Optimizing of Consumption Energy in Smart building

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Abstract- Intelligent technologies have advanced significantly over the past two decades and have integrated with cities to enhance citizen lives. Additionally, the amount of energy consumed varies depending on the weather, the number of occupants, and the type of building—commercial, residential, or administrative. In contrast, the citizen must make a trade-off between the building's environmental impact, comfort levels, and energy use.

In this essay, we'll suggest a smart model that enables management, control, and regulation of energy usage in accordance with a set of standards. As a result, this approach enables real-time calculation, regulation, and optimization of energy usage as well as comfort for the occupants. As a result, the person can learn about their energy consumption without having to read electricity measurements or wait for a billing cycle. Additionally, this method enables energy resource conservation and increases system output even during periods of high demand.

Keywords- Smart Energy System, Energy consumption, multi-agent system, genetic algorithm.

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1 Introduction

Enhancing citizen quality of life is the goal of smart cities (SC). It has been rising in relevance on policymakers' agendas, [1]. As a result, the City is an urban region made up of a variety of interconnected elements such as the population, various networks such as the electricity or water network, buildings, etc. Actually, the smart city is built to make the best use of resources like energy, water, and internet. We can install sensors and lighting that can collect and deliver information to reduce energy consumption. In order to create a smart city, the streets must be connected. The brains of smart cities are these electronically interconnected streetlights. There are structures throughout the city that have off-peak times. For instance, if a residential building houses students who are in class or studying throughout the day, the demand for energy will be reduced. But in the evening, things are different. Even if they use a lot of energy throughout the day in commercial or administrative buildings, they use less in the evening. Additionally, we can detect a peak off hour and low usage in the same building. In order to manage, regulate, and optimize the energy usage of all these different types of buildings, we must develop a smart model. In order to control and manage energy usage while preserving occupant comfort, smart buildings need an interior environment control system, [2].

In this study, we suggest using a multi-agent system that allows for the distribution of various duties among the agents while allowing for real-time energy consumption optimization using genetic algorithms by each agent, allowing for quick adaptation to building consumption.

As a result, we will employ some agents to act as the building's meter. Additionally, we assign a resource agent—a type of agent that can interact with other actors or meter agents—to each energy resource that supplies energy to streets in order to control and optimize energy use. In order to identify the optimum solution that can control energy consumption for all types of buildings, all agents can work together and engage in negotiation. Then, we create a GIS system that enables us to know the location of a building and any information related to it, such as the building's ID, energy usage, billing information, etc.

Following a thorough investigation of the matter, we discover that there are three variables that can impact energy consumption, including system peak times, energy prices, peak energy demand, and the amount of energy consumed each hour, among other things. Additionally, there are two types of energy-consuming equipment that we commonly utilize, including lighting systems and

HVAC (Heating, Ventilation, and Air Conditioning) systems.

We have seen significant advancements in intelligent technology over the past two decades, which have fused in cities to enhance the quality of life for citizens. With the aid of these intelligent building technologies, tenants' lives can be made easier. Generally speaking, smart buildings are anticipated to use cutting-edge computing systems and intelligent technology to accomplish the best possible trade-offs between total occupant comfort and energy consumption, [3]. In this context, we can point out that the primary energy consumers in residential, office, and commercial buildings are HVAC and lighting systems. Demand-driven control measures like turning off or dimming smart lighting systems, controlling ventilation, and regulating the amount of heating and cooling provided to buildings using actual building occupancy data all contribute to improving the energy performance in buildings, [4]. Up to 60% of the energy for buildings is used by these systems. Depending on how well the structure functions, the remaining energy is used by various types of equipment, [5]. Because they can handle distributed and adaptive conditions, multi-agent systems are the best method for modeling complex systems. In order to control environmental factors and resolve potential conflicts that could arise between energy consumption and customer comfort, we will apply this approach in this study to manage, regulate, and optimize the energy consumption in residential buildings.

A multi-agent system has been primarily used to coordinate the use of building electrical devices and heating as an HVAC-L system in order to reduce energy demand in a smart building that enables to optimize the energy consumption and energy cost in order to increase the comfort level of building occupants. In this section, we evaluate the current state of the art for using a multi-agent system to balance energy usage with the satisfaction of building inhabitants.

In order to reduce building energy consumption and maintain occupant comfort, Hagras et al. suggest using a system to learn how a building reacts thermally to both interior and external occupancy loads, [6].

