applied sciences

MDPI

Article

Enhancing Energy Efficiency by Improving Internet of Things Devices Security in Intelligent Buildings via Niche Genetic Algorithm-Based Control Technology

Rui Liang [1], Yalong Xing [2] and Linhui Hu [3,*]

[1] School of Architecture and Urban Planning, Guangdong University of Technology, Guangzhou 510090, China; liangrui@gdut.edu.cn
[2] Faculty of Innovation and Design, City University of Macau, Macau 999078, China; xingyalong@cityu.mo
[3] College of Art and Design, Guangdong University of Technology, Guangzhou 510090, China
* Correspondence: hlh@gdut.edu.cn

Abstract: The security measures of IoT devices used in intelligent buildings are one of the ways by which energy efficiency can be accomplished. IoT devices are very important for data collecting and monitoring in intelligent buildings, but a lack of security could result in errors in energy consumption decisions that result in energy waste. To ensure the success of the control systems used for energy optimization, it is necessary to address the security of IoT devices in order to avoid illegal access, data manipulation, and disruptions. This work proposes a research idea and scheme for energy-saving optimization of intelligent buildings by assuring the security of IoT devices used in intelligent buildings. First of all, we defined several parameters that are related to IoT devices' security, energy consumption, and occupant comfort in the intelligent building environment. Secondly, we collected data for each of these parameters by utilizing IoT devices such as actuators, sensors, and other control systems. The niche genetic algorithm (NGA) refers to a particular class of genetic algorithms that is used to tackle problems involving many optimization objectives. We focused on optimizing both energy consumption and occupants' comfort; therefore, we used an NGA for the preprocessed data with the goal of evaluating the data for the purpose of ensuring the comfort of occupants and protection of the security of IoT devices, which eventually leads to energy optimization. Finally, the results of the proposed approach are analyzed and carefully compared with earlier work, demonstrating that our proposed approach is significantly more effective and energy-optimized than earlier approaches. The results show that the total power consumption of the intelligent building system after using our proposed model is generally reduced by more than 18% compared with that before optimization, which shows that the intelligent building system-adaptive optimization control model can effectively optimize the operating parameters of the energy-saving system and achieve the security of IoT devices.

Keywords: IoT devices security; niche genetic algorithm; intelligent building; energy-saving optimization

check for updates

Citation: Liang, R.; Xing, Y.; Hu, L. Enhancing Energy Efficiency by Improving Internet of Things Devices Security in Intelligent Buildings via Niche Genetic Algorithm-Based Control Technology. *Appl. Sci.* **2023**, *13*, 10717. https://doi.org/10.3390/app131910717

Academic Editor: Miguel García-Pineda

Received: 22 August 2023
Revised: 18 September 2023
Accepted: 22 September 2023
Published: 26 September 2023

1. Introduction

The term "intelligent buildings" was first used in the early 1970s and has only recently come to mean more than a conceptual framework for the representation of structures of the future. But as time goes on, intelligent buildings are quickly taking on a fundamental role in determining how future building rules will be developed [1]. Without a doubt, cities are going to be significantly influenced by intelligent buildings in order to support smart growth, sustainable development, and healthy ecosystems [2]. According to various authors and researchers, the term "intelligent buildings" has many different definitions, but the most comprehensive one is "one that offers an efficient and economical atmosphere via the optimization of its four basic elements, including structures, systems, services, and management, and the interrelationships between them" [3]. The term "intelligent building" was first used to describe a building focused on sustainability rather than cutting-edge technology, but more recently, both have been used. The Internet of Things (IoT), artificial intelligence (AI), and information and communication technology (ICT) serve as the foundations for intelligent buildings. With the use of these cutting-edge technologies, smart building not only tries to provide ease but also minimize energy consumption because more energy consumption is not only a waste of resources but also causes environmental problems.

IoT is without a doubt the key component of intelligent buildings because it integrates a variety of systems, sensors, and gadgets [4]. With the help of IoT, data collecting and monitoring tasks are carried out in the context of intelligent buildings while also being automated, which is crucial for sustainability and energy savings. Despite the countless advantages of IoT in the context of intelligent buildings, there are certain difficulties as well. Security and privacy issues are the most significant among all the difficulties intelligent buildings face when implementing IoT [5]. The extensive security and privacy features included in IoT devices used in smart buildings contribute to accurate data, reliable functioning, and occupant confidence. In intelligent buildings, these components serve as the cornerstone of successful energy optimization measures [6]. Building managers can make wise choices that result in greater energy saving without affecting the safety of the building's occupants or the accuracy, security, and privacy of the data collected and used for optimization.

Energy conservation has gained widespread attention and grown to be a crucial issue in the evolution of the global environment as a result of the increasingly serious environmental issues and the sense of crisis caused by the declining energy. There is a certain contradiction between building waste of resources and indoor thermal comfort in the process of constructing energy-efficient buildings [7]. On one hand, the national economy of China has been greatly harmed by the building waste of resources, which is one of the most significant aspects of resource waste and is expanding overall in China every year. Therefore, saving energy is a task that needs to be carried out immediately [8]. On the other hand, people's living conditions have significantly improved, and their demands for indoor comfort have grown as a result of economic growth and rising living standards. In order to create a better indoor thermal environment, homeowners are installing a rising number of air conditioners in their homes, and as a result, these air conditioners are using up an increasing amount of energy, which lowers the rate at which buildings conserve energy. Major concerns regarding livelihood are raised by the improvement in the living environment, and saving energy and reducing emissions is a significant national strategy. The guiding idea behind developing energy-efficient designs is to take both into account [9].

In order to fully address global concerns, it is crucial to incorporate energy sustainability into the context of the Sustainable Development Goals (SDGs) of the United Nations. In order to meet present requirements while preserving the ability of future generations to meet their own, energy sustainability refers to the wise and effective use of energy resources. This idea reflects the connection of environmental, social, and economic sustainability and has an unbreakable connection to multiple SDGs [10]. The SDGs are a series of 17 global goals that were announced by the United Nations in 2015 to address a variety of global concerns. Progress toward a number of these objectives depends critically on energy sustainability. The following are some of the objectives for energy sustainability. The goal of energy sustainability is to guarantee that everyone has access to modern, affordable, dependable, and sustainable energy [11]. A crucial prerequisite for economic growth, poverty reduction, and better living conditions is access to affordable, clean energy. In order to combat climate change, energy sustainability is essential since it encourages the use of renewable and low-carbon energy sources. To do this, it is necessary to switch to sustainable energy sources, cut greenhouse gas emissions, and lessen the effects of global warming. Technology and infrastructure innovation are fueled by sustainable energy. It encourages the development of resilient infrastructure, promotes innovation in renewable energy technology, and enables the creation of cleaner, more effective industrial processes, all of which promote economic growth and job creation [12].

Energy-saving techniques and improved occupant comfort have become crucial in the goal of sustainable and effective building design. Using cutting-edge techniques, architects, engineers, and designers are developing intelligent structures that support these goals. These structures aim to maximize energy consumption while offering residents a higher standard of living by utilizing the power of state-of-the-art techniques such as AI, data analysis, IoT, and evolutionary algorithms. A genetic algorithm (GA) is a kind of evolutionary algorithm that mimics some of the qualities of natural species such as evaluation and heredity. The GA always tries to find one global optimum solution; hence, it cannot be used for solving multi-modal function optimization problems. Keeping in mind the weakness of the conventional GA, researchers proposed a modified and advanced version of it called the niche genetic algorithm [13]. A niche genetic algorithm is a random global search and optimization method developed by imitating the biological evolution mechanism in nature [14]. In each generation of genetic algorithms, individuals are selected according to the fitness value of individuals in the problem domain, and the reconstruction method is borrowed from natural genetics to produce a new approximate solution. This process leads to the evolution of individuals in the population, and the new individuals are more adaptable to the environment than the original individuals, just like the transformation in nature [15]. In order to solve a multi-objective optimization problem and find the best solutions that simultaneously optimize many goals, such as energy conservation by ensuring the security of IoT devices and user comfort, this study uses the niche genetic algorithm. There are a lot of other optimization algorithms that specifically suit energy optimization for intelligent buildings. Some of the well-known algorithms, in this case, are simulated annealing, Tabu search, and other natural-inspired algorithms. However, we utilized NGA for our problem because we focused on energy optimization, IoT security, and occupant comfort in general. The other listed algorithms are suitable for some objectives but not for others. For example, the simulated annealing technique can be employed specifically for energy optimization by taking temperature, cooling schedule, etc. into account but it cannot give us a tradeoff line between occupant comfort, IoT security, and energy saving.

The basic structure of the niche genetic algorithm for the energy-saving optimization of intelligent buildings is similar to that of a genetic algorithm for single-objective optimization [16]. On the other hand, when using niche genetic algorithms to solve multi-objective optimization problems, it is necessary to consider how to evaluate the optimal solution and how to design the selection operator, crossover operator, mutation operator, etc., which are suitable for the energy-saving optimization problems of intelligent buildings. Therefore, the algorithm has its own unique features in implementation. In the implementation of the algorithm, the individual selection operation can be carried out on the basis of the optimization relationship among the sub-objective functions. The independent selection operation can also be performed for each sub-objective function; the niche technique can also be utilized. We can combine the original multi-objective optimization problem-solving method with the niche genetic algorithm to form a hybrid niche genetic algorithm. This paper contributes to the literature in the following ways.

After examining the problems with energy-saving optimal control technology and IoT security of intelligent buildings, this study discovered an optimal solution for the problem of resource waste in intelligent buildings. We proposed a state-of-the-art technique by utilizing the niche genetic algorithm to enhance life comfortability inside intelligent buildings by consuming the minimum energy possible. We presented a novel method that makes a tradeoff between energy saving by ensuring the security of the IoT devices utilized by the intelligent building and the comfort level of its occupant. In this paper, the problems of energy-saving optimal control technology of intelligent buildings by considering the security of IoT devices are studied, and the framework is as follows:

Section 1 is the introduction. This part mainly expounds on the research background and significance of intelligent building energy-saving optimization and puts forward the technical methods, advantages, and innovations adopted in this paper. Section 2 is a summary of relevant literature, summarizing its advantages and disadvantages, and putting forward the research ideas of this paper. Section 3 is the method part, focusing on the method of intelligent building energy-saving optimization control technology on the basis of a niche genetic algorithm. Section 4 is the experimental analysis. In this part, experiments are carried out on data sets to analyze the performance of the model. Section 5 is the conclusion and prospects. This part mainly reviews the main contents and results of this research, summarizes the research conclusions, and points out the direction of further research.

