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Comfort Level and Increased Utilization in Smart Buildings by Promoting Sustainability: A New Hybrid Genetic and Bat Algorithms

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ABSTRACT

The challenge of effectively managing energy consumption in smart buildings has become increasingly significant in recent years. Both macroeconomic and microeconomic frameworks stand to benefit from efficient energy management strategies. Additionally, it is essential to ensure that tenants in smart buildings experience acceptable levels of comfort. By utilizing optimization algorithms, we can minimize energy consumption while maximizing user convenience. In this paper, we propose an agent-based optimization method grounded in a multi-layered architectural framework and its architecture comprises an intelligent agent that communicates with one another within a three-tier network system. Our research specifically focuses on reducing energy consumption costs and peak demand rates while simultaneously enhancing user comfort to the highest possible standard. However, this optimization challenge is notably complex due to the vast array of electrical devices and their varying functionalities. To address this complexity, we propose a hybrid optimization approach that leverages both Genetic Algorithms (GA) and Bat algorithms and evaluated the performance of our method using specific objective functions and drawn comparisons with recent studies on Smart Home and CU-BEM datasets. The switch layer is responsible for monitoring user preferences and comfort levels. The coordination layer features a coordinating agent tasked with determining the optimal scheduling of electrical appliances to achieve cost reductions in electricity consumption while maximizing user comfort. Finally, the execution layer consists of performing agents directly managing device operations. This comprehensive approach seeks to create a more sustainable energy management system in smart buildings, contributing to both economic efficiency and enhanced tenant satisfaction.

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1. INTRODUCTION

Energy management has garnered significant attention in recent decades due to its critical role in the economic development process. This focus has led to numerous studies in the field of energy resource management [1]. Given that appliances account for a substantial portion of energy consumption, enhancing the efficiency of energy use in these devices can have a profound impact on the economy [2],[3]. With the proliferation of smart and intelligent electronic devices in modern life, energy consumption has surged in both the short-term and long-term sectors. Consequently, optimizing energy consumption in appliances has emerged as a vital challenge. To effectively utilize smart electronic devices, it is essential to transform traditional energy consumption patterns, employ optimization techniques, and manage usage schedules efficiently. Demand-side management (DSM) plays a pivotal role in smart grids, aiming to optimize load scheduling and electricity consumption, thereby enhancing overall energy efficiency [4]. However, while smart grids incorporate tools for user interaction to manage electrical devices, these tools often lack the necessary incentives to motivate users to engage effectively. For instance, individuals may become preoccupied with their daily routines and fail to manage their electrical devices optimally. Therefore, there is a pressing need for a smart grid system capable of performing this management autonomously and efficiently [5]. On one hand, reducing energy consumption and costs is imperative for residents; on the other hand, ensuring that their comfort levels remain satisfactory is equally important. A well-designed smart grid should balance these two aspects, providing not only cost savings but also maintaining an acceptable quality of life for users. By integrating advanced algorithms and user-friendly interfaces, smart grid systems can enhance user engagement, optimize energy consumption, and ultimately contribute to sustainable energy practices. This holistic approach not only addresses the immediate challenges of energy management but also fosters long-term economic and environmental benefits.

Smart air conditioners are integral components of advanced air conditioning systems that enhance environmental quality. These intelligent devices regulate temperature, humidity, and ventilation to create a comfortable indoor atmosphere. To achieve optimal user comfort while minimizing energy consumption, there is a critical need to refine both traditional and innovative methods through the application of optimization techniques. Such improvements not only enhance energy efficiency but also bolster the stability and reliability of smart systems [6]. By leveraging data analytics and machine learning algorithms, smart air conditioners can learn user preferences and environmental conditions, adapting their performance in real-time. This leads to a more sustainable approach to climate control, ultimately contributing to energy conservation and improved user satisfaction [7].

Given that more than 90% of individuals spend the majority of their time indoors [8], the built environment significantly influences inhabitants' productivity, morale, and overall satisfaction. Consequently, addressing economic competitiveness while adhering to increasingly stringent environmental standards within the building industry presents an ongoing challenge for researchers. Building Energy Resource Management (BERM) serves as a crucial mechanism for achieving the critical objectives of enhancing environmental quality and promoting energy conservation in building operations. By implementing effective BERM strategies, inhabitants can reduce their energy bills while simultaneously improving their quality of living and comfort. Generally, three primary parameters define a building's indoor comfort conditions: thermal comfort, visual comfort, and air quality [9].

Thermal comfort is primarily indicated by the temperature index experienced by inhabitants. Auxiliary heating and cooling systems are employed to maintain a comfortable indoor temperature. Visual comfort, on the other hand, is assessed through the brilliance level of indoor lighting, which can be achieved using both natural and artificial lighting fixtures to meet the required visual comfort standards. Air quality is measured by the concentration of carbon dioxide (CO_2) within the indoor environment; both natural and mechanical ventilation systems are utilized to ensure acceptable CO_2 levels in buildings.

It is well established that thermal comfort is quantified using the Predictive Mean Vote (PMV) index, which depends on various factors, including temperature, airflow rate, humidity, mean radiant temperature, and clothing insulation. The PMV index typically ranges from -3 to $+3$, with a fluctuation range of -0.5 to $+0.5$, resulting in a satisfaction rate of approximately 90% among users [10]. Given that temperature is the most significant factor influencing the PMV index and is relatively easy to measure, it has been identified as the primary thermal comfort factor for this study. Similarly, visual comfort is assessed through the brilliance level measured in lux, although other factors such as glare and wall color reflections are subjective and more challenging to quantify. Indoor air quality is primarily influenced by the concentration of pollutants within the controlled space. Research indicates that CO_2 concentration can serve as a proxy for user presence and various pollution sources within the building [11]. The presence of an intelligent control system for Building Energy Management (BEM) is essential for optimizing energy consumption while minimizing indoor discomfort. The primary objective of such a control system is to achieve minimal energy usage and reduced discomfort levels by optimally utilizing outdoor environmental conditions. Two crucial factors influence these objectives: user preferences and outdoor climatic conditions. Recent studies have explored BEM systems in modern smart buildings, highlighting the importance of effective control strategies [12].