Following that, Liao and Barooah create a Multi-Agent System to simulate the actions of every building tenant and produce reduced-order graphical representations from simulations of the agent-based model, [7].

A Multi-Agent System was also created by Joumaa et al. to manage proactive and reactive control of building HVAC and lighting systems. They choose the agent-based methodology because distributed systems can simulate building energy usage. These systems rely on HVAC-L system and sensor interaction with facility systems and appliances,[8].

We might also mention the work of Azar and Menassa, who create a novel agent-based methodology that enables us to model the energy consumption of commercial buildings. This simulation takes into account different types of occupants and potential changes to occupant behavior as a result of their interactions with the built environment and one another, [9].

All of these prior multi-agent systems look for ways to better manage building systems and energy resources while also reducing building energy consumption through direct interaction and coordination with building occupants. However, there are no methods that have been created to maximize energy consumption and meet occupant comfort requirements. In this article, we'll introduce a hybrid technique called the multi-agent system and genetic agent (SMA-GA), which enables each agent to discover the best strategy for maximizing energy efficiency and passenger comfort.

This paper is organized as the following. First, we outline our suggested strategy, which is based on the Multi-Agent System and Genetic Agent methods (SMA-GA). Then, we include a summary and any recommendations for follow-up work.

2 Materials and Methods

2.1 Smart Building

The idea of a smart building is actually first introduced in intelligent systems that can regulate energy usage and occupant comfort. In order to maximize energy efficiency, occupant comfort, resource savings, and system overall productivity, smart buildings manage, regulate, and control their indoor environment using intelligent technologies. By utilizing current technologies, these systems seek to reduce energy consumption, conserve resources, and meet occupant comfort demands. HVAC-L systems and other intelligent energy appliances help reduce energy use. Saving resources entails protecting them from threats. By adding HVAC-L values that adjust the building environment in accordance with occupant preferences, demand from occupants is satisfied. On the other hand, when a building is intelligently controlled to accommodate tenant preferences by modifying the lighting and heating/cooling level, these preferences must be carefully evaluated and discovered through occupant input or behaviors. The corresponding agent must be able to detect and learn from behaviors in order to use this skill. Through learning the activities of the agents and the corresponding responses of the inhabitants, the process is carried out interactively based on the reinforcement mechanism.

To meet the needs of energy efficiency and occupant satisfaction, a variety of activities must be finished for minimizing energy consumption in buildings and evaluating occupant comfort in reaction to changes in the building environment. However, the relationship between energy use and occupant comfort is typically inverse. Therefore, resolving the conflicts between energy usage and occupant comfort is one of a smart building's main objectives. Typically, environmental criteria used to assess occupant comfort levels include indoor temperature, ventilation, air conditioning, and lighting level. In addition to preserving the use of devices against hazards, the decision of the control strategy is crucial to lowering energy consumption in the building. The system efficiency is also influenced by the energy consumption. Application of an intelligent controller that attempts to reduce energy usage without lowering occupant comfort can accomplish these goals. A smart system-equipped home is shown in Figure 1.

Fig. 1: A smart building.

2.2 Multi-agent System and Genetic Algorithm

2.2.1 Why We Use the Multi-Agent System in Smart Cities

An agent is a software system that is embedded in a certain environment and has the ability to act autonomously in order to achieve its intended goals, [10]. The multi-agent system is utilized in this study because it offers a number of benefits in the areas of energy consumption and occupant comfort. The advantages of multi-agent systems that provide autonomy to address energy consumption issues and meet occupant comfort demands. It thus offers a structure that is appropriate for these systems. Additionally, they offer a number of crucial traits like mobility, flexibility, cooperation, and bargaining. In other words, this autonomous agent senses its surroundings on the one hand while changing it on the other hand by its behaviors. As a result, an agent can quickly adapt to a changing environment.

2.2.2 Why We Use the Genetic Agent

In [11], genetic algorithms are created to mimic the phenomenon of adaptation in live things. They are an optimization method based on the ideas of genetics and natural selection. Within a fair amount of time, it examines a vast number of potential solutions for the best one (the process of evolution takes place in parallel). Each of these solutions has a set of specifications that fully characterize the solution. Then, with each parameter consisting of one or more "chromosomes," this collection of parameters can be thought of as the "genome" of the person. They enable a population of solutions to gradually converge on the best option. They will accomplish this via a system for selecting from the population of people (potential solutions). The chosen individuals will be crossed with one another (crossover), and some of them will mutate by avoiding local optima as much as they can. Both issues are primarily handled by genetic algorithms, [12].