2. Related Works

Intelligent building energy saving is an important part of green and sustainable buildings. Building energy-saving design with the purpose of reducing wasting of resources is one of the core contents of green building design, but it faces three challenges: uncertainty, multi-objective, and trial and error. Intelligent building energy-saving optimization design is a new design idea and method to deal with these three challenges, and it is one of the research hotspots in the current international architecture field. Performance-based architectural design and its optimization methods have gradually become a research priority at home and abroad, and have played an important role in promoting green, low-carbon, and energy-saving intelligent architectural design. Wasting resources is the most important, most common, and most concerned kind of building performance. Therefore, building energy-saving optimization design has become the main research direction of performance-based building design and its optimization methods.

The main goal of building control is to provide a comfortable, highly environmentally friendly building environment. A multi-zone building model is created by segmenting the entire structure into various zones in order to create an efficient energy management system. For intelligent building control, Yang R et al. [17] proposed a multi-agent control system paired with an intelligent optimizer. By increasing the multi-zone building's operational intelligence, particle swarm optimization (PSO) is used to optimize building energy management. Xia Y et al. [18] combined the niche genetic algorithm with the theory of pattern theorem, tested the algorithm in the optimization process, initially formed a simplified workflow of the niche genetic algorithm, and finally obtained a conclusion that is beneficial to the follow-up research work and has theoretical guiding significance. Work on the smart home energy consumption system was carried out by Zhao, B. et al. [19]. They provided a brief description of the functional components and architecture of a smart home energy management system (HEMS). Then, a complete analysis and study of the cutting-edge HEMS infrastructures and home appliances in smart homes is conducted. Additionally, a survey is conducted on the use of several building renewable energy sources such as solar, wind, biomass, and geothermal energy in HEMS. Finally, several home appliance scheduling techniques were examined in an effort to lower domestic electricity costs and boost energy efficiency from power-producing utilities.

In a typical existing building, Douckas, H. et al. [20] presented an innovative intelligent decision support model based on the systematic integration of building energy management system (BEMS data (loads, demands, and user requirements) for the identification of the need for intervention and further evaluation of energy saving measures. The model's functioning provides assistance to the decision-makers charged with overseeing the building's management and energy-efficient performance (energy auditors and building administration). The goal of Yang, CH et al. [21] was to identify the critical variables that would enable decision-makers to choose among a wide range of IoT-focused Intelligent Building Management System (IBMS) adoption strategies. An IoT-oriented decision-making model uses the multiple-criteria decision-making (MCDM) method to measure IoT characteristics for the evaluation and determination of management systems for intelligent buildings. They also incorporated an evaluation of Activity-Based Costing and resource constraints into Zero-One Goal Programming in the process of choosing the best portfolio. Via the identification of the relevant features and the use of Soft Computing techniques to produce prediction models of energy consumption in buildings, Moreno, M.V. et al. [22] offered an innovative approach to energy conservation in buildings. Such models can be used to establish plans for reducing how much energy buildings use on a daily basis. They used their method on a reference building for which we have contextual data from a full year of monitoring in order to confirm the viability of this suggestion.

Researchers have looked into different aspects of resource waste and energy inefficiency in the field of optimizing building energy consumption rather than just one perspective. In order to monitor and manage energy use in intelligent buildings in real time, Wei et al. [23] proposed a building energy monitoring and analysis system using the IoT. The need for sophisticated building energy monitoring is among the challenges discussed by the author. The results of the study highlighted the potential of their proposed system to improve energy-saving capabilities. Ren H et al. [24] investigated the basic situation of buildings, the waste of resources in single buildings, the total waste of resources of residential buildings, and the coal consumption in heating areas, and compiled the statistical software of building waste of resources. Chi et al. [25] analyzed the wasting of resources data of similar buildings, predicted the wasting of resources of similar buildings more accurately, and summarized the development trend of wasting resources. Jun G U et al. [26] analyzed the energy-saving potential of large public buildings and thought that comprehensive utilization of various building energy-saving technologies could save energy by 30~50%.

Metallidou et al. [27] proposed the effect of the Internet of Energy (IoE) on the power sector of smart cities by integrating IoT technology for the purpose of energy efficiency, waste reduction, and environment purification. Using IoT technology, a smart building template is used to optimize technical systems for energy efficiency. The results demonstrate the potential of IoE in furthering smart city goals and the efficiency improvements possible with intelligent building management. The author, however, did not fully address issues beyond energy efficiency or offer a thorough examination of potential restrictions. Jagadeesan, S. et al. [28] made another very similar proposal and focused on the application of a smart grid as an improved energy management system to optimize energy usage. In order to effectively manage energy consumption in intelligent buildings, the author concentrated on the application of optimization techniques, such as machine learning (ML) and GA. Priority scheduling is used to maximize appliance utilization, while sensors from IoT are used to collect information about the environment outside. The integration of ML and IoT in the study helps to improve energy efficiency in smart buildings [29,30].

The conclusion we reached after carefully evaluating the work that was already proposed in the context of energy optimization for intelligent buildings was that the positive optimization algorithm is very important to the best design technology of building energy saving, so it is very important to choose the right algorithm and set the algorithm parameters sensibly. If the algorithm is not properly selected, it may reduce the design efficiency, and the optimal design scheme cannot be found, and even lead to the failure of the whole design process. Therefore, it is necessary to conduct in-depth research on the optimization algorithm in building energy-saving optimization designs. However, due to the barriers of professional knowledge and other reasons, the field of architecture only stays at the stage of indiscriminately using common optimization algorithms for energy-saving optimization design. Little is known about the efficiency of the algorithms, and it is impossible to avoid costly optimization failures.

3. Energy Optimization of Intelligent Building by Using Niche Genetic Algorithm

The model we proposed for intelligent building energy optimization by ensuring the security of IoT devices uses a niche genetic algorithm is shown in Figure 1. We started by defining control variables that directly relate to the energy efficiency and livability of intelligent buildings. The main components of these variables are new energy, which is simply another way of saying renewable energy sources, energy delivery temperature, which is the thermal energy distribution across the building for various purposes, and water supply temperature, which is simply another way of saying the temperature of the water provided for various purposes [31,32]. On the basis of these defined variables, data is collected from various IoT devices, such as sensors, actuators, and control systems, and it is ensured that the data collected is correct, reliable, and related to the building's energy usage. After the data collection, an objective function is created that computes the energy consumption and IoT devices' security risk of intelligent buildings based on the control parameters. The objective function is built in a way that takes into account the tradeoffs between various levels of energy consumption and lifestyle comfort. The solution space is then expressed in a fashion that the genetic algorithm can work with. This entails encoding the control parameters into a real-valued string that corresponds to the appropriate chromosomal format. The initial population of potential solutions is created to represent IoT devices' security configuration and various sets of control parameter values, such as the integration of renewable energy, optimization of thermal energy distribution, control of water supply temperature, smart heating, ventilation, and air conditioning (HVAC), temperature optimization of energy delivery, and energy monitoring and real-time feedback. The fitness of each solution in the entire population is assessed on the basis of the defined objective function. The fitness value, which simply indicates how well each solution performs in terms of energy consumption reduction and security enhancement, is the output of the fitness evaluation [33].

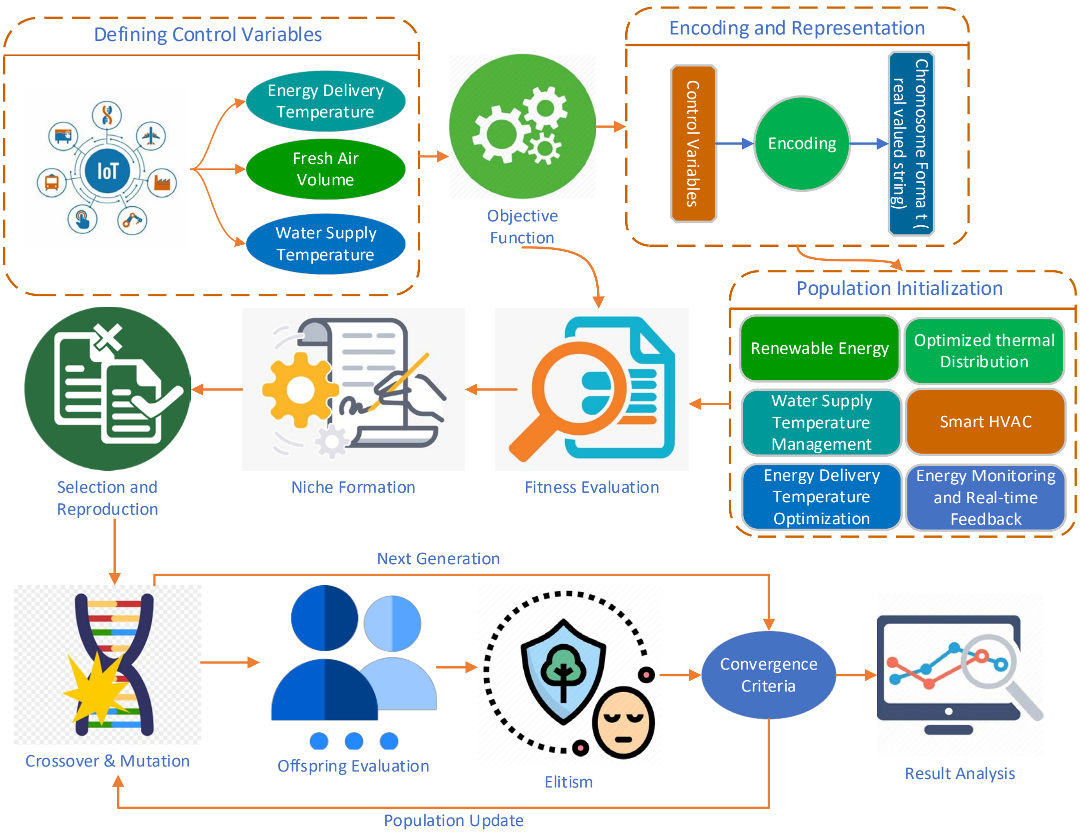

Figure 1. Block diagram of intelligent building optimization.

