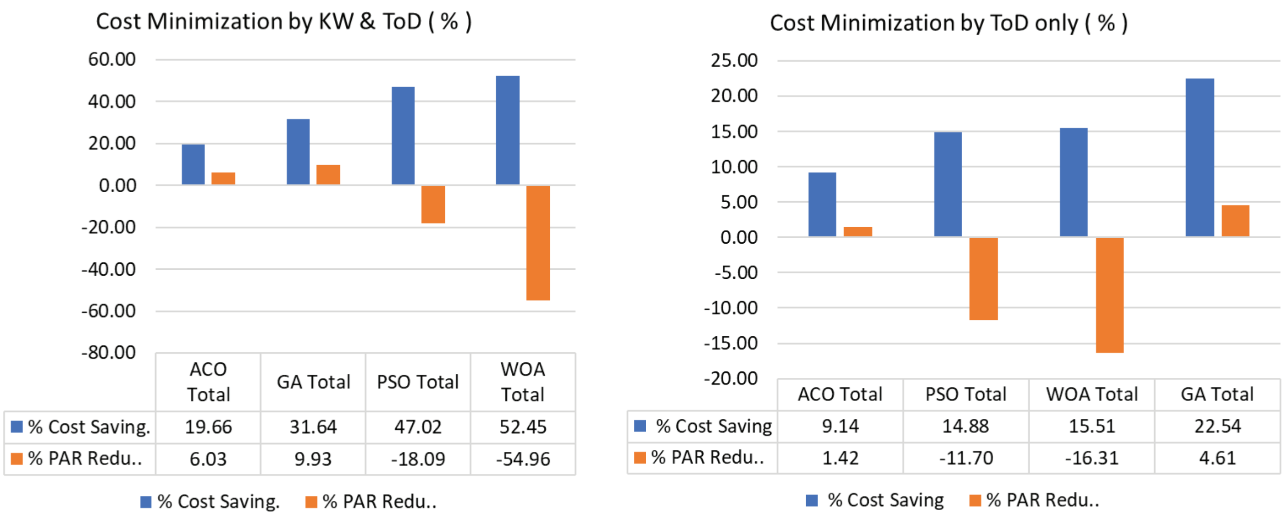
Table 4. Comparative results for cost minimization only by ToD tariff saving

Algorithm	Pricing		Result	KW saving	Cost Saving	% KW saving	% Cost Saving	PAR Redu	% PAR Redu.
ACO	KW Slab	Scheduled KW	23.85	0		0		0.05	1.77
		Scheduled Cost	229		0		0.00		
	ToD	Scheduled KW	23.85	0		0		0.04	1.42
		Scheduled Cost	208.06		16.01		7.15		
		Total Saving		0	20.94	0	9.14	0.04	1.42
WOA	KW Slab	Scheduled KW	23.85	0		0		-0.39	-13.83
		Scheduled Cost	229		0		0.00		
	ToD	Scheduled KW	23.85	0		0		-0.46	-16.31
		Scheduled Cost	193.48		30.59		13.65		
		Total Saving		0	35.52	0	15.51	-0.46	-16.31
PSO	KW Slab	Scheduled KW	23.85	0		0		-0.36	-12.77
		Scheduled Cost	229		0		0.00		
	ToD	Scheduled KW	23.85	0		0		-0.33	-11.70
		Scheduled Cost	194.93		29.14		13.00		
		Total Saving		0	34.07	0	14.88	-0.33	-11.70
GA	KW Slab	Scheduled KW	23.85	0		0		0.14	4.96
		Scheduled Cost	229		0		0.00		
	ToD	Scheduled KW	23.85	0		0		0.13	4.61
		Scheduled Cost	177.38		47.43		21.10		
		Total Saving		0	51.62	0	22.54	0.13	4.61

time. The percentage reduction in cost by optimal scheduling in case I with the help of all four algorithms comparison is shown in Fig. 9. (a) It is observed that ACO, WOA, PSO & GA algorithms minimized the electricity cost by 19.66%, 52.45, 47.02% and 31.52% respectively. In the same fig. PAR reduction is also shown for same as 6.03%, -54.96%, -18.09% and 9.93% respectively. Which shows that the optimal scheduling decreases cost but PAR reduction increases in some cases which is not good for the system. The best results are obtained by GA in consideration with cost saving and PAR reduction i.e 31.64% & 9.93%.