1. There are several parameters that need to be optimized at once or the search space is huge.

2. A precise mathematical model cannot easily capture the nature of the issue.

We connect Multi-Agent Systems with Genetic Algorithms to allow the agent to freely choose the optimum course of action (SMA-GA). As a consequence, our proposed model is based on the three concepts listed below.

1. A building agent is a software agent that has the ability to manage, control, and exchange pertinent data with nearby agents.

2. The genetic algorithm uses genetic patrimony that has been altered across agents as an input. This genetic heritage represents data on the HVAC-L system's energy

consumption that was gathered by the sensor system.

3. To discover the best configuration for the current situation, a genetic algorithm is applied. This algorithm considers two goal functions: energy consumption and occupant comfort.

2.3 Building Agent

As we previously mentioned, a smart building has the ability to manage, control, and regulate its indoor environment to optimize energy consumption, ensure the comfort of the occupants, save energy resources, and boost system productivity. Therefore, the primary goal of a smart building is to resolve any conflicts that may arise between satisfying the comfort needs of its inhabitants and consuming less energy. Both the environmental conditions and the occupant's preferences for the surroundings have an impact on their level of comfort satisfaction. Environmental factors may be used as indices to construct the function of occupant comfort by taking into account both the actual value of the factors and the preferences of the occupants to determine how comfortable the building's occupants are. As a result, three components have been included in the design of the building agent to control and regulate its indoor climate and reduce energy usage. An optimizer, a simulator, and a comfort model make up these elements.

2.3.1 An Optimizer

A genetic algorithm is used. In this study, GA runs 100 times in each time step to maximize the likelihood of reaching the global optimization, save energy resources, and satisfy occupant preferences because heuristic techniques cannot be guaranteed to identify the global optimal solution within the finite number of iterations. The possibility of getting better results from running the optimization method more often should theoretically increase, but this will certainly require more processing time. Following numerous experiments, it was shown that 100 runs is a practical quantity for balancing the solution quality and computing time cost.

2.3.2 Simulator

Each building agent has a simulator that is utilized in tandem to determine the inhabitants' level of comfort and their optimal energy usage under the current circumstances. To achieve a suitable balance between discovery time and system performance, the simulator's output could be adjusted. The optimizer estimates the satisfaction of occupants' comfort by repeatedly running energy flow simulations for each iteration. The best occupant comfort level is then used to develop the following generation of general occupant comfort levels, and this process is repeated over a number of generations to obtain the optimum candidate comfort level.

2.3.3 Comfort Model

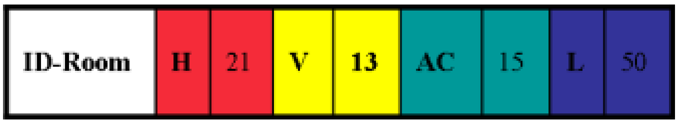
The comfort model enables computer-based indoor climate control in smart buildings to optimize energy use, ensure occupant comfort, conserve energy resources, and boost system productivity. Building agents must assess energy usage and occupant comfort levels in reaction to changes in the indoor environment in order to reach a balance between energy efficiency and occupant comfort. However, the relationship between energy use and occupant comfort is typically inverse, [13]. An agent building's primary objective is to resolve conflicts between lowering energy usage and raising occupant comfort. The degree of occupant comfort is influenced by the environment's state as well as occupant preferences. The actual value of the relevant environmental characteristics and the occupants' preferences of these parameters may be used as indices to develop the function of occupant's comfort in order to evaluate the occupants' comfort in their living environment. The indoor temperature, light intensity, air conditioning, and ventilation levels within the building are typically utilized as measures to assess occupant comfort.

2.4 Building Agent's Optimizer

As we already said, the building agent includes an optimizer and simulator that work together to determine the HVAC-L system parameters in order to maximize energy usage while still satisfying occupant comfort requirements. The use of genetic algorithms has a significant advantage over systems that rely on predefined values because each building agent enables a genetic algorithm to discover the values of the HVAC-L system, which may not resemble any predefined values but may be appropriate values for the current interior conditions. The optimizers should strike a good balance between the time it takes to find solutions and the amount of energy used. Thus, each building agent uses a genetic algorithm to identify the best HVAC-L system values that may be attributed to each system in order to maximize energy efficiency and occupant comfort.