The niche technique is employed to promote population variety. This assists in preserving an equilibrium between the two activities and prevents solutions from converging prematurely to local optima. Crossover and mutation operations are applied to the solutions that are chosen as having a greater fitness value. Via the use of the objective function, the fitness of the recently produced offspring is assessed. This stage makes sure that the energy consumption of the new solutions is accurately calculated. By keeping a specific portion of the finest ideas from the previous generation, elitism is introduced. This makes sure that effective solutions are kept and do not disappear during the process of evolution. The next generation of the population is generated by combining parent solutions, offspring solutions, and elite solutions. Convergence criteria, such as a maximum number of generations or a suitable amount of energy consumption drop are selected to stop the algorithm on a satisfactory solution. The optimal option with the greatest potential for energy savings is found by analyzing the final population of solutions [34].

3.1. Intelligent Building Control System

Among the control variables of an intelligent building control system, three control parameters, namely new energy, energy delivery temperature, and water supply temperature play a key role in the overall wasting of resources and operation characteristics of the system, while other control variables have little influence on the wasting of resources of the system [35]. Aiming at these three variables, an optimal control objective function is established, and a niche genetic algorithm is used for optimization, so as to obtain the optimal control variable value that minimizes the objective function and realizes the control of the air-conditioning equipment system. The control goal of intelligent building system optimization is to minimize the waste of resources of the system on the premise of ensuring comfort. Comfort can be measured by building thermal comfort and air quality. Therefore, the optimal control objective function of the system is

$$\mathrm{F} = \int_0^{\nabla} (\alpha\mathrm{P} + \beta\mathrm{MV} + \gamma\mathrm{Y})\mathrm{dt} \tag{1}$$

where α, β, and γ are the control parameters of new energy, energy delivery temperature, and water supply temperature, respectively. For buildings with different use properties, the values of the three parameters are also different. When the building has higher requirements for new energy and energy delivery temperature, the values of β and γ are greater than 1, and the values of α are less than 1; when buildings have high requirements for wasting of resources, the value of α is greater than 1, while the values of β and γ are less than 1.

In the same evolutionary environment, the improved niche genetic algorithm is not affected by the population size and evolutionary algebra, and it can obtain the same optimal solution, and its convergence will not change with the increase in evolutionary algebra. Moreover, it takes the shortest time in the whole iterative evolution process, and the average time of each generation in the same iterative evolution is also the shortest. Therefore, the improved niche genetic algorithm has relatively good convergence performance and the lowest running time complexity of the algorithm [36,37]. Its relatively stable convergence is also an optimization of the traditional algorithm, and it is not easily influenced by some excellent individuals, which makes the evolutionary direction move in the opposite direction or in a direction unfavorable to the population evolution, which leads to premature falling into a certain local cycle, thus reducing the diversity of the new generation of individuals, and even the whole population will be quickly covered by a large number of these excellent individuals, resulting in a fast stable state, as shown in Figure 2.

Compared with the traditional genetic algorithm and differential evolution algorithm, the improved niche genetic algorithm takes the shortest time in the whole evolution process and obtains the optimal solution after iteration. The convergence performance is not reduced by increasing the population size, and the same optimal solution can be obtained after iteration [38]. The evolution algebra of the improved niche genetic algorithm is larger than that of the genetic algorithm when it tends to a stable state, but its convergence performance is improved. From the evolution data, the genetic algorithm quickly enters a stable state in the early stage of evolution, while the difference algorithm is relatively slow, but the final convergence performance is higher than that of the traditional genetic algorithm. on the basis of the traditional algorithm, the improved niche genetic algorithm improves the evolution speed, avoids the limitation of premature local convergence of the genetic algorithm, and the whole running process takes a relatively short time. This Algorithm shows the overall process of the niche genetic algorithm for the energy optimization of intelligent buildings. Specific issues related to each step of the algorithm and their corresponding solution are discussed in the subsequent sections.

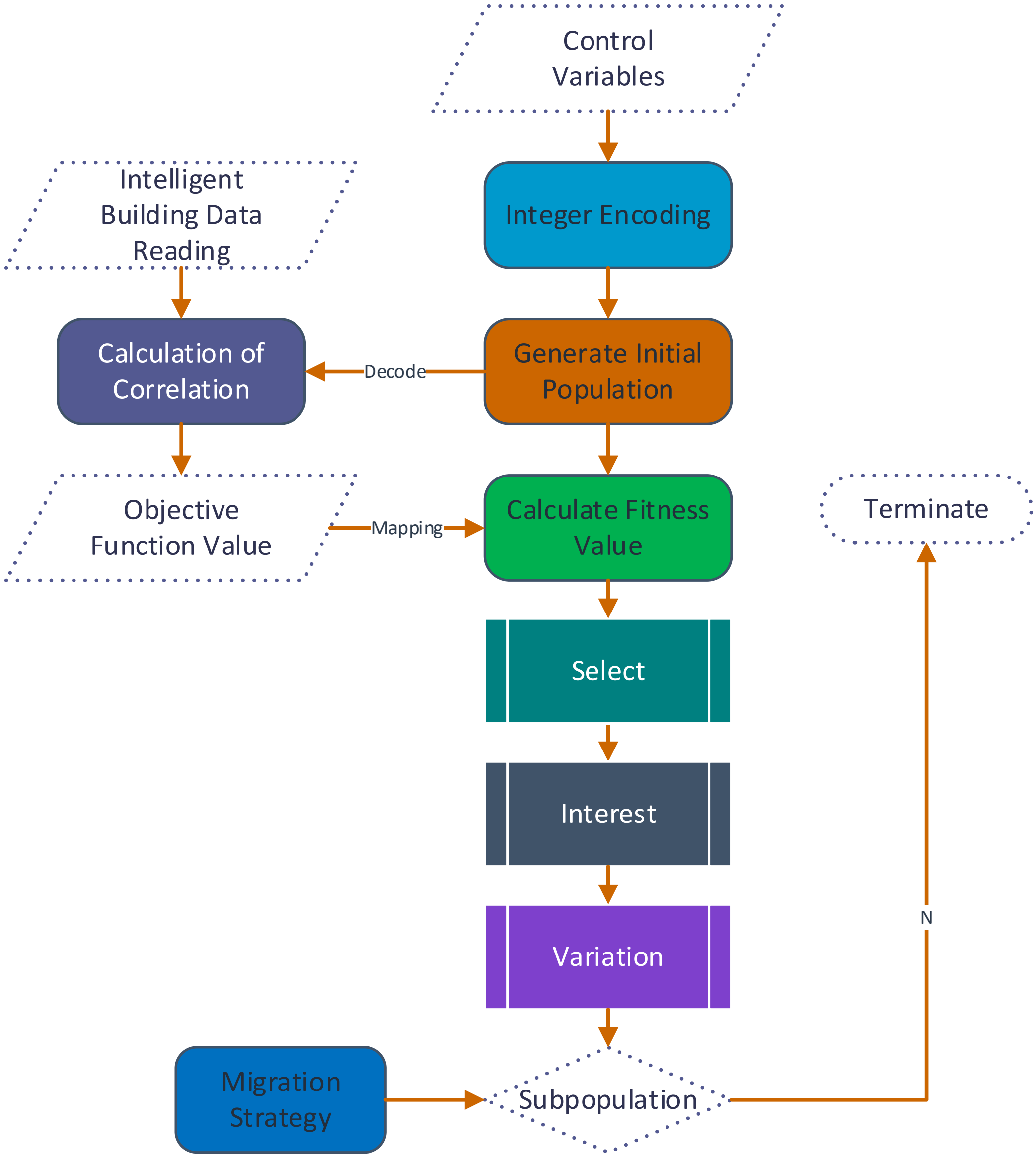

Figure 2. Flow diagram of intelligent building control system.

3.2. Fitness of Niche Genetic Method

The theory of genetic algorithm optimization starts with a randomly generated population that represents the possible solution set of the problem, selects a relatively good individual as the parent by adopting the strategy of "survival of the fittest", and then performs genetic operations among the parents to evolve the offspring population, as shown in Figure 3.

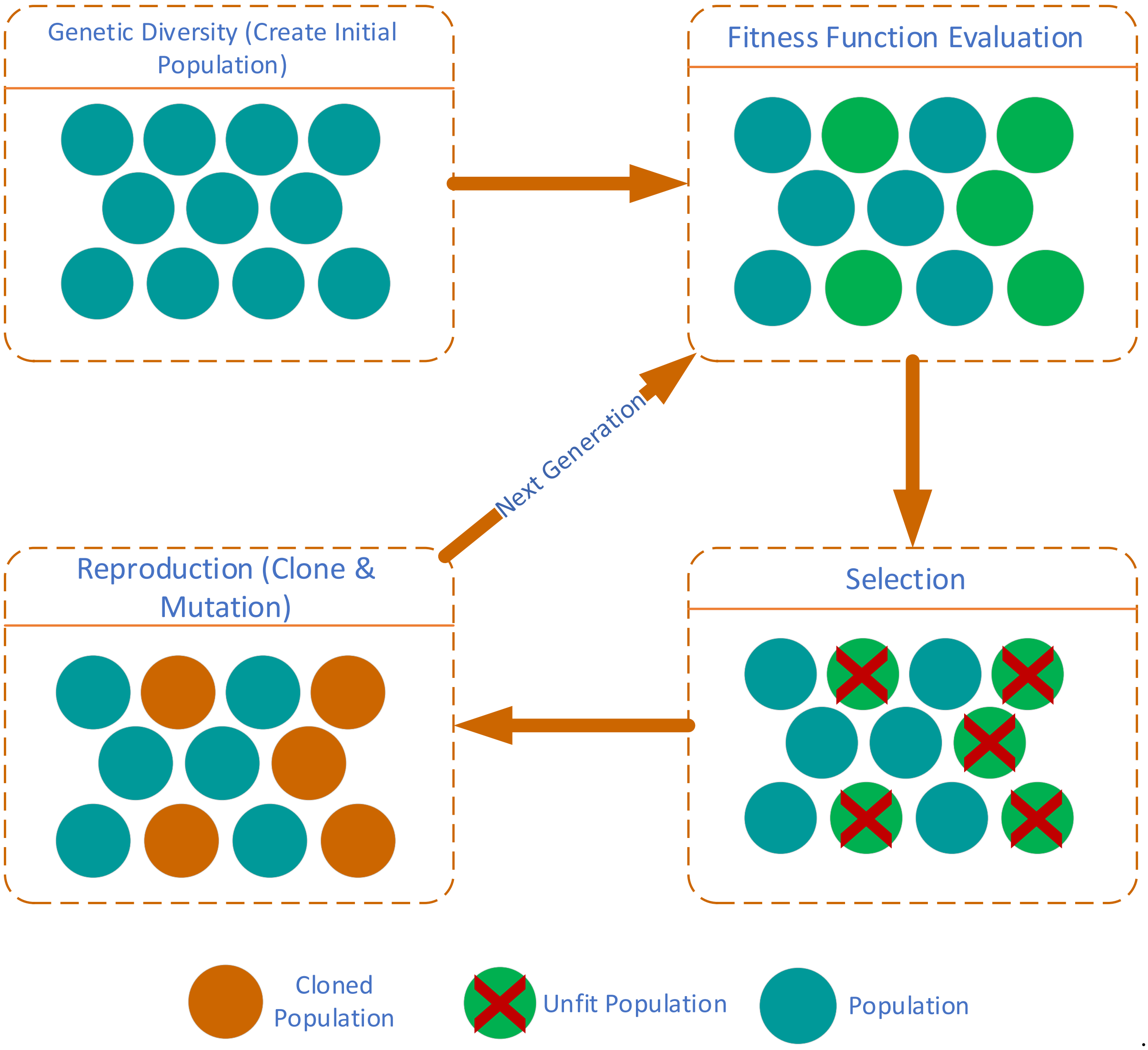

Figure 3. Evolution process of genetic algorithm.