Various approaches to comfort control have been developed, with conventional ON/OFF and Proportional Integral Derivative (PID) controls being widely utilized [13]. However, these traditional methods often lead to excessive energy consumption due to frequent overshooting and oscillations in comfort parameter set points. Consequently, conventional control strategies typically fail to deliver optimal performance. Feedback PID controllers, characterized by constant parameters and a lack of information regarding the control process, often exhibit poor performance, particularly in the presence of noise and nonlinearities [14]. In contrast, advanced control schemes and artificial intelligence applications [15] have emerged, including predictive [16], adaptive [17], and optimal controllers [18] designed to ensure thermal comfort while minimizing overshoots in comfort set points. Adaptive control strategies employing pole placement optimal regulators have been implemented for temperature control [19]. Furthermore, predictive control utilizing weather forecasts has been applied to heating, ventilation, and air conditioning (HVAC) systems, incorporating mathematical models to evaluate energy-saving potential [20],[21].

Fuzzy logic approaches for visual comfort have been explored, notably by Dounis et al. [13], while the integration of daylighting with lighting control is discussed in [16]. Robust airflow rate control strategies have been investigated [17], and fuzzy reasoning has been employed for air quality control [18]. Additionally, various computational methods, such as Artificial Neural Networks (ANN) and neuro-fuzzy systems [23], as well as Genetic Algorithms [24], have been proposed for optimized control within smart buildings. Building system optimization can also include weighted fuzzy rule bases [25], contributing to more efficient energy management and enhanced comfort levels. The integration of advanced technologies in smart buildings represents a significant advancement in energy management and occupant comfort. By leveraging innovative control strategies and optimization techniques, the building industry can address pressing environmental challenges while enhancing the quality of life for its occupants. As research continues to evolve in this field, the potential for smart buildings to contribute to sustainable development and energy efficiency remains promising, paving the way for a more environmentally responsible future.

The research presented in [26] focuses on a neural-fuzzy algorithm that utilizes object information for energy optimization in smart homes. The proposed system considers three critical variables: energy consumption rate, electronic energy rate, and waste energy rate, with the aim of saving and reducing overall electricity consumption. To accurately calculate the energy consumption rate in smart homes, various components are employed, and the coefficients for each of these components are derived using the Analytic Hierarchy Process (AHP) algorithm. This systematic approach allows for a more nuanced understanding of energy use patterns within residential settings. In another study [27], the application of artificial intelligence (AI) and its extensive impact on living conditions and lifestyle dynamics are examined. The primary advantage of AI systems over traditional systems lies in their enhanced ability to optimize both management and technical aspects of energy consumption. This capability is crucial in the context of smart buildings, where efficient resource management directly correlates with occupant comfort and energy savings.

Further exploring this theme, the research in [28] investigates the implementation of AI in smart buildings, specifically focusing on the regulation of lighting and heating systems. The findings suggest that integrating AI technologies can lead to substantial improvements in energy efficiency and occupant satisfaction. Additionally, the article [29] describes the development of a smart building framework that involves defining and implementing specific protocols, alongside producing network-equipped devices. This research delves into the selection of appropriate protocols tailored to the unique conditions and needs of a building, and it highlights the successful implementation of these solutions in real-world scenarios. In a separate study [30], statistics reveal that residential buildings in Neyshabur exhibit the highest levels of energy consumption. This research aims to optimize energy usage in reception halls within the city, employing fuzzy logic and fuzzy control systems to achieve this goal. Notably, the data extracted from sensors in this study are dynamic, reflecting real-time changes in energy consumption patterns. This adaptability is essential for effective energy management in smart homes.

The research presented in [2] introduces a general approach to demand management, formulating the problem based on the complexities associated with the woolen knapsack problem and ant colony optimization techniques. The findings indicate that energy management controllers utilizing ant colony optimization demonstrate superior performance compared to traditional methods. This insight underscores the potential of bio-inspired algorithms in enhancing energy management strategies. In article [31], a scheduling algorithm for the activation of electronic devices is proposed, designed to maximize performance in terms of peak average rate, execution time, and user-friendliness. This paper employs a time-use scheduling scheme, relying on genetic algorithms to optimize device activation. The results show that while the proposed method effectively reduces peak average rates and electricity costs, there remains room for improvement in terms of user-friendliness, highlighting a critical area for future research. The study in [32] presents a real-time framework for the energy management system of a smart microgrid, utilizing smart agents to facilitate communication and coordination. This integration of energy management with power systems through telecommunication networks allows for the development of algorithms that provide optimal solutions based on various scenarios and system characteristics. The framework enables a comprehensive evaluation of energy management designs and the impact of the developed algorithms within the smart agent-based system. The use of smart agents is increasingly recognized as a powerful approach in energy optimization, owing to their capabilities in communication, coordination, and task allocation, which enhances the robustness of energy management systems. A review article [33] explores the applications of agent-based systems in addressing optimization problems, specifically focusing on the development of smart home systems in the realm of energy management. This review highlights the growing importance of agent-based approaches in creating responsive and adaptive energy management solutions.

Moreover, the study in [34] tackles the challenge of reducing energy consumption while simultaneously increasing user comfort in the operation of heating and cooling devices within smart homes. The findings indicate that residents often express dissatisfaction with the labor-intensive tasks associated with adjusting their preferences and learning to operate these systems. To address this issue, the study proposes a system capable of learning from residents' behaviors, thereby automating heating and cooling planning. This adaptive learning approach not only enhances user experience but also contributes to more efficient energy usage. The integration of advanced algorithms and intelligent systems in energy management within smart homes and buildings is critical for optimizing energy consumption and enhancing occupant satisfaction. As research continues to evolve in this field, the potential for these technologies to contribute to sustainable energy practices and improved living conditions remains significant. The ongoing exploration of AI, fuzzy logic, and agent-based systems offers promising avenues for further development, paving the way for smarter, more efficient energy management solutions in the future.