2.4.1 Chromosome Structure

We must define the genes and the chromosome structure in order to use the genetic algorithm. The gene's identification and a set of HVAC-L system parameters that can be used to perform the best energy consumption and satisfy the comfort level of the occupants can be used to describe the gene. We code the genes using various forms. In order to code the identifiers, we first utilize strings. Then, we use real numbers to code the temperatures, ventilation, air conditioning, and lighting system values. The gene's structure is shown in Figure 2.



ID-Room : room identify in the building,

H: heating system,

V : ventilation system,

AC: Air Conditioning system,

L: light System.

Fig. 2: Gene structure of the room.

A sequence of genes from various room agents that can provide the best response to the HVAC-L system values are represented by the chromosome. The optimizer use a genetic algorithm with its various traditional processes, like selection, crossover, and mutation, to determine the optimal chromosome from the population. The optimizer repeatedly runs the energy consumption simulator for each HVAC-L system in a particular generation, allowing each building agent to select the optimal option from the population. The values discovered by their optimizers are used as sub-values to provide the ultimate solution of the present energy consumption of the HVAC-L system after interaction and negotiation between the various building agents. The HVAC-L system's top candidate values are found after a number of generations. Figure 3 shows an example of a solution that is found by the building Agent.

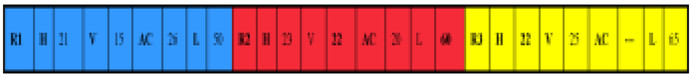


Fig. 3: The chromosome of the solution.

2.4.2 Genetic Algorithm Steps

a) Initialization

Each chromosome's initialization for participation in the genetic algorithm's population is controlled by the initialization operator. The genetic material from which all novel solutions will arise is present in this chromosome. In this work, the Steady State will be used to start the generation process and choose the genetic algorithm's population for the following generation. First, Steady State clones the initial chromosomes to produce a population of individuals. Subsequently, during the course of evolution, a temporary population of individuals is produced, added to the previous population, and then the worst individuals are eliminated in order to bring the present population back to its original size. According to this technique, the newly produced offspring may or may not stay within the new population, depending on how they compare to the current population members.

b) Crossover

The process for creating a child from two parent chromosomes is defined by the crossover operator. The crossover operator creates new people as offspring who share traits from both parents. The likelihood of crossover influences the frequency of crossover at each generation. The single point crossover strategy will be used in this method for all tests. At each generation, 50% of the new population was created by joining two pieces of each chromosome's parents to create a new chromosome, which is how the data for all experiments described in this paper were formed. The crossover operator is depicted in Figure 4.

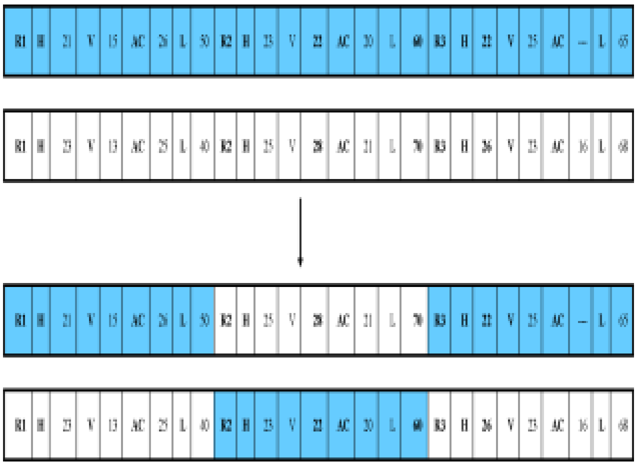


Fig. 4: Crossover operator.

c) Mutation

The mutation operator plays a crucial role. The process for modifying the chromosome is described. When a child experiences mutation, a gene may be randomly altered with a low likelihood. It offers a modest degree of random search that makes convergence at the world's best possible easier. The amount of each genome's genetic material that is altered or mutated depends on the chance of mutation. A portion of the chromosome is altered if the mutation is carried out. The search effort would be harmed if the mutation happened too frequently. The results in this study were produced using a 1% mutation probability that was established experimentally using a single vector HVAC-L system case. In picture 5, we show a random mutation.