The primary operation of the niche genetic algorithm is to determine the objective function, the variables involved in the function, and the implicit constraints. According to different problem situations, the decision variables will also be subject to different constraints of the problem, and finally be treated as penalty functions to be considered together in the problem. The niche inheritance method is mainly composed of genetic factors, chromosomes, and population. Among them, genetic factors can be used as any decision variable, and chromosomes are regarded as the main carrier of genetic material, which is a collection of many genetic factors [27]. Therefore, the objective function of solving the problem can be abstracted as a function about chromosomes, and the population is defined as a set of chromosomes. The internal expression (i.e., genotype) of chromosomes is a combination of certain genes, which plays a decisive role in the shape and external expression of the individual, and is also the expression form of internal genotype. Therefore, the phenotype is mapped to the genotype by coding. After the initial population is generated, it evolves from generation to generation according to the "survival of the fittest", and finally some relatively good approximate solutions to the problems are produced. In the process of evolution, individuals with larger fitness are searched via the differences of fitness of different individuals in the problem domain. After the selection operation is completed, crossover and mutation operations are carried out, and finally, a solution set that can represent the new generation population is generated, so that the offspring population gradually adapts to the environment. The relatively optimal individual in the final generation population will be decoded to obtain the solution of the problem, which is the approximate optimal solution of the problem.

In the evolutionary search process of genetic algorithm, the selection operation only takes Fitness as the only niche genetic basis, and basically does not use other external information, and the search operation is performed by the fitness values of different individuals in the population. Because of the niche genetic algorithm, it is very important to select the appropriate fitness function for solving the problem, which may have a direct impact on the final convergence speed, convergence effect, and whether the optimal solution to the problem can be found.

The fitness function is to directly convert the objective function to be solved, then

$$Fit(f(x)) = -f(x) \tag{2}$$

If the goal is to minimize the problem, then

$$Fit(f(x)) = \begin{cases} cmax - f(x), \ f(x) \leq cmax \\ 0, \end{cases} \tag{3}$$

Among them, $cmax$ is the estimated maximum value of $f(x)$, which is also an improvement on the basis of the direct transformation objective function method. It has some problems, such as the maximum value is difficult to estimate and inaccurate.

If the goal is the minimization of the problem, then

$$Fit(f(x)) = \frac{1}{1 + c + f(x)} \tag{4}$$

Among them, $c \geq 0$, $c + f(x) \geq 0$, c are conservative estimates of the boundary value of the objective function.

3.3. Convergence Rate

The convergence rate is an important performance index of multi-objective optimization algorithms. The single-objective optimization algorithm has two conflicting performance indexes: speed and coverage. Similarly, the multi-objective optimization algorithm has two conflicting performance indexes: convergence speed and diversity of Pareto's solution. If a multi-objective optimization algorithm converges too fast, it will cause the algorithm to be unable to search the solution space in a wider range, and the diversity of the Pareto solution finally obtained will be poor. On the contrary, if the multi-objective optimization algorithm is to search for more solutions as much as possible, it will take a longer time to search in a wider range of the feasible solution space, resulting in a slower convergence speed of the algorithm and a longer running time of the whole optimization. Therefore, when evaluating the efficiency of a multi-objective optimization algorithm, it is necessary to evaluate not only the diversity of Pareto's solution but also the speed of convergence to the Pareto optimal set. Figure 4 shows the convergence rate of three different optimization methods including Levenberg–Marquardt (LM), local search (LS), and crowding strategy (CS) [39].

The convergence rate of a multi-objective optimization algorithm can be measured by the number of objective function calculations used when the algorithm finds the best solution on the Pareto frontier, which is represented by the symbol conv. The smaller the Conv value, the faster the convergence rate of the algorithm.

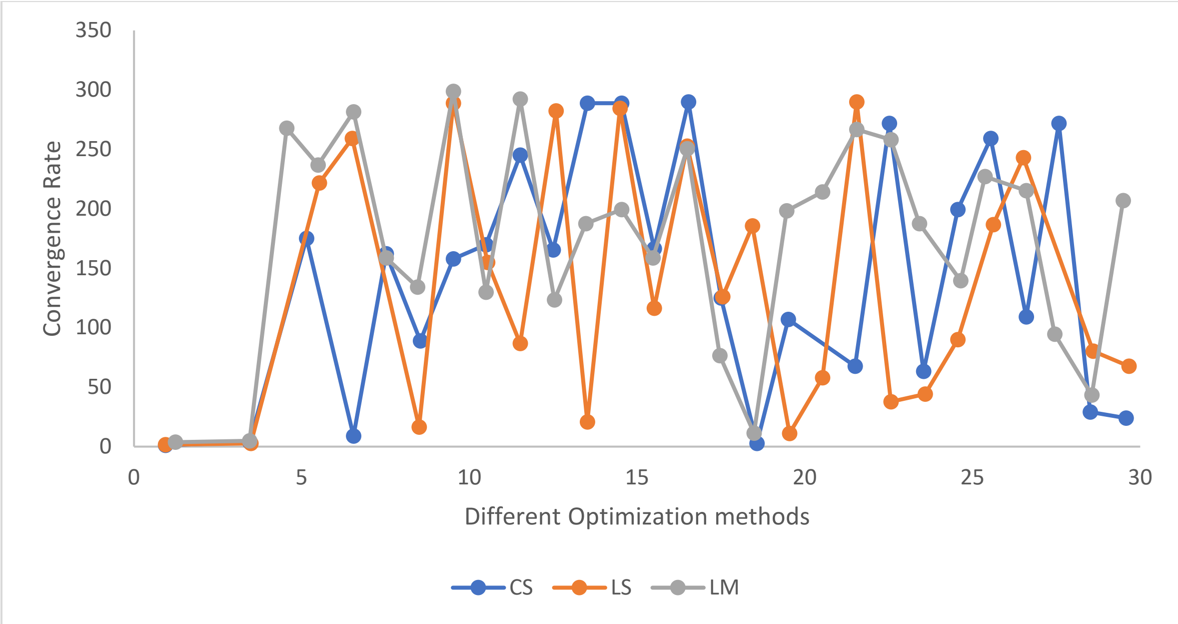

Figure 4. Convergence rate of different optimization methods.

3.4. Diversity of Pareto's Solution

The number of Pareto's solutions obtained via the multi-objective optimization algorithm is not infinite, so it is very important to ensure the diversity of solutions, which can not only depict the true Pareto frontier as accurately as possible but also avoid losing the potential better solutions to the greatest extent. Generally speaking, Pareto's solution with good diversity should be evenly distributed on the entire Pareto frontier as much as possible. The scale of the Pareto optimal set refers to the number of solutions contained in the Pareto optimal set. Ideally, if there are continuous optimization variables in an optimization problem, the real Pareto optimal set should contain an infinite number of Pareto's solutions. However, finding all Pareto's solutions is not feasible in the calculation, and multi-objective optimization algorithms can only find a limited number of Pareto's solutions. At this time, the scale of the Pareto optimal set is very important because it directly determines the number of candidate solutions that can be provided to architects. In addition, it also reflects the ability of multi-objective optimization algorithms to find non-dominated solutions. The larger the scale of the Pareto optimal set, the stronger the ability of the algorithm to find non-dominated solutions.

In order to quantitatively evaluate the diversity of solutions on the Pareto frontier, the standardized distance measurement method can be used to investigate the distribution of solutions on the Pareto frontier. First, calculate the Euclidean distance di between any two adjacent solutions on the Pareto frontier, then calculate the average value d of all Euclidean distances, then calculate the average value DS of all the differences between di and d, and finally divide DS by the sum of all Euclidean distances to obtain the standardized distance measurement index SS. The detailed calculation formula is as follows:

$$di = \sqrt{\sum_{j=1}^{m} \left(F_i^j - F_{i+1}^j\right)^2} \quad (5)$$

In the above formula, di is the Euclidean distance between points F_i^j *and* F_{i+1}^j. F_i^j shows the jth feature of feature i and F_{i+1}^j is the jth feature of feature i + 1.

$$d = \frac{\sum_i^{n-1} di}{n-1} \quad (6)$$

Here, d is the average distance of between individual points di, and n is the total number of data points.

$$DS = \frac{\sum_{i}^{n-1} di - d}{n-1} \tag{7}$$

Here, DS is the average deviation of individual distance, di is the individual distance, and d is the mean distance, as calculated by Equation (6).

$$SS = \frac{DS}{(n-1)d} \tag{8}$$

Here, SS is the standard deviation of the average deviation DS, which is calculated in Equation (7), n is the number of data points, and d is the average distance calculated by Equation (6).

$$li = \min_{k \in 100} \sqrt{\sum_{j=1}^{m} \left(F_i^j - F_k^j \right)}^2 \tag{9}$$

Here, the li represents the minimum Ecludian distance between point F_i^j and F_k^j. This part $\sum_{j=1}^{m} \left(F_i^j - F_k^j \right)$ of the equation calculates the distance in general after the $\min\limits_{k \in 100}$ is applied, which look for the minimum values among 100 distances.

$$SGD = \sqrt{\frac{\sum_{i=1}^{n} l^2}{n}} \tag{10}$$

Here, the SGD is the standard deviation of the value in set i.