Research has demonstrated that smart grids offer new opportunities and techniques to address the increasing energy demand within the rapidly growing energy sector. This evolution presents a significant challenge in the field of energy management systems, ultimately leading to the development of innovative software solutions for smart grids in the future. A critical factor for the successful advancement of a smart grid is the ability to manage energy resources effectively, encompassing aspects from generation to storage. This paper conducts a thorough review of prior studies related to energy management within smart grids, examining the objectives, limitations, and communication models inherent in various energy management frameworks. By synthesizing insights from these previous works, we aim to propose an effective methodology for enhancing energy consumption while simultaneously increasing user comfort, with a focus on mitigating the shortcomings identified in the existing approaches. In this study, we employ a hybrid method that combines genomic algorithms with detection algorithms. We compare the performance of this hybrid approach with that of other methodologies previously presented in the literature. The proposed approach consists of a system structured around three interconnected layers: switch agents, coordinator agents, and execution agents. This networked architecture facilitates seamless information sharing among the various layers of the model, resulting in enhanced performance and efficiency in energy management. Ultimately, our research contributes to the ongoing development of smart grid technologies, fostering improved energy efficiency and user satisfaction.

In general, the two primary objectives of minimizing energy consumption within systems and maximizing user comfort often conflict with one another. This optimization problem presents two opposing goals, striving to achieve the best possible outcomes for both parameters simultaneously. The primary aim of this research is to identify a solution that minimizes costs while maximizing utility for residents. To summarize, the objectives of this research are: (1) to model the interrelationship between energy consumption and user comfort, taking into account real-world requirements, and (2) to provide an optimal and efficient method for resolving the associated optimization problem. The literature on optimizing and scheduling devices to enhance energy consumption and user satisfaction indicates that algorithms such as Health Planning and Dynamic Planning, despite their high accuracy, struggle to manage a large number of electrical devices effectively. Consequently, addressing multi-objective problems with these methods becomes a complex and challenging endeavor. In the remainder of this article, we will review relevant research in Section 2. Section 3 will define the problem at hand and present a model for it. Subsequently, the proposed method will be detailed in Section 4. Following that, Section 5 will outline the implementation approach, including the experiments conducted and the results obtained. Finally, in Section 6, we will discuss our findings and offer suggestions for future research, with the goal of further advancing the field of energy management and enhancing user experiences in smart environments.

2. PROBLEM DEFINITION

The primary issue addressed in this paper is the reduction of energy consumption, monetary costs, and the peak average rate, while simultaneously maximizing user comfort at the highest level of machine operation. In this context, we classify electrical devices into four categories: fixed devices, dimmable devices (T), and removable devices (I). Power consumption, along with the costs associated with controlling energy usage, can be reduced by strategically changing the on/off states of these devices, all while ensuring energy efficiency is maintained. To mitigate the peak average rate and lower financial costs, we propose shifting the load of removable electrical devices from peak periods to off-peak hours. An upper limit is established for electrical load during peak times to prevent excessive consumption. Additionally, user energy efficiency is evaluated based on temperature (TE), and our goal is to achieve optimal air quality (AI) while adhering to energy consumption constraints. It is essential to note that these factors hold varying degrees of importance from the user's perspective. To represent this, we utilize parameters μ and μ_2, indicating the relative significance of each factor within the optimization framework. We ensure that each factor satisfies the conditions outlined in Equation (1), thus providing a balanced approach to energy management and user satisfaction.

$$\mu_1 + \mu_2 + \mu_3 = 1 \tag{1}$$

$$Min \sum_{j=1}^{nT} Cj \left(\sum_{i=1}^{nDf} \rho_{ij}^{f} + \sum_{i=1}^{nDt} \rho_{ij}^{t} x_{ij}^{t} + \sum_{i=1}^{nDi} \rho_{ij}^{i} x_{ij}^{i} + \sum_{i=1}^{nDs} \rho_{ij}^{s} x_{ij}^{s} \right) \tag{2}$$

$$Max\ min_j \sum_{i=1}^{nD} \mu_1 TE_{ij} + \mu_2 IL_{ij} + \mu_3 AI_{ij} \tag{3}$$

$$TE_{ij} = (te \times nDf) + \sum_{j=1}^{nT} \left(\sum_{i=1}^{nDt} T_{ij}^{t} x_{ij}^{t} + \sum_{i=1}^{nDi} T_{ij}^{i} x_{ij}^{i} + \sum_{i=1}^{nDs} T_{ij}^{s} x_{ij}^{s} \right) \tag{4}$$

$$IL_{ij} = (il \times nDf) + \sum_{j=1}^{nT} \left(\sum_{i=1}^{nDt} I_{ij}^{t} x_{ij}^{t} + \sum_{i=1}^{nDi} I_{ij}^{i} x_{ij}^{i} + \sum_{i=1}^{nDs} I_{ij}^{s} x_{ij}^{s} \right) \tag{5}$$

$$AI_{ij} = (il \times nDf) + \sum_{j=1}^{nT} \left(\sum_{i=1}^{nDt} A_{ij}^{t} x_{ij}^{t} + \sum_{i=1}^{nDi} A_{ij}^{i} x_{ij}^{i} + \sum_{i=1}^{nDs} A_{ij}^{s} x_{ij}^{s} \right) \tag{6}$$

$$MnTE_{ij} \leq TE_{ij} \leq MxTE_{ij} \tag{7}$$

$$MnIL_{ij} \leq IL_{ij} \leq MxIL_{ij} \tag{8}$$

$$MnAI_{ij} \leq AI_{ij} \leq MxAI_{ij}\ ) \tag{9}$$

$$x_{ij}^{t} \geq 0 \tag{10}$$

$$x_{ij}^{i} \in \{0\ 1\} \tag{11}$$

$$x_{ij}^{s} \in \{0\ 1\} \tag{12}$$

Energy optimization in smart systems is frequently framed as multi-objective problems characterized by high complexity. Consequently, traditional exact optimization methods may prove inefficient in addressing these challenges. In contrast, meta-optimization methods, such as genetic algorithms and particle swarm optimization, have emerged as effective alternatives. These approaches are capable of navigating the intricate solution spaces of complex problems, offering acceptable and near-optimal solutions. By employing these methods, researchers can enhance energy efficiency while considering various conflicting objectives, ultimately contributing to the development of more sustainable smart systems. Genetic algorithms, ant colony optimization [35], particle swarm optimization [36], flower pollination algorithms [37], and diffusion algorithms [5] are among the most effective optimization methods utilized for addressing a variety of problems that have garnered significant interest from researchers in both academia and industry. While these methods may not always identify the optimal solution, they frequently yield acceptable and viable alternatives. In recent years, numerous optimization methods and approaches have been proposed specifically for minimizing energy consumption costs. Most of the existing approaches tend to rely on a single optimization method to derive all relevant parameters for the problem, which can compromise the quality of the solutions obtained. Consequently, many optimization techniques are highly dependent on their initial conditions, making them susceptible to suboptimal outcomes. A systematic and intelligent combination of multiple optimization methods can effectively mitigate the inherent limitations of individual techniques while leveraging their strengths. Each optimization method operates differently and extracts diverse characteristics from the problem at hand.