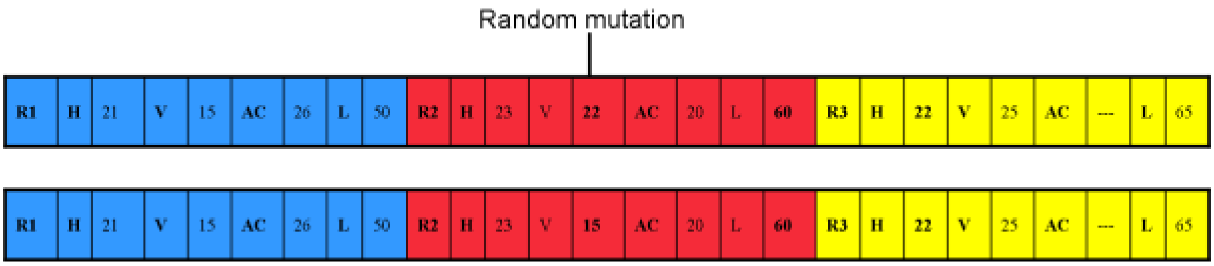


Fig. 5: Mutation operator.

d) Evaluation of solutions

We can argue that the objective function of every discrete optimization problem, whose goal is to deliver a metric for any given solution that expresses its relative quality, is what determines if the problem is successful. The goal function employed in this method for solving the energy consumption issue in buildings calculates and adds the penalties related to temperature, illumination, indoor air quality, and ventilation inside our state representation. As a result, we will utilize objective functions to assess potential energy-saving measures and look at the weighted link between actual measured values for the following parameters: temperature, ventilation, indoor air quality, lighting level, and occupant comfort level. Several definitions that model the underlying structure of the problem are necessary for the objective functions used to evaluate solutions, specifically:

- $R = \{R_1, R_2, R_3, ...R_n\}$ is the set of all room in the building,
- $H = \{H_1, H_2, H_3, ...H_n\}$ is the set of all heating systems in the building,
- $L = \{L_1, L_2, L_3, ...L_n\}$ is the set of all illumination systems in the building,
- $A = \{A_1, A_2, A_3, ...A_n\}$ is the set of all air conditions in the building,
- $V = \{V_1, V_2, V_3, ...V_n\}$ is the set of all ventilation system in the building,
- H_m, L_m, A_m, *and* V_m are the measured values of the temperature, the illumination, and the indoor air quality and ventilation respectively.
- H_c, L_c, A_c, *and* V_c are the comfort values of the temperature, the illumination, and the indoor air quality, respectively.
- *N1, N2, N3, N4* is the all number of the temperature, the illumination, and the indoor air quality and ventilation system respectively.
- $[T_{min}, T_{max}]$ represent the interval time where the values of the three parameters were measured.
- $[C_{min}, C_{max}]$ represent the comfort range. This range can be defined by customers.
- $[E_{min}, E_{max}]$ represent the consumption energy range.

Two essential components of our SMA-GA are the allotted energy to the HVAC system EH and the assigned energy to the lighting system EL.
In this situation, the two significant functions f(C) and f(E) allow us to assess the effectiveness and performance of the suggested strategy. Building agent calculates these two functions.

In order to assess the effectiveness and efficiency of our system, the goals of this optimization mechanism are to optimize occupant comfort (C) and reduce energy usage (E). First, there is

$$f(C) = C_1 * {}^{H_c}\!/_{H_m} + C_2 * {}^{L_c}\!/_{L_m} + C_3 * {}^{A_c}\!/_{A_m} \qquad (1)$$

The user-defined weighting variables, C1, C2, and C3, highlight the significance of three comfort factors and address any equipment conflicts. These variables accept values between [0, 1]. Depending on the situation and the time of year, occupants can choose their own desired values. As we previously stated, the design of the control method should take occupancy duration into consideration because it has a significant impact on energy savings. The building agent activates the optimizer during hours of occupancy in order to adjust the set point and achieve the desired indoor visual comfort while using the least amount of energy.

In the absence of occupants, the agent building maintains the blind position and shuts off all resource lights to conserve energy. The objective function is described in equation 1 and its maximization is the aim of optimization. The control goal is accomplished in part via the comfort value ratio, which is selected by the occupants and is displayed on a graphic user interface. As a result, it enables both an increase in occupant comfort and energy efficiency.

The building's inside environment can be controlled with the help of the second goal function. The goal of this function is to reduce the HVAC-L system's overall energy usage. Thus, the following is a definition of this objective function.

$$f(E) = E_{HVAC} + E_L \tag{2}$$

E_{HVAC} and E_L represent the consumption energy of the HVAC system and the lighting system, respectively.