Among them, SS is the index to evaluate the diversity of Pareto's solution; di is the normalized Euclidean distance between two adjacent solutions i and $i+1$ on the Pareto front, of which, $i = 1$; d is the average of all di; DS is the average of all the differences between di and d; n is the number of solutions on Pareto frontier; and m is the number of optimization design goals. F_i^j and F_{i+1}^j are the normalized values of two adjacent solutions i and $i+1$ on the Pareto frontier on the jth optimization design goal. The smaller the value of SS, the more uniform the distribution of solutions on the Pareto frontier, and the better the diversity of Pareto's solution.

4. Experimental Setup and Result Analysis

In this section, we covered the implementation level details of the paper that cover how all these experiments are conducted. This section also covered a thorough evaluation of the method proposed in this paper.

4.1. Experimental Setup

The primary objective of this research work is to find out the optimal solution of energy consumption and people satisfaction in the context of intelligent buildings. To do so, we utilized the niche genetic algorithm that best suits our problem because we aim to tradeoff between energy consumption and people's satisfaction. We also focused on the security improvement in IoT devices to ensure the correctness of data related to energy consumption and occupant satisfaction. With the help of simulation, we predict the overall operating characteristics of the system, and the optimal control variable values, i.e., fresh air volume, supply air temperature, and supply water temperature, which minimize the objective function and are obtained via the optimization calculation of niche genetic algorithm, which is used as the set values of the lower computer controller. The niche genetic algorithm code is written in MATLAB advanced language, which is best for the problem of visualization of scientific data, modeling and simulation of linear dynamic systems, etc. This simulation is conducted in a Windows environment, which is very convenient to use. MATLAB has a built-in module that can be utilized for the implementation of niche genetic algorithms, which provides a wide variety of practical functions for genetic algorithm researchers, as shown in Table 1.

Table 1. List of common functions of niche genetic algorithm.

	Function Type	Function
Create a population	Crtbase	Create basis vector
	Crtbp	Create any discrete random population.
	Crtrp	Create a real-valued initial population
Fitness calculation	Rws	Roulette wheel selection
	Select	Advanced selection process
	Sus	Random sampling
Select function	Recdis	Discrete variation
	Recint	Linear recombination
	Reclin	Real value variation

4.2. Results and Discussion

Generally speaking, a single-objective optimization problem means that there is only one optimization objective function, and when there are two or more optimization objective functions, it becomes a multi-objective optimization problem. In this research, we deal with multi-objective optimization problems because our objectives are to save energy and provide life comfort in intelligent building scenarios. Figure 5 shows the result of the proposed model for 30 iterations.

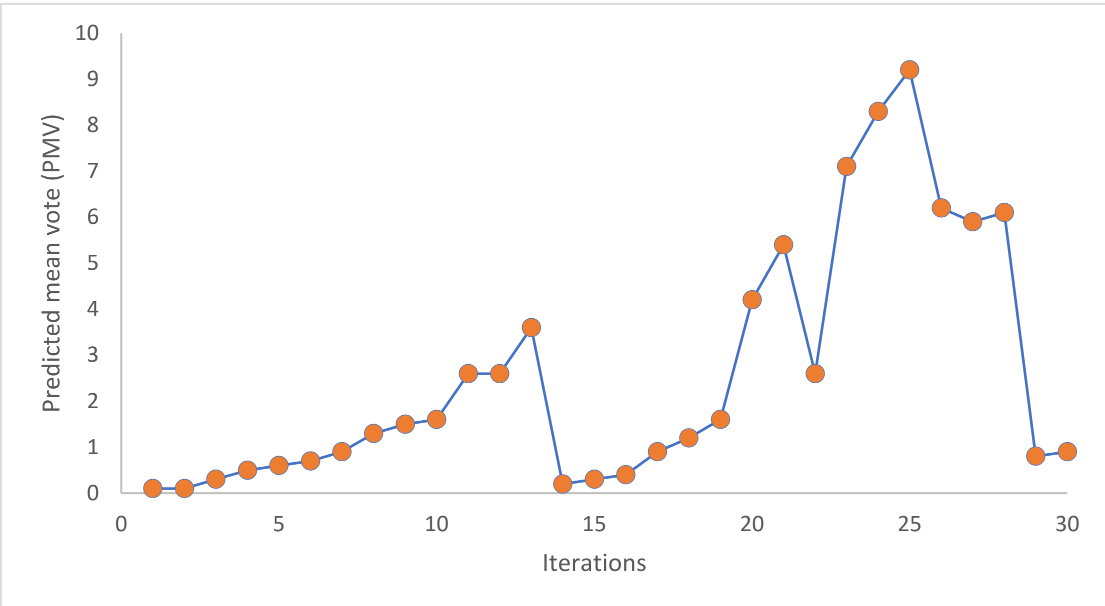

Figure 5. Change in the mean value of objective function during 30 iterations.

As shown in Figure 5, the heat transfer coefficients of southeast, northwest, and facing the exterior wall are 0.66, 0.8, 6.1, and 3.6, respectively. Therefore, it can provide a reference for the selection of exterior wall insulation materials. At this time, the power consumption is 9.2, the absolute value of the predicted average number of predicted mean vote (PMV) is 1.9, and the cost of external wall insulation materials and windows is 452,600 yuan. Because it is difficult to achieve the best state of building wasting resources, cost, and thermal comfort in practical projects, a niche genetic algorithm is used to provide some reference for intelligent building design so that the three can reach a relatively good state.

Tables 2 and 3 summarize the heat transfer coefficient and various parameters related to power consumption, respectively.

Table 2. Heat transfer coefficients for different exterior wall directions.

Exterior Wall Direction	Heat Transfer Coefficient (k)
Southeast (k1)	0.66
Northwest (k2)	0.8
Facing Exterior (k3)	6.1
Facing Exterior (k4)	3.6

Table 3. Various parameters related to power consumption.

Parameters	Values
Power Consumption	9.2
PMV Value	1.9 (absolute value)
Cost of Insulation Materials	452,600 yuan

From the simulation results in Figure 6, it can be seen that the multi-objective optimization theory and the principle of genetic algorithm choose the heat transfer coefficient of the building exterior wall and window as the optimization variables, so as to achieve the goals of lower building waste of resources, enclosure cost, and better thermal comfort.

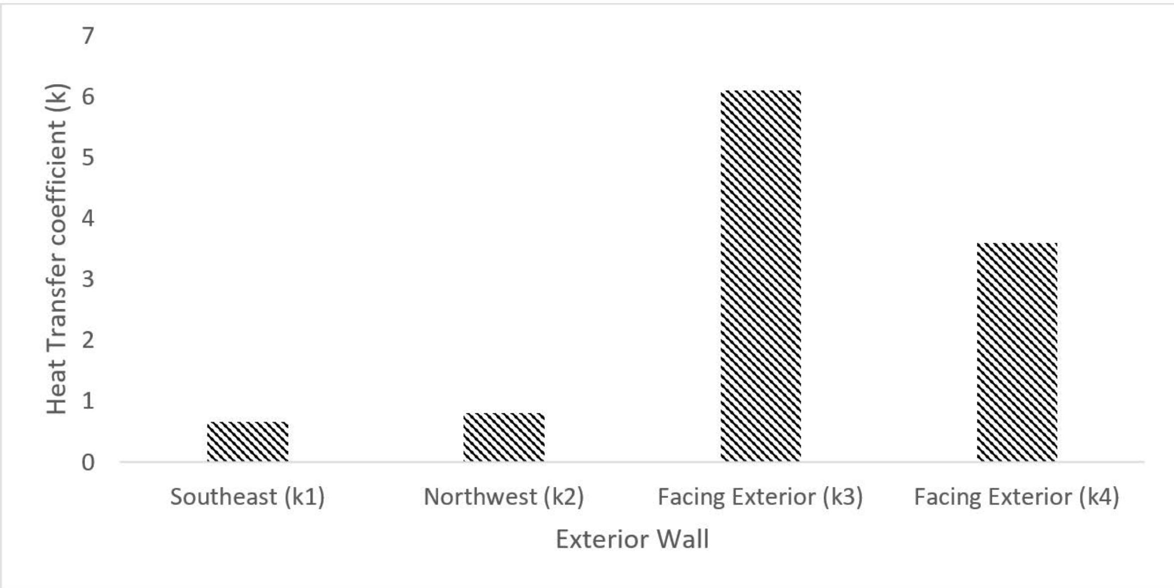

Figure 6. Heat transfer coefficients of exterior walls in the window.

Table 3 shows the cost and value of different parameters including general power consumption, PMV value, and cost of insulation materials.

When a niche genetic algorithm is used to solve optimization problems, the algorithm does not limit the number of identical individuals or similar individuals. However, when niche technology is introduced into genetic algorithms, the number of them will be limited in order to produce more kinds of different optimal solutions. For an individual, how many kinds and how many similar individuals exist in its vicinity can be measured, and this measurement is called a niche number.

Table 4 shows the evaluation data of different zonal areas within the intelligent building environment such as the living room, bedroom, bathroom, kitchen, and offices. We evaluated the security measures of IoT devices implemented in an intelligent building context whose value can be high, medium, or low. The energy optimization score is evaluated in terms of percentages ranging from 0 to 1. The occupant comfort rating is analyzed in the range of 1 to 5.

Table 4. Intelligent building zonal areas analysis.

Building Zone	IoT Security Level	Energy Optimization Score	Occupant Comfort Rating
Living room	High	0.85	4.2
Bedroom	Medium	0.75	4.5
Kitchen	Low	0.82	4
Office	High	0.78	4.3
Bathroom	Medium	0.77	4.4

Energy optimization of intelligent buildings is evaluated by utilizing the power of IoT devices and niche genetic algorithms. The result of our proposed method is thoroughly compared with very similar work found in the literature such as the work proposed by Xia Y et al. [12] and Zhao X F et al. [13], as shown in Figure 7. It is clearly seen in the figure that our proposed approach optimized the energy level in intelligent buildings context more than already proposed approaches. The different zonal areas of the building are taken into consideration for energy optimization by different researchers. They used different approaches toward the energy optimization of these areas. The figure clearly states that our proposed method optimized the resources of all mentioned areas of intelligent buildings at a rate of higher than 80%.