In the context of a hierarchical hybrid intelligent system, each layer contributes valuable insights to the layers above it, enhancing the overall decision-making process. The collective performance of such a system is contingent upon the efficient functioning of its constituent layers. Our proposed approach for energy consumption management is structured around intelligent agents, where several agents are interconnected within a network, as illustrated in Figure 1. The first layer of the system is composed of the switch agent, which is responsible for determining and monitoring user preferences and satisfaction levels. This agent gathers data through sensors embedded within the smart system, ensuring accurate and timely information collection. The subsequent layer—the coordinator agent—serves as the central decision-making entity, focusing on optimizing the timing of electronic devices. Its objectives are to minimize electricity consumption costs while maximizing user satisfaction, which remains the primary focus of our research. Finally, the execution layer implements the decisions made by the coordinator agent by activating various agents and devices as required. This layered architecture fosters an adaptive and responsive energy management system capable of addressing the complex dynamics of energy consumption. By integrating these different optimization methods and employing a hybrid system of intelligent agents, our approach aims to strike an optimal balance between energy efficiency and user comfort. The interplay among agents not only enhances the robustness of the system but also provides a comprehensive framework for addressing the multifaceted challenges associated with energy management in smart systems. Ultimately, this methodology represents a significant advancement in the field of energy optimization, paving the way for more efficient and user-centered solutions in energy management applications. Through continued research and development, we hope to refine these approaches further, leading to greater sustainability and improved quality of life for users in smart environments.

In this study, we propose a novel method based on genomic and echolocation algorithms to address the optimization problem at hand. The echolocation optimization algorithm is an evolutionary strategy inspired by the hunting characteristics of echolocation in nature. This method utilizes sound reflections to detect prey, drawing parallels to how agents can identify optimal solutions within complex problem spaces. This method aims to enhance the efficiency and effectiveness of the optimization process, leading to improved results in energy management applications.
The echolocation optimization algorithm consists of several key steps:

1. Creating an initial set of echo agents.
2. Determining the speed, frequency, pulse rate, loudness, and location of each echo agent.
3. Comparing the positions of the echo agents to identify the optimal echo location.
4. Updating the status of the echo agents based on the best identified location.
5. Generating a random step towards the selected optimal solution.
6. Creating new solutions derived from modifications in the positions of echo agents.
7. Evaluating the convergence condition of the nodes, or repeating step 4 as necessary.

The sequential orientation and exploitation of the best solutions derived from the Tafash algorithm renders this method a viable option for addressing optimization problems. However, a notable drawback of this approach is its reliance on initial solutions and its high sensitivity to the initial environment, which can significantly influence the outcome. In contrast, the flower pollination algorithm, inspired by the natural process of pollen transfer among flowers, facilitates the development and survival of plant species. This algorithm operates through four primary components:

1) Global and Opposite Pollination: This step aims to identify the best solution among all existing solutions within the current generation.

2) Local Pollination and Mass Pollination: This process enhances the exploration of the solution space by allowing for localized adjustments and broader searches.

3) Insect Pollination: This component defines the movement patterns of pollinating insects, simulating their role in the pollination process.

4) Balancing Local and Global Pollination: This step ensures a harmonious integration of local and global search strategies, optimizing the exploration and exploitation of solutions.

By leveraging these mechanisms, the flower pollination algorithm effectively addresses the challenges associated with optimization tasks. One of the most significant limitations of the flower pollination method is its lack of a mechanism to escape local optima, resulting in a high probability of becoming trapped within them [38]. To address this issue, our proposed method incorporates the genomic algorithm, renowned for its robust exploration capabilities, to prevent entrapment in local optima. In this approach, the optimization problem is first addressed using the genomic algorithm, and the resulting solution is subsequently utilized as the initial solution for the search algorithm. This strategy effectively mitigates the challenge of determining a suitable initial solution for the search algorithm. The process underlying our proposed method is illustrated in Figures 2 and 3. Throughout the operation of this system, various data description activities are conducted on the embedded dataset to facilitate a comprehensive understanding of the data. These activities involve several criteria that establish an initial overview of the dataset, including aspects such as the number of observations, the number of features, skewness, kurtosis, the types of features, and the identification of outliers. Following the data identification phase, the quality of the dataset is meticulously assessed for ambiguities, missing values, and inconsistencies. This stage is crucial, as ensuring high data quality is foundational to the effectiveness of the optimization process. Once the data identification is successfully completed, preprocessing is performed to rectify potential errors within the dataset. Such errors may include values that deviate from defined standards or limits, duplicate features, and data that are in unsuitable formats for subsequent modeling. By addressing these issues, our method enhances the reliability and accuracy of optimization results, leading to improved overall system performance.