Simulation Results for Case-II

The load curve of Smart home before & after scheduling the appliances for each algorithm in case I is shown in Fig. 5, Fig. 6, Fig. 7 & Fig. 8. After load scheduling under slab rate



(a) Case I (b) Case II

Figure 8. Comparison of % cost saving & % PAR Reduction (a) case I (b) case II.

and ToD rate peak of load curve is minimized hence peak clipping is done. More amount of load is shifted in valley and flat tariff zone of ToD as compare to cost minimization by case I. In the case II cost minimization & PAR reduction by optimal scheduling of appliances in smart home with the help of ACO, WOA, PSO & GA algorithms is given in Table 4. The percentage reduction in cost by employing the algorithms are ACO (9.14%), WOA (15.51%), PSO (14.88%) & GA (22.54%). PAR reduction for the same are ACO (1.42%), WOA (-16.31%), PSO (-11.70%) & GA (4.61%) Which shows that cost saving is achieved in each case but reduction in PAR is not in every case. Total cost saving by scheduling the appliances by GA is 22.54% by shifting load in low ToD Tariff rate & PAR reduction is 4.61% which is greater than ACO, WOA & PSO.

If GA is employed for load scheduling under ToD tariff rate, without changing consumer power consumption (23.85 kW keeping Constant), cost saving in actual energy bill (22.54%). Also, the PAR reduced by 4.61% which is greater than KW slab rate this not happen in cost minimization by KW & ToD tariff.

CONCLUSION

In this study, the focus was on reducing electricity expenses for residential consumers while maintaining user comfort and decreasing the peak power demand to average demand ratio. Comparative results were obtained for fixed charges under the current scenario and after applying Time of Day (ToD) tariff. Different algorithms were used to optimize appliance scheduling and minimize costs. The results shows that ToD tariff led to cost savings of 2% compared to the current scenario.

The simulation results for case-I presented in this study demonstrate the effectiveness of employing like Ant Colony Optimization Algorithm (ACO), Whale Optimization Algorithm (WOA), Particle Swarm Optimization Algorithm (PSO), and Genetic Algorithm (GA) for optimal scheduling of appliances in a smart home under flat rate and ToD tariff pricing. The analysis of electricity pricing and adjustments to the load curve, conducted both prior to and subsequent to the implementation of scheduling, reveals significant decreases in expenditures; however, it is important to note that certain disruptions to consumer comfort may arise as a result of load unavailability during pivotal periods. Among the various algorithms scrutinized, the Genetic Algorithm (GA) emerges as the most effective in achieving a balanced interplay between cost reductions (31.64%) and reductions in the Peak-to-Average Ratio (PAR) (9.93%).

In the context of case-II, the findings reveal that load scheduling in accordance with Time-of-Day (ToD) tariff pricing facilitates peak clipping and promotes enhanced load distribution efficiency. The Genetic Algorithm (GA) once again surfaces as the preeminent algorithm, demonstrating noteworthy cost reductions (22.54%) and PAR decreases (4.61%) in comparison to the Ant Colony Optimization Algorithm (ACO), Whale Optimization Algorithm (WOA), and Particle Swarm Optimization Algorithm (PSO). In summary, the Genetic Algorithm (GA) substantiates its status as a viable option for the optimization of appliance scheduling within intelligent home environments, delivering significant advantages in terms of cost efficiency and reductions in PAR.

NOMENCLATURE

C_{P_f}	Specific heat, kJ / kg °C
AEC^S	Appliance Energy Consumption for slot, watt.
AEC_n	Nth Appliance Energy Consumption, watt.
AEC_T	Total Appliance Energy Consumption, watt.
C	Energy Cost, Rupees
E_{rate}	Energy Rate, Rupees
P_{rate}	Power rating, Watt
ω_T	Waiting Time, Sec.

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