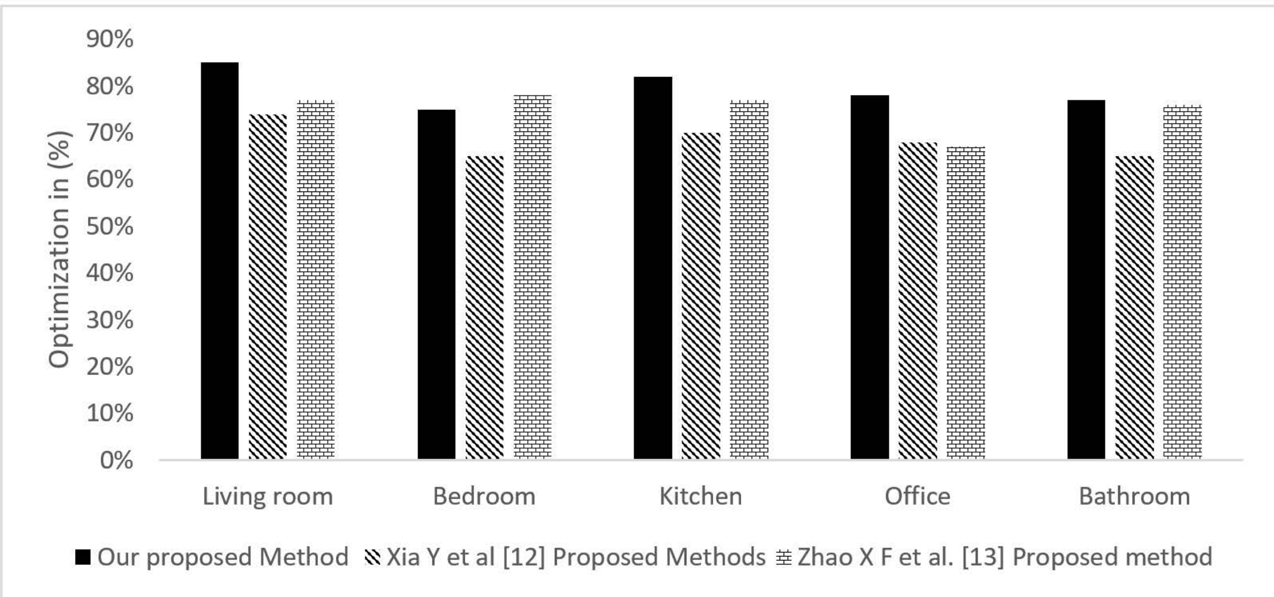

Figure 7. Energy optimization score of intelligent buildings.

Figure 8 shows the occupant comfortability level in the intelligent buildings' environment after the energy optimization. The basic aim of checking the occupant comfort level is to check whether the energy optimization and security measure of IoT devices affects their comfort or not. We compared our proposed work with very similar work proposed by Xia Y et al. [12] and Zhao X F et al. [13]. We measure occupant comfortability on a scale of 1 to 5, whereas previous studies measured it on a scale of 1 to 10. We adjusted our scale to make comparisons easier. It can be seen from Figure 8 that in most of the zonal areas of intelligent buildings, we are the winner. However, in some areas, the score of the prior work is higher. The occupant comfort level is evaluated in different areas of the building including the bedroom, living room, kitchen, office, and washroom by different authors. They utilized different optimization approaches for this and obtained quite satisfactory results. It can be seen in Figure 8 that the level of comfortability of all authors' proposed methods had a rate greater than 4. However, none of them are clearly winning, as one approach shows a higher comfortability level in one area, while the other in another area.

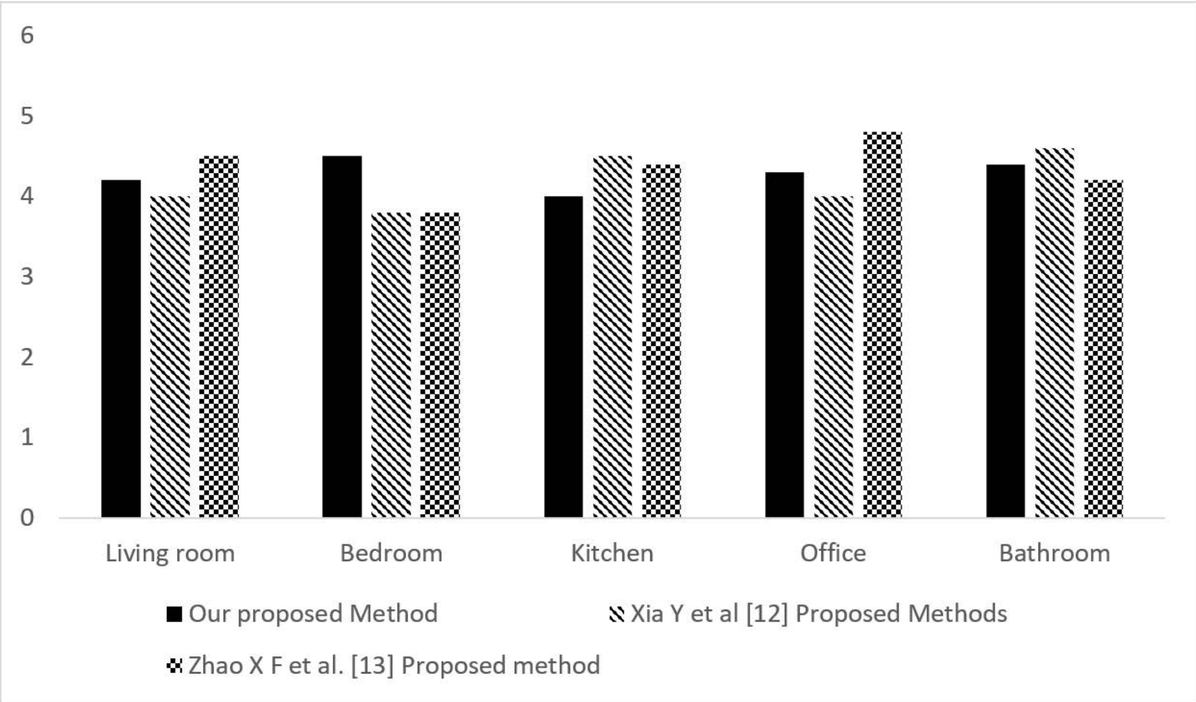

Figure 8. Occupant comfortability in the intelligent buildings.

The value of the fitness function over 90 generations is depicted in Figure 9 for the niche genetic algorithm. In this study, we used a specialized evolutionary algorithm to identify the best possible solution to the problem of energy consumption in intelligent buildings. The lowest value in the range (zero), if the fitness function monitors energy consumption that we want to reduce, would be considered the "best" value. In this scenario, better performance or a more optimal solution is indicated by a lower fitness rating. However, we also want to make sure that the occupants of intelligent buildings are comfortable, so our goal is not just to reduce the energy consumption of these buildings. Therefore, the midpoint between the maximum and minimum would be the optimal value.

Table 4 shows the results of the partial optimization calculation after using the adaptive optimization control model. After calculation and analysis, the electric power of the optimized system is generally reduced by more than 8% compared with that before optimization, which indicates that the adaptive optimization control model of the air intelligent building system can effectively optimize the operation parameters of the energy-saving system and achieve the purpose of energy saving, as shown in Table 5 below.

Figure 10 shows the power consumption rate before and after optimization. However, it is still difficult to directly interpret how much energy is saved after the optimization. Therefore, in Figure 11 we have shown the power reduction in percentage, which provides ease of interpretation.

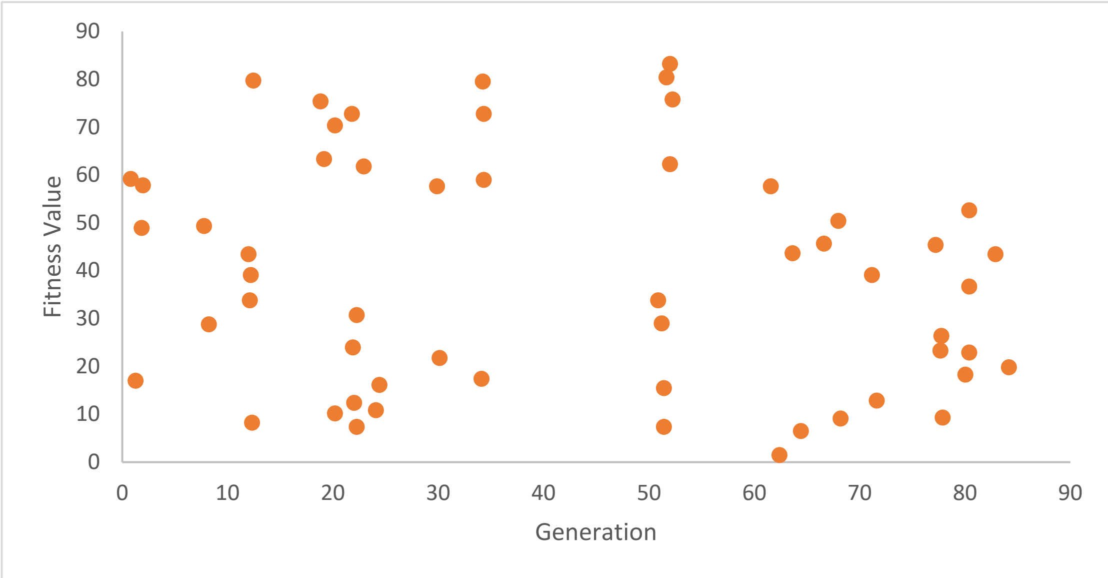

Figure 9. The value of fitness function over 90 generations.

Figure 10 shows the total amount of power consumed before and after applying the niche optimization in kilowatt hours. Here, the horizontal axis represents various numbers of samples taken over different time periods of 8 to 8:30. Similarly, the vertical axis represents the total amount of power consumed in each time period.