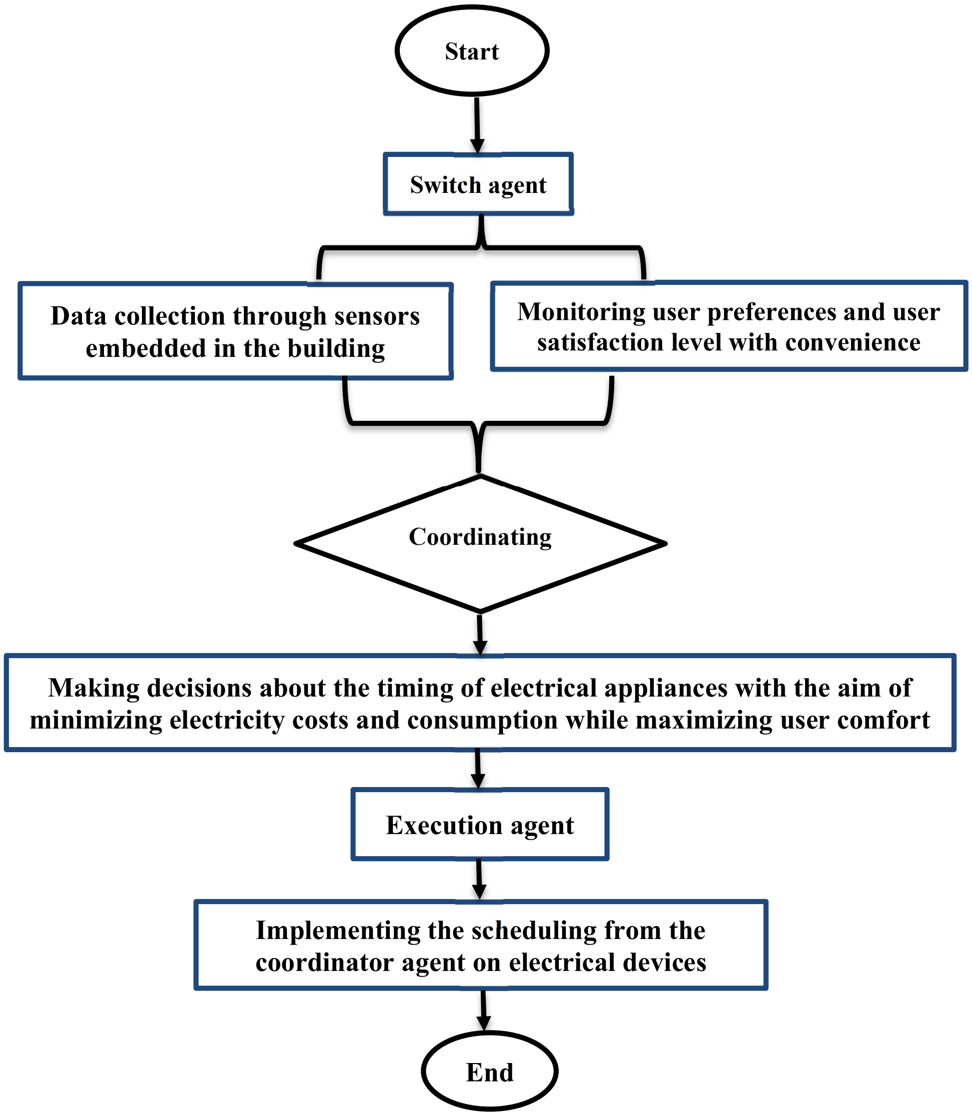

Figure 1. Displaying the structure of the proposed agent-based methodology.

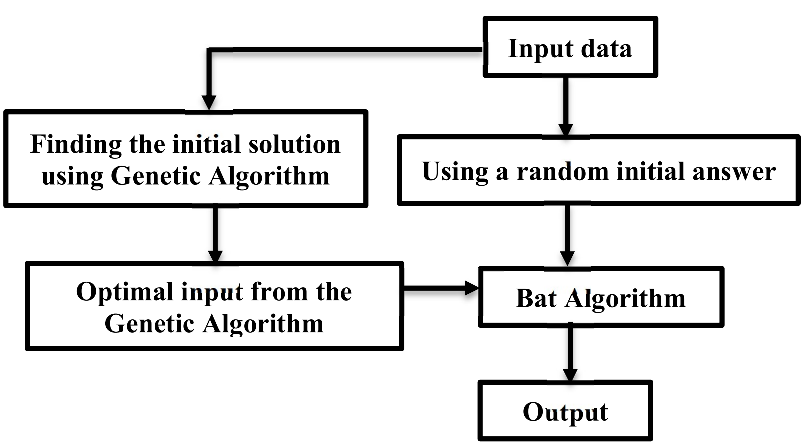

Figure 2. Process of the hybrid model of GA and Bat algorithm.

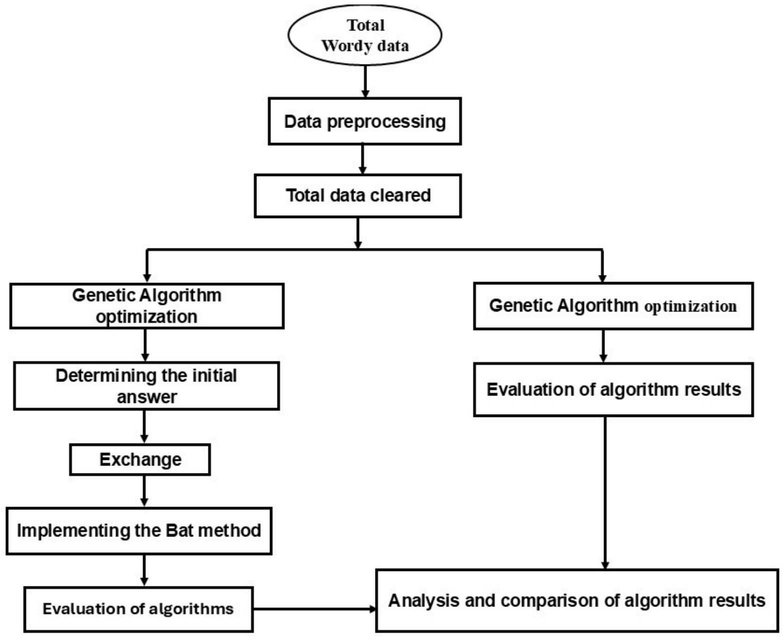

Figure 3. Data flowchart and proposed hybrid method based on GA and Bat Algorithm.