2.5 System Architecture

Our system primarily uses three different sorts of agents: profile agents, room agents, and building agents. These agents are capable of working together in a building setting. The profile agent gets its data from the inhabitants who can describe their level of comfort, whereas the room agents get their data from sensors. Throughout the entire structure, sensors are dispersed to track the effectiveness and operation of various technologies that have been installed. The sensor network can provide three different types of data: environmental data, occupancy data, and energy data. Environmental data refers to the environmental characteristics of the building, such as the temperature inside and outside, the amount of light, the air conditioning, and the ventilation. The number of occupants, their presence or absence, and their preferences for occupancy are all common components of occupancy statistics. Energy data primarily focuses on the status of energy supplied, including the price of electricity and the accessibility of other energy resources. Different room agents will use these measured data to determine how their respective occupants behave. The many systems that are installed in the room can be controlled by the room agent, who can also adjust the gas, lighting, and HVAC systems' settings, among others. Our SMA-system GA's design is depicted in Figure 6.

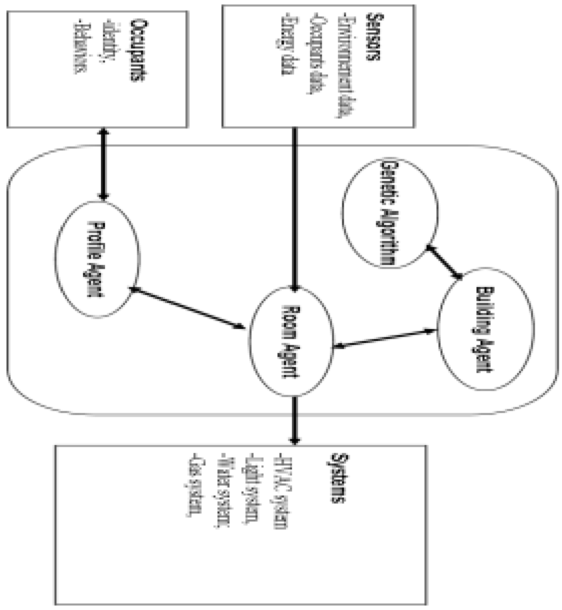


Fig. 6: The architecture of our Multi-agent system.

2.6 Negotiation and Cooperation

The multi-agent system and genetic algorithm (SMA-GA) requires us to present an effective process of negotiation, cooperation, and coordination amongst various agents in order to simulate an ideal energy consumption. We are aware that a single agent is unable to complete some complex tasks, such as solving the energy problem, due to individual limitations or because, even though it can, its performance and efficiency are drastically inferior to those achieved through the cooperation and coordination of many agents, [14]. The room agents bargain, each seeking to collect enough energy needed to discover the optimal ratio between measured values of temperature, illumination, ventilation, and air quality in the indoor environment and the comfort values of the occupants, in order to resolve consumption energy conflict. Therefore, it's crucial to keep their impacts in check when conflicts arise between these many parameters. In this situation, negotiating strategies help the interested room agents settle their disputes by finding concessions between the residents' degree of comfort and the building's energy consumption. The room agents can resolve multiple problems at once and avoid the emergence of new ones thanks to this negotiation. Additionally, it might be required if there is a quarrel between two or more building agents who are from separate houses. When there are disputes between buildings over who has the right amount of energy to keep their residents comfortable, we also employ negotiation to solve the problem of energy usage. These residential building agents bargain with one another to determine the best plan that may be used to satisfy the building's need for energy while also satisfying the comfort level of the residents. As a result, under our suggested method, the building agents bargain with one another to get to the best agreement. Through negotiation, they are able to resolve several conflicts at once and prevent the emergence of new ones. Figure 7 shows an illustration of a negotiation between two building agents, Building Agents 1 and 2. In order to reach an agreement, these two agents propose a course of action that can be built around measurable and occupant comfort values. Each time a cycle occurs, one building agent proposes a plan to the other building agents, who might accept or reject the idea. Negotiations come to a close if they agree; if not, the other building agent makes a proposal during the subsequent round.