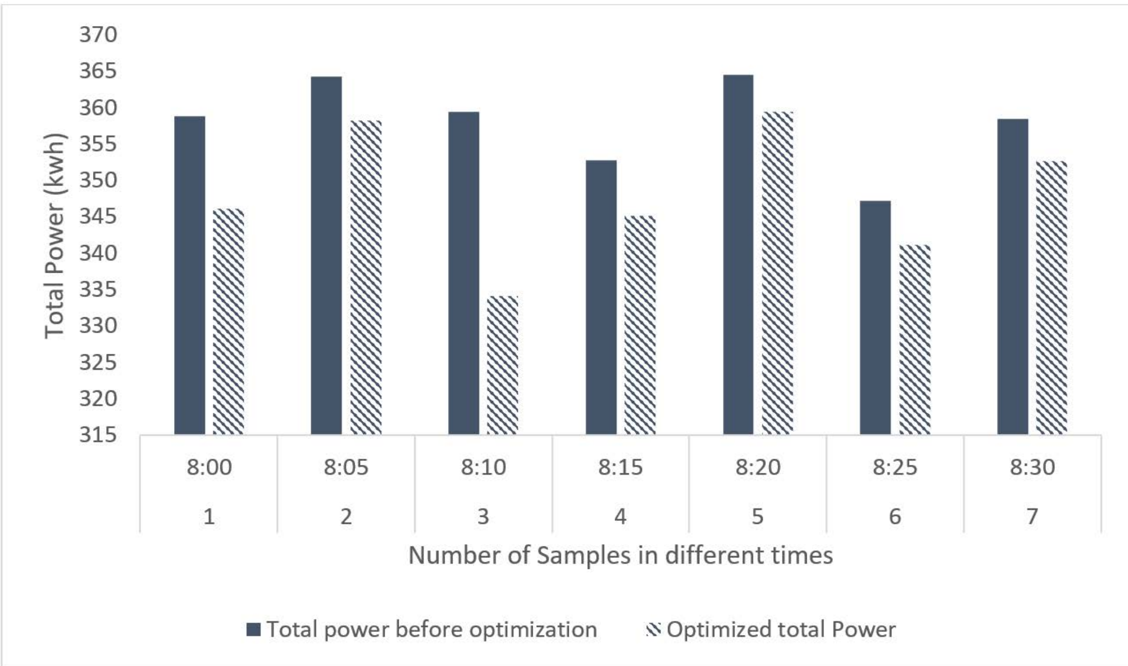

Figure 10. Total power consumption before and after optimization.

In order to effectively improve the efficiency of energy utilization and achieve the goal of energy saving and emission reduction, a wind power generation system is set up in the intelligent building. The energy generated during the operation of the system can share 1% of the daily waste of resources. After the calculation of the system, it is found that the system can provide 197,500 kilowatt hours of power supply for the equipment on the sightseeing floor every year, which not only reduces the cost of electric energy but also, as typical clean energy, the environmental impact of its energy production is very small.

The intelligent building is partially integrated with renewable energy power generation devices, which provides auxiliary support for meeting the power demand of intelligent buildings. As the height of the intelligent building exceeds 600 m, the wind level is high. After measurement, it is found that the daily average wind speed is as high as 9 m/s. In order to make full use of the advantages of wind energy, it is proposed to install vertical axis wind turbines. Because this floor can provide all-around wind energy without dead angle, the advantage of 360° utilization of wind energy by vertical axis wind turbine can be fully highlighted here. In a large number of practical experiences, the reliability and stability of the equipment have been fully verified. As for the selection of specific models, we chose the second-generation vertical axis wind turbine on the market, with a life cycle of 7 years, low overall wasting of resources, and high power generation efficiency, which can effectively meet the auxiliary power supply load demand of intelligent buildings as shown in Figure 12.

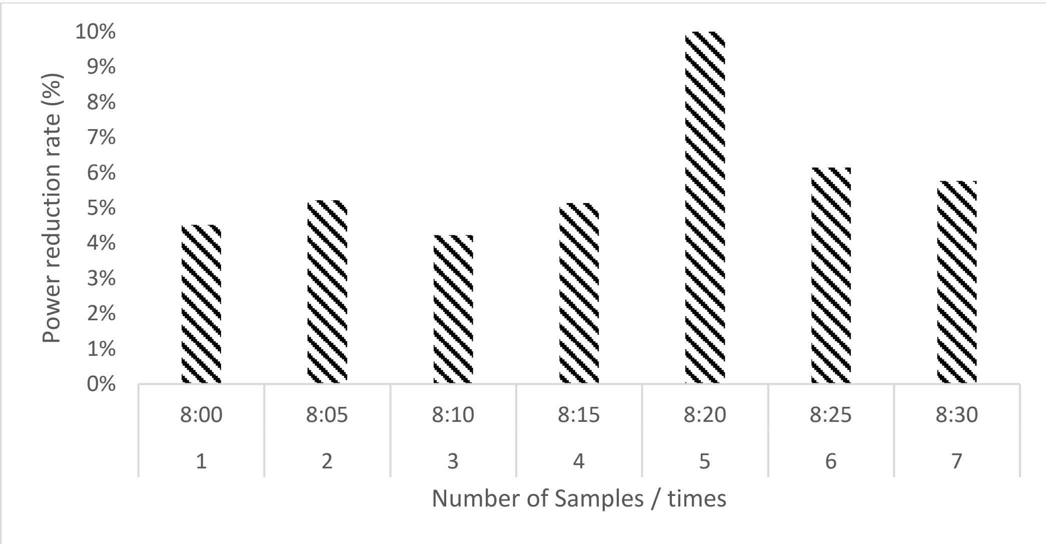

Figure 11. Power saving rate in percentage.

Table 5. Comparison and analysis of system wasting of resources calculation results before and after algorithm optimization.

Number	Sampling Moment	Total Power before Optimization	Optimized Total Power	Total Power Reduction Rate
1	8:00	358.77	346.12	4.52%
2	8:05	364.22	358.22	5.22%
3	8:10	359.47	334.12	4.23%
4	8:15	352.77	345.16	5.14%
5	8:20	364.52	359.41	10.45%
6	8:25	347.18	341.18	6.15%
7	8:30	358.45	352.68	5.77%

At the same time, the high-temperature flue gas generated by the startup generator set during its operation is purified, and then the waste heat boiler and Huankeng refrigeration unit are used to meet various hot water needs of intelligent buildings. This typical combined cooling, heating, and power supply system has greatly improved the comprehensive utilization effect of resources, and its important role in energy saving and emission reduction deserves our due recognition. In the specific application process, the system generates electricity to supply the electricity demand of intelligent buildings and completes the waste heat recovery via the flue gas–water heat exchanger, thus providing necessary energy support for the operation of the Huanhuakeng absorption refrigerator. In the process of operation, the low-area energy center will provide hot steam for the low-area energy-consuming units. At the same time, it is also responsible for chilled water supply services. Two energy centers can provide power load during the power failure period and provide a backup cold source for users in the form of a lease. In the normal operation state, the generator set is merged into the mains network; however, after a fault occurs, the standby power supply can be provided for the intelligent building by switching the line to ensure the normal power supply of the intelligent building.

The experimental results show that the energy-saving optimization control of intelligent building via the niche genetic algorithm greatly improves the comprehensive utilization effect of resources, the convergence speed of resources in intelligent building is faster, the diversity of Pareto's solution is higher, and the objective function reaches the global maximum optimization value, which has a good energy-saving optimization effect of intelligent building.

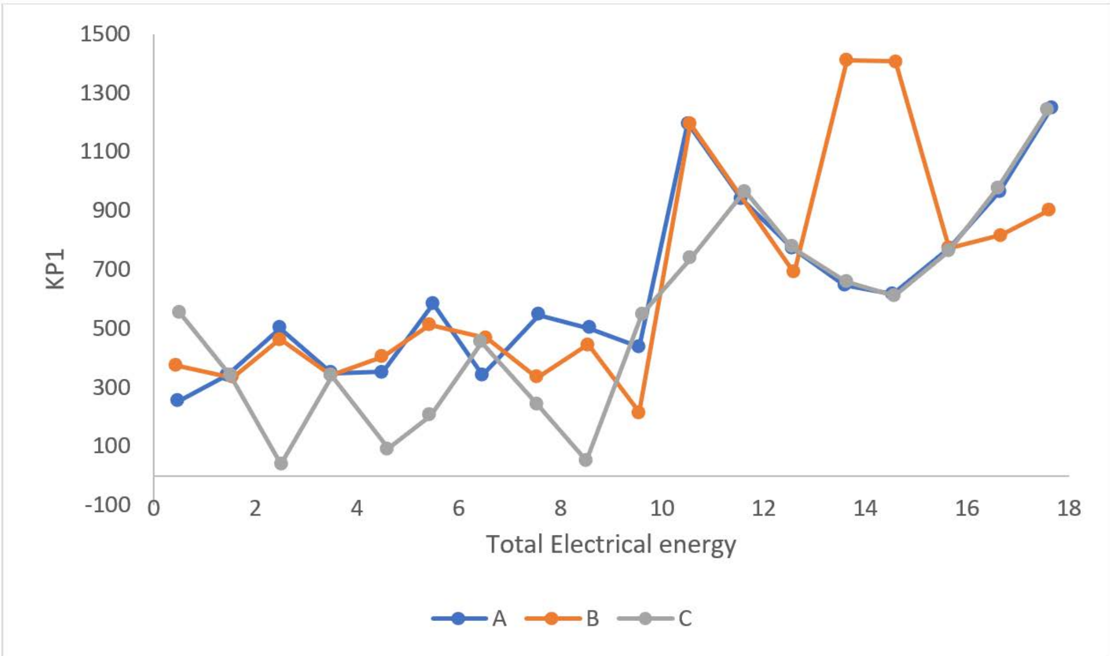

Figure 12. Total power utilization diagram.

5. Conclusions and Future Works

IoT is the primary technology that powers the data collection and intelligent control systems in intelligent buildings. IoT devices have been integrated more and more recently in almost every smart environment in general and intelligent building environments in particular. The integration of these devices not only provides ease but also automates the process and reduces human effort. However, it poses some serious issues concerning security that directly affect energy optimization and user comfort. The energy optimization of intelligent buildings is an important part of green and sustainable buildings. Therefore, in this paper, we worked on the energy optimization of intelligent buildings by taking the security of the IoT devices into account. We, first of all, defined various variables concerned with the security of IoT devices and energy optimization of intelligent buildings. With the help of IoT gadgets such as sensors and other IoT control systems, we collected data on these variables. After that, we applied one of the multi-objective evolutionary algorithms called the niche genetic algorithm for security insurance and energy optimization. This paper not only focused on the security of IoT devices and energy optimization but also on the comfort of occupants of intelligent buildings. We proposed a state-of-the-art technique to enhance life comfortability inside intelligent buildings by consuming the least amount of energy possible. Our presented method makes a tradeoff between energy-saving optimal control technology and IoT security of intelligent buildings, and this study discovered an optimal solution for the problem of resource waste in intelligent buildings. Compared with traditional energy-saving design methods, our proposed method significantly improves the IoT devices' security and tradeoff between energy consumption and residence comfortability. The proposed security solutions will need to be improved and expanded in the future to keep up with the development of IoT threats and vulnerabilities in intelligent buildings. Additionally, by investigating adaptive control techniques and using cutting-edge technologies such as edge computing and 5G networks, researchers can go further into optimizing energy use. As part of ongoing efforts, substantial real-world case studies and pilots can be carried out to verify the viability of the suggested approaches in various intelligent building situations and to gather useful information for broader application.