3. RESULTS AND DISCUSSIONS

One of the most crucial activities in the data preprocessing phase when working with large databases is feature selection. Feature selection involves identifying and incorporating features into the model that provides the most information and has the greatest impact on decision-making, while simultaneously removing irrelevant and insignificant features. Utilizing an excessive number of features, particularly when the feature count is high, can lead to increased memory consumption and, consequently, data inefficiency. In the data preprocessing phase, several essential steps are performed: data selection (including averaging, feature reduction, feature ranking, etc.), data refinement (addressing missing data, imprecise data, duplicate data, etc.), and data transformation (which encompasses data normalization, the addition of new features, and the splitting of values for associated features). The data selection phase focuses on averaging and managing missing, imprecise, and duplicating data effectively. In this research, the Greedy Hill Climbing method with backtracking is employed to determine the optimal number of features. This method iteratively explores the feature space to identify the most relevant features while ensuring that the model remains efficient and effective. After completing the data preprocessing, which includes selection, refinement, transformation, and integration activities, the input dataset is transformed using the Genomic Algorithm Optimization method, and the optimal solution is calculated. This solution is subsequently provided as the initial solution for the transformation algorithm. The errors generated by the genomic algorithm serve to improve the overall optimization performance. The proposed hybrid algorithm, which integrates the genomic algorithm and the T-switch, is illustrated in Figure 4. In this figure, the optimal training data input sets, denoted as D and T, are introduced in steps 1 and 2. In step 3, the data undergo normalization, scaling the dataset D to values between zero and one. Step 4 involves initializing the dataset, while step 6 entails creating initial chromosomes with random values for T, which are utilized in the genomic algorithm. In step 7, the generation number is initialized to zero. In step 8, the fitness of each chromosome is calculated using a cost curve, allowing for the evaluation of the performance of different solutions. The algorithm continues iterating until a stability condition is met, at which point the genomic algorithm is reapplied to the resulting solutions ($X1, X2, \ldots, Xn$). In step 11, the first solution derived from the genomic algorithm is selected for further use in the differentiation algorithm. Step 12 designates this solution as the initial solution for the differentiation algorithm, setting the stage for subsequent optimization processes. In step 13, parameters such as pulse rate, frequency, and loudness are initialized within the differentiation algorithm. Steps 14 and 15 involve executing the genomic algorithm process, during which all organisms are selected to participate in the combination process. Following this, a predetermined probability is applied to increase the mutation effect on the organisms, introducing variability and enhancing exploration of the solution space.

The fitness of the organisms is then calculated within the target environment, leading to the creation of a new environment, and one unit is added to the evolutionary stages. In step 16, the first solution obtained from the genomic algorithm and differentiation process is evaluated to ensure that it meets the criteria of minimizing consumption costs while maximizing efficiency during different times of the day. To evaluate the efficacy of the proposed method, data from two Smart Home databases [38]-[39] sourced from the Kaggle 3 database are utilized. The Smart Home dataset comprises readings taken at one-minute intervals over a span of 360 days, capturing the energy consumption in kilowatt-hours (kWh) of smart appliances managed by a smart home controller, along with corresponding weather conditions in a controlled laboratory environment. This dataset contains a total of 498,200 records with 25 attributes, which include 27 decimal attributes, 3 integer attributes, and 2 categorical attributes. Additionally, the Ubiase dataset encompasses the electricity consumption data of ventilation, air conditioning, and lighting systems measured in kilowatt-hours (kWh) for a seven-story building with a total area of 12,000 square meters located in Bangkok, Thailand. The Datli sensors utilized in this study measure air temperature, relative humidity, and illumination levels, providing a comprehensive view of the environmental factors affecting energy consumption. The experiments were conducted on a computer equipped with an Intel Dual Core processor running at 1 GHz and 2 GB of RAM. The Min-Max normalization method was applied to standardize the data, ensuring that all features contributed equally to the model's performance. Additionally, the Weka software tool was employed to facilitate the data normalization process, enhancing the overall efficiency of the data preprocessing phase. The proposed hybrid algorithm demonstrates a robust methodology for optimizing energy consumption in smart home environments. By effectively integrating genomic algorithms with the T-switch mechanism, this approach not only addresses the challenges associated with feature selection and data preprocessing but also leverages the strengths of both methods to achieve superior optimization results. Future work will focus on refining the algorithm further and exploring its applicability in various real-world scenarios, ultimately contributing to the development of more efficient energy management systems.

To model and prepare data for the genomic algorithm, we consider that there are four registered electronic devices, and thus, we define 96 genes for each chromosome. Each gene represents the operational state of an electronic device at a specific time, where a value of one indicates that the device is on and a value of zero indicates that it is off. For instance, the 35th gene corresponds to the operational state of the second electronic device during the time interval from 10:00 to 11:00. The fitness of each chromosome is determined using relationships (2) and (3). The primary objective is to minimize the electricity consumption rate while maximizing the user's minimum comfort level. To achieve this, we transform these two relationships into a single objective of minimizing the difference between total consumption and user comfort. Consequently, each chromosome is evaluated based on the value derived from relationship (2) subtracted by the value from relationship (3). In the genomic algorithm, we employ univariate cut-and-trial mutation and the roulette wheel selection method. The genomic algorithm continues to iterate until it meets the stopping condition, which is set at 180 iterations. The optimal solution generated by the genomic algorithm serves as the initial solution for the screening method. In this screening method, parameters such as frequency, pulse rate, and loudness are randomly initialized for each screening iteration. The fitness of each screening is assessed based on the solution they obtain, leading to updates of the frequency, pulse rate, and loudness parameters according to this fitness evaluation.

A key feature of the screening algorithm is its mechanism for escaping local optima. This is achieved by allowing screening to randomly reassign its parameters during the optimization process with a certain probability. These iterative steps are repeated until the best solution remains unchanged for ten consecutive iterations, indicating convergence. To evaluate user-friendliness and cost-effectiveness, we analyze the flower pollination and dispersal methods presented in the research [40], as well as the proposed hybrid method, which integrates dispersal and the genomic algorithm. Each method is executed separately on the dataset, and the proposed hybrid method consistently achieves the best solution in a relatively short time frame. Furthermore, we compare the proposed hybrid method, which combines dispersal and the genomic algorithm, with other established hybrid methods that utilize dispersal in conjunction with optimization techniques, such as ant colony optimization [41] and particle swarm optimization [5]. The rationale for selecting ant colony optimization and particle swarm optimization methods stems from their popularity and proven effectiveness in various optimization scenarios [42].