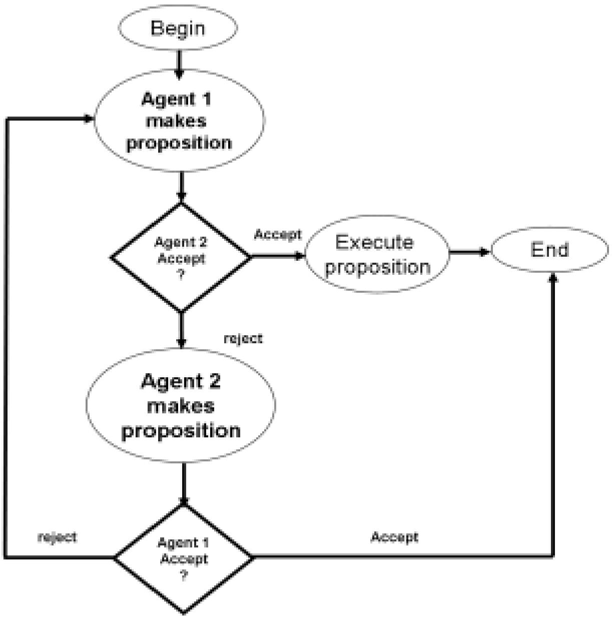


Fig. 7: Negotiation between two agents.

Coordination between building or room agents to determine the best course of action for every system to resolve energy conflicts is another definition of cooperation. In this essay, we discuss using collaboration to resolve conflicts that arise between energy use and occupant comfort. Each room agent works together with the other room agents to discover the best solution that enables to decrease energy consumption and raise the degree of comfort for the inhabitants. To enable the building agent to analyze this data and run its evolutionary algorithm, each room agent gives the building agent some HVAC-L data. When the HVAC-L system's optimizer has found a sequence of values, each building agent communicates the values to the other agents in a series of requests. The next step is for each agent to review the requests on its list, handle them, and attempt to determine the HVAC-L system's final optimal sequence of values that will allow it to resolve the conflict and prevent future conflicts. Depending on their existing circumstances, the building agents may accept or reject the request of other agents. Thus, the building agent requests a solution from its neighbors and waits to hear back from them. After analyzing their responses, the building agent decides whether or not a solution is feasible. If a solution is workable, it notifies its neighbors who agreed to the solution that it is viable. A straightforward arrangement of agent collaboration is shown in Figure 8.

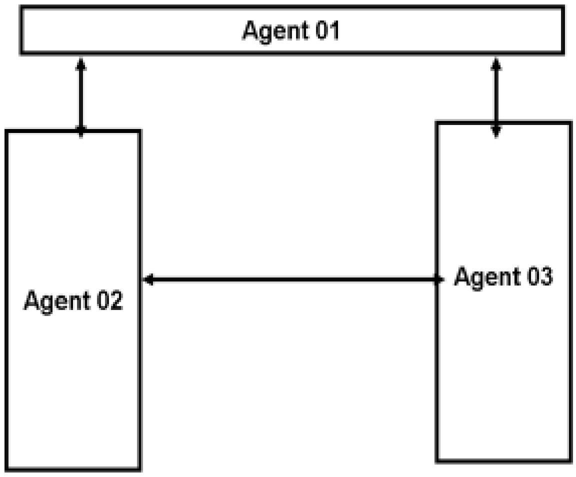


Fig. 8: Cooperation between Agents.

The signals sent and received by agents during the resolution of disputes between room agents and building agents in order to determine the best energy consumption. Table 1 provides a summary of these messages.

Table 1. Messages exchanged between agents.

Message	Comments
Inform (Distance, energy, time)	The building agent receives a message from the room agent. It has the necessary quantity of energy.
Inform (Conflict_Resolution)	Message delivered by the agent to a neighbor with whom it has a disagreement.

	The message includes the outcome of the agent's use of its dispute resolution process.
Notify (Conflict)	Message delivered by the building's agent to one of its neighbors informing them of the emergence of a fresh dispute.
Notify (Satisfaction)	Message delivered by a room agent to a building agent informing them of the completion of the procedure.
Help (Demand)	Message from a room agent to a building agent asking if there is any way they can assist.
Help (Response)	Message issued by a building agent to a station agent in a room asking if they can assist.
Negotiate(Demand)	Message sent to another building agent by one asking the other whether a negotiation is possible.
Negotiate(Response)	Message sent to another building agent by one asking whether it is possible to negotiate with the other agency.
Inform(Confirmation)	Agent transmits a message It notifies its neighbors who agreed to the solution that it is workable by sending them a confirmation.

3 Results and Discussion

In this section, we give a case study that demonstrates how to create the various system agents and demonstrate inter-agent cooperation. To implement the various agents, including the building agent, profile agent, and room agent, we use Jade (http://jade.tilab.com/). Additionally, we use Java (https://www.java.com/fr/) to develop the evaluation function, crossover operator, and mutation operator among other elements of the genetic algorithm. A comfortable atmosphere for all building residents is the goal of the smart building, which is a residential structure. The room agents first use the sensor to learn the HVAC-L data so that it may be fed into the genetic algorithms. Through a graphic interface, the occupants (users) can describe their preferences to the profile agent. The building agent uses a genetic algorithm to determine the HVAC-L system's ideal settings, which allows for the optimization of energy usage and improvement of occupant comfort.