Author Contributions: Conceptualization, R.L. and L.H.; Software, L.H.; Formal analysis, Y.X.; Writing–original draft, L.H.; Writing–review & editing, Y.X.; Project administration, Y.X. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the project FJ2020C051 from Social Science Planning Program of Fujian Province in 2020.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Qian, L.; Zheng, Y.; Li, L.; Ma, Y.; Zhou, C.; Zhang, D. A new method of inland water ship trajectory prediction based on long short-term memory network optimized by genetic algorithm. *Appl. Sci.* **2022**, *12*, 4073. [CrossRef]
2. Ma, K.; Li, Z.; Liu, P.; Yang, J.; Geng, Y.; Yang, B.; Guan, X. Reliability-constrained throughput optimization of industrial wireless sensor networks with energy harvesting relay. *IEEE Internet Things J.* **2021**, *8*, 13343–13354. [CrossRef]
3. Omar, O. Intelligent building, definitions, factors and evaluation criteria of selection. *Alex. Eng. J.* **2018**, *57*, 2903–2910. [CrossRef]
4. Alam, M.; Skahil, A.K.; Khan, S. *Internet of Things (IoT): Concepts and Applications*; Springer: Cham, Switzerland, 2020.
5. Zeadally, S.; Tsikerdekis, M. Securing Internet of Things (IoT) with machine learning. *Int. J. Commun. Syst.* **2020**, *33*, e4169. [CrossRef]
6. Lilis, G.; Conus, G.; Asadi, N.; Kayal, M. Towards the next generation of intelligent building: An assessment study of current automation and future IoT based systems with a proposal for transitional design. *Sustain. Cities Soc.* **2017**, *28*, 473–481. [CrossRef]
7. De Paola, A.; Ortolani, M.; Lo Re, G.; Anastasi, G.; Das, S.K. Intelligent management systems for energy efficiency in buildings: A survey. *ACM Comput. Surv. (CSUR)* **2014**, *47*, 1–38. [CrossRef]
8. Zhao, X.G.; Jiang, G.W.; Li, A.; Wang, L. Economic analysis of waste-to-energy industry in China. *Waste Manag.* **2016**, *48*, 604–618. [CrossRef]
9. Qiang, G.; Tang, S.; Hao, J.; Di Sarno, L.; Wu, G.; Ren, S. Building automation systems for energy and comfort management in green buildings: A critical review and future directions. *Renew. Sustain. Energy Rev.* **2023**, *179*, 113301. [CrossRef]
10. Luo, J.; Zhao, C.; Chen, Q.; Li, G. Using deep belief network to construct the agricultural information system based on Internet of Things. *J. Supercomput.* **2022**, *78*, 379–405. [CrossRef]
11. Dai, X.; Xiao, Z.; Jiang, H.; Alazab, M.; Lui, J.C.; Dustdar, S.; Liu, J. Task co-offloading for d2d-assisted mobile edge computing in industrial internet of things. *IEEE Trans. Ind. Inform.* **2022**, *19*, 480–490. [CrossRef]
12. Bleischwitz, R.; Spataru, C.; VanDeveer, S.D.; Obersteiner, M.; van der Voet, E.; Johnson, C.; Andrews-Speed, P.; Boersma, T.; Hoff, H.; Van Vuuren, D.P. Resource nexus perspectives towards the United Nations sustainable development goals. *Nat. Sustain.* **2018**, *1*, 737–743. [CrossRef]
13. Liang, X.; Huang, Z.; Yang, S.; Qiu, L. Device-free motion & trajectory detection via RFID. *ACM Trans. Embed. Comput. Syst. (TECS)* **2018**, *17*, 1–27.
14. Glibovets, N.N.; Gulayeva, N.M. A review of niching genetic algorithms for multimodal function optimization. *Cybern. Syst. Anal.* **2013**, *49*, 815–820. [CrossRef]
15. Zheng, Y.; Lv, X.; Qian, L.; Liu, X. An optimal bp neural network track prediction method based on a ga–aco hybrid algorithm. *J. Mar. Sci. Eng.* **2022**, *10*, 1399. [CrossRef]

16. Koper, K.D.; Wysession, M.E.; Wiens, D.A. Multimodal function optimization with a niching genetic algorithm: A seismological example. *Bull. Seismol. Soc. Am.* **1999**, *89*, 978–988. [CrossRef]
17. Yang, R.; Wang, L. Multi-zone building energy management using intelligent control and optimization. *Sustain. Cities Soc.* **2013**, *6*, 16–21. [CrossRef]
18. Xia, Y.; Ding, L.; Tang, Z.C. Interaction effects of multiple input parameters on the integrity of safety instrumented systems with the k-out-of-n redundancy arrangement under uncertainties. *Qual. Reliab. Eng. Int.* **2023**, *39*, 2515–2536. [CrossRef]
19. Zhou, B.; Li, W.; Chan, K.W.; Cao, Y.; Kuang, Y.; Liu, X.; Wang, X. Smart home energy management systems: Concept, configurations, and scheduling strategies. *Renew. Sustain. Energy Rev.* **2016**, *61*, 30–40. [CrossRef]
20. Jiang, H.; Xiao, Z.; Li, Z.; Xu, J.; Zeng, F.; Wang, D. An energy-efficient framework for internet of things underlaying heterogeneous small cell networks. *IEEE Trans. Mob. Comput.* **2020**, *21*, 31–43. [CrossRef]
21. Yang, C.H.; Lee, K.C.; Li, S.E. A mixed activity-based costing and resource constraint optimal decision model for IoT-oriented intelligent building management system portfolios. *Sustain. Cities Soc.* **2020**, *60*, 102142. [CrossRef]
22. Moreno, M.V.; Dufour, L.; Skarmeta, A.F.; Jara, A.J.; Genoud, D.; Ladevie, B.; Bezian, J.J. Big data: The key to energy efficiency in smart buildings. *Soft Comput.* **2016**, *20*, 1749–1762. [CrossRef]
23. Khan, M.I.; Jan, M.A.; Muhammad, Y.; Do, D.-T.; Rehman, A.U.; Mavromoustakis, C.X.; Pallis, E. Tracking vital signs of a patient using channel state information and machine learning for a smart healthcare system. *Neural Comput. Appl.* **2021**, 1–15. [CrossRef]
24. Ren, D.H. Research Intelligent Building Electrical Energy Saving Design. *Intell. Build. Smart City* **2017**, *31*, 23.
25. Fu, Q.; Li, Z.; Ding, Z.; Chen, J.; Luo, J.; Wang, Y.; Lu, Y. ED-DQN: An event-driven deep reinforcement learning control method for multi-zone residential buildings. *Build. Environ.* **2023**, 110546. [CrossRef]
26. Ni, Q.; Guo, J.; Wu, W.; Wang, H. Influence-based community partition with sandwich method for social networks. *IEEE Trans. Comput. Soc. Syst.* **2022**, *10*, 819–830. [CrossRef]
27. Metallidou, C.K.; Psannis, K.E.; Egyptiadou, E.A. Energy efficiency in smart buildings: IoT approaches. *IEEE Access* **2020**, *8*, 63679–63699. [CrossRef]
28. Jagadeesan, S.; Ravi, C.N.; Sujatha, M.; Southry, S.S.; Sundararajan, J.; Reddy, C.V.K. Machine Learning and IoT based Performance Improvement of Energy Efficiency in Smart Buildings. In Proceedings of the 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 23–25 March 2023; pp. 375–380.
29. Chang, D.X.; Zhang, X.D.; Zheng, C.W.; Zhang, D.M. A robust dynamic niching genetic algorithm with niche migration for automatic clustering problem. *Pattern Recognit.* **2010**, *43*, 1346–1360. [CrossRef]
30. Zheng, Y.; Liu, P.; Qian, L.; Qin, S.; Liu, X.; Ma, Y.; Cheng, G. Recognition and depth estimation of ships based on binocular stereo vision. *J. Mar. Sci. Eng.* **2022**, *10*, 1153. [CrossRef]
31. Yin, B.; Khan, J.; Wang, L.; Zhang, J.; Kumar, A. Real-time lane detection and tracking for advanced driver assistance systems. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 6772–6777. [CrossRef]
32. Cheng, B.; Wang, M.; Zhao, S.; Zhai, Z.; Zhu, D.; Chen, J. Situation-aware dynamic service coordination in an IoT environment. *IEEE/ACM Trans. Netw.* **2017**, *25*, 2082–2095. [CrossRef]
33. Kumar, A.; Shaikh, A.M.; Li, Y.; Bilal, H.; Yin, B. Pruning filters with L1-norm and capped L1-norm for CNN compression. *Appl. Intell.* **2021**, *51*, 1152–1160. [CrossRef]
34. Ali, M.; Yin, B.; Kunar, A.; Sheikh, A.M.; Bilal, H. Reduction of Multiplications in Convolutional Neural Networks. In Proceedings of the 2020 39th Chinese Control Conference (CCC), Shenyang, China, 27–29 July 2020; pp. 7406–7411. [CrossRef]
35. Hazrat, B.; Yin, B.; Kumar, A.; Ali, M.; Zhang, J.; Yao, J. Jerk-bounded trajectory planning for rotary flexible joint manipulator: An experimental approach. *Soft Comput.* **2023**, *27*, 4029–4039. [CrossRef]
36. Bilal, H.; Yin, B.; Aslam, M.S.; Anjum, Z.; Rohra, A.; Wang, Y. A practical study of active disturbance rejection control for rotary flexible joint robot manipulator. *Soft Comput.* **2023**, *27*, 4987–5001. [CrossRef]
37. Lu, S.; Guo, J.; Liu, S.; Yang, B.; Liu, M.; Yin, L.; Zheng, W. An improved algorithm of drift compensation for olfactory sensors. *Appl. Sci.* **2022**, *12*, 9529. [CrossRef]
38. Xu, H.; Sun, Z.; Cao, Y.; Bilal, H. A data-driven approach for intrusion and anomaly detection using automated machine learning for the Internet of Things. *Soft Comput.* **2023**, *27*, 14469–14481. [CrossRef]
39. Lu, S.; Ban, Y.; Zhang, X.; Yang, B.; Liu, S.; Yin, L.; Zheng, W. Adaptive control of time delay teleoperation system with uncertain dynamics. *Front. Neurorobot.* **2022**, *16*, 928863. [CrossRef]