The simulation results demonstrate that the proposed hybrid method, which integrates clustering with the genomic algorithm, significantly enhances power consumption efficiency and user-friendliness compared to other hybrid approaches that combine clustering with ant colony optimization, clustering with particle swarm optimization, as well as standalone ant colony optimization [43] and particle swarm optimization [44]. These findings are visually represented in Figure 4, which illustrates the comparative performance of the proposed method against its counterparts. The integration of the genomic algorithm with the screening method provides a robust framework for optimizing energy consumption in smart electronic devices. The systematic approach to feature selection, combined with the adaptive mechanisms for escaping local optima, ensures that the proposed method is both effective and efficient. Comparative analysis with existing methods highlights the strengths of the proposed hybrid approach, paving the way for future research in energy optimization strategies.

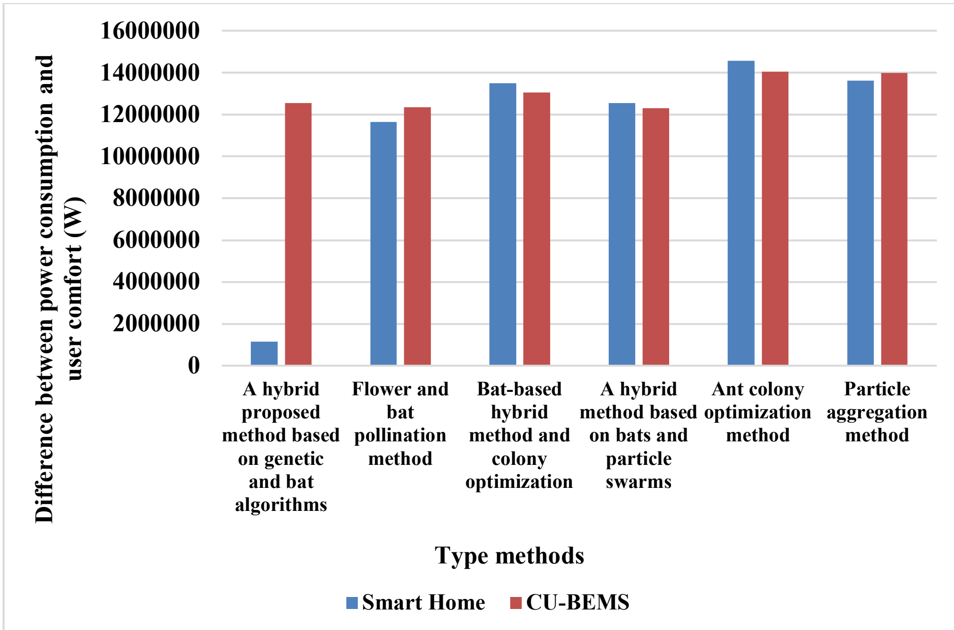

Figure 4. Comparison of CU-Bems and Smart home methods (based on differences in power consumption and optimal user comfort).

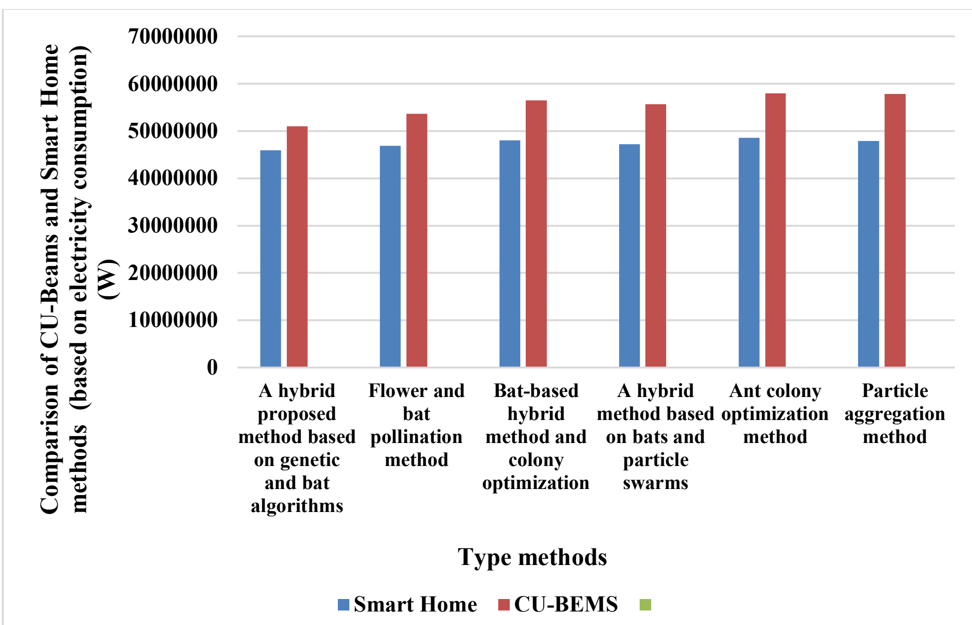

Figure 5. Comparison of CU-Bems and Smart home methods (based on electricity consumption).

Next, we will compare the resulting figure with two studies [42] and [33] that utilized the aforementioned datasets. In accordance with the findings reported in these studies, we employ the common criterion of electricity consumption costs to evaluate the effectiveness of the methods. The results depicted in Figure 5 illustrate that the proposed method has demonstrated a significant improvement in consumption costs for both the Smart Home and CUB datasets. Compared to methods such as flower pollination and its enhancements [5], as well as the combinations of pollination with ant colony optimization and pollination with particle aggregation, our proposed approach outperforms the standalone ant colony optimization [33] and particle aggregation methods [42]. This illustrates the effectiveness of our combined approach in reducing electricity consumption costs while enhancing overall efficiency. Some suggestions can be implemented to enhance the energy management in buildings. The integration of advanced machine learning techniques and data-driven modeling, as demonstrated in recent studies [44]-[45] provides significant opportunities for improving energy systems and building energy management. Predictive modeling approaches such as those used to estimate surface roughness and grinding forces under different coolant conditions [44] can be adapted to monitor and optimize energy-intensive systems within buildings. Furthermore, decentralized multi-agent learning frameworks [45] offer scalable solutions for energy load balancing and real-time decision-making across smart grids and building networks. The integration of AI in understanding dynamic systems in analyzing market-driven responses to technology adoption [46]. Ref. [47] explores how contemporary business dynamics can benefit from the integration of academic research into practical management strategies—an approach crucial for energy and building systems that require both technical efficiency and managerial foresight. Ref. [48] demonstrates how AI-assisted topic modeling can be leveraged to synthesize large volumes of data, a capability that is increasingly valuable in smart building management where real-time data must be interpreted for optimal decision-making. Additionally, [49] highlights the broader economic impacts of Silicon Valley's technological ecosystem, particularly the role of venture capital in accelerating innovation—a factor that directly influence the development and deployment of cutting-edge energy technologies. These recent contributions underscore the expanding role of machine learning and cybersecurity in shaping the future of digital infrastructures, including energy management and smart building systems. The authors of [50] have proposed a novel intrusion detection system for mobile social networks, offering methodologies that can also be adapted for securing smart energy grids and IoT-based building environments. Meanwhile, [51] applies machine learning techniques to analyze the impact of various factors on business economics—a framework that can similarly be utilized to assess and optimize energy consumption, cost efficiency, and operational performance in intelligent building systems. These additional studies emphasize the integration of intelligent decision-making, energy efficiency, and advanced modeling techniques, all of which are highly relevant to the development of sustainable energy and building management systems. Jamali and Abbasalizadeh [51] present a cost-aware, multi-criteria decision-making framework for co-locating IoT services—an approach that can be directly applied to optimize service placement and resource allocation in smart buildings. Soltani et al. [52] introduces a trust-aware and energy-efficient data gathering method using Particle Swarm Optimization (PSO) in wireless sensor networks, providing a valuable foundation for improving the energy performance and reliability of sensor-based monitoring in building environments. Meanwhile, Ghorbanian et al. [53] explore advanced machine learning techniques—specifically approximate Bayesian neural networks with functional priors—for surrogate modeling, which can enhance predictive maintenance and control in energy systems. Additionally, Farajijalal et al. [54] review mechanical parameter optimization in agricultural harvesting, offering insight into the broader application of smart system modeling, which can be adapted for optimizing mechanical and energy operations in building management. Collectively, these works demonstrate how advanced computational techniques, energy optimization, and smart decision-making are converging to improve the efficiency, sustainability, and intelligence of modern infrastructure systems. These studies, focusing on fault diagnosis and controller design in nonlinear and noisy systems, can be applied to building energy management systems by enabling early fault detection in HVAC equipment and energy distribution lines, thereby improving energy efficiency and system reliability [55]-[57]. Progressive collapse in structures can enhance building energy management by improving system resilience and ensuring continuous energy operation during component failures [58]. MCDM-based 3PL selection informs energy-aware logistics optimization [59]. Multistage stochastic model enhances energy efficiency in pharmaceutical supply chains by optimizing production, inventory, and logistics [60]. energy-efficient energy management can be improved by optimizing deep learning models for interpretability and resource constraints [61]. This approach can provide energy-efficient energy management by optimizing deep learning models for interpretability and resource constraints [62-63]. This study [64] enables energy optimized smart-building ML by combining real-time interpretability and quantization. This method can be used in energy management systems for GPU-accelerated, sampler-based CNN control of complex spatio-temporal dynamics [65].

4. CONCLUSION

Numerous researchers have focused on optimizing and scheduling electronic devices to enhance energy consumption and user satisfaction, predominantly utilizing health planning algorithms and dynamic scheduling techniques. While these methods exhibit high accuracy, they often struggle to manage a large number of electrical devices and to address multi-objective problems comprehensively, making their implementation complex and challenging. In this study, we propose a novel combined method that integrates the genomic algorithm with advanced analysis techniques to examine its performance in optimizing energy consumption. Furthermore, we have introduced the concept of incorporating air quality factors into the user satisfaction metric. In addition to reducing costs during optimization, we formulated the problem as a dual-objective programming challenge. The presentation of this combined approach is recognized as a significant innovation in our research. Our empirical results indicate that the proposed hybrid method, which integrates genomic algorithms and analytical techniques, has outperformed other methods examined in this study. These findings suggest a substantial improvement in both energy management and user satisfaction metrics. For future research, several avenues are recommended. In the current model, the number of electronic devices considered is fixed; however, a dynamic assessment could yield valuable insights, particularly within the context of graph-based methodologies. Additionally, the initial environment employed in the genomic algorithm was generated randomly. Utilizing local optimal solutions as starting points could enhance the overall solution quality. To achieve this, the divide-and-conquer strategy may be effectively employed to identify local solutions. Ultimately, this paper validates the proposed algorithm's effectiveness in managing energy consumption while optimizing user satisfaction. The potential application of this algorithm in addressing complex optimization problems could yield further advantages, emphasizing the need for continued exploration of innovative methodologies in energy management systems.

Acronyms:

Variables	Definition
nT	Number of time intervals
C_j	Electricity cost in time interval j
nDf	Number of fixed electrical appliances
ρ_{ij}^{f}	Electricity consumption rate of fixed electrical appliance i at time j
nDt	Number of electrical appliances with adjustable power levels
ρ_{ij}^{t}	Electricity consumption rate of variable electrical appliance i at time j
nDi	Number of electrical appliances that can be disconnected and reconnected
ρ_{ij}^{i}	Electricity consumption rate of variable electrical appliance i at time j
nDs	Number of movable electrical appliances
ρ_{ij}^{s}	Electricity consumption rate of movable electrical appliance i at time j
x_{ij}^{t}	Degree of activity of adjustable electrical appliance i at time j
x_{ij}^{i}	Operational status (On or Off) of switchable electrical appliance i at time j
x_{ij}^{s}	Operational Status (On or Off) of Movable Electrical Appliance i at time j
TE_{ij}	Temperature recorded from appliance i at time j
IL_{ij}	Illumination level recorded from appliance i at time j
AI_{ij}	Air quality level recorded from appliance i at time j

DECLARATIONS

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