The data utilized in the simulation were collected from June 1 through July 30, with 20 iterations per hour of computing. Because south zones utilize more energy during this time, the simulation was started in June. Temperature, illumination, and air quality are the three variables we will use to determine the comfort function f(C), hence the vector of weighting factors is (C1, C2, C3) = (1, 1, 1).

We employ the air quality index, which is shown appropriately in Table 2, in our simulation.

Table 2. Air quality index, [15].

Air quality index	category
1-50	Good
51-100	moderate
101-150	unhealthy
151-200	Very unhealthy
201-300	Extremely Unhealthy

Most building occupants are able to bear some discomfort. This is primarily unaffected by temperature changes of up to a few degrees Celsius. As a result, rather than a single temperature point, inhabitants may prefer a temperature. The majority of the residents will be significantly less satisfied with temperatures outside of this range, and this will also be true for users. We list the various temperature value intervals in Table 3.

Table 3. Intervals of temperature values.

Temperature interval	category
[-3,-1]	Very cold
0,7	Cold
8,16	Slightly cold
17,31	Good
32,41	hot

In Table 4, we introduce the different intervals of occupants' satisfaction and energy consumption.

Table 4. Intervals of occupants' satisfaction and the energy consumption.

Evaluation Parameters	Unacceptable	Less satisfaction	Highly satisfaction
Occupants' satisfaction	[1,4.5]	[5,8]	[8.5, 10]
Energy consumption (KWh)	[5,30]	[20,25]	[15,20]

The room agent uses certain data from the HVAC-L system to regulate the various systems. As is well known, increasing energy usage is necessary to maintain a higher occupant comfort level. The smart building agent, on the other hand, strives to strike a balance between energy usage and the comfort level of the higher tenants. In order to calculate the energy consumption allocated to the HVAC system and the lighting system, it should therefore discover the optimized values.
Keep in mind that this self-optimization system aims to optimize occupant comfort while minimizing the smart building's overall energy usage. In Fig. 9, we show that the two approaches—one with SMA-GA and the other without—have different levels of occupant comfort. In comparison to the second technique, which omits SMA-GA, the system achieves a higher level of occupant comfort using SMA-GA. As a result, the SMA-occupants' GA's level of comfort has increased quickly in comparison to the second method.

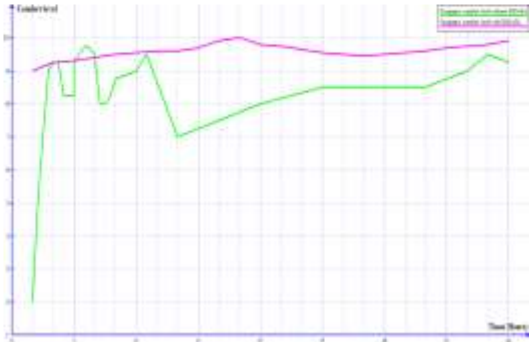


Fig. 9: Occupants' comfort level with and without SMA-GA.

Figure 10 demonstrates how our suggested methodology reduces energy usage when compared to the conventional method, which may also be utilized to increase energy efficiency. As a result, when we apply the SMA-GA approach, we may lower the energy consumption. In comparison to the traditional technique, which excludes SMA-GA, the SMA-GA approach allows us to optimize the energy consumption.

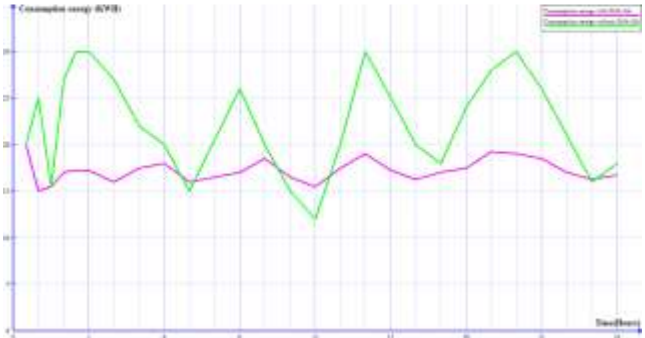


Fig. 10: Shows the energy consumption with and without SMA-GA.

By learning the behaviors of the occupants, the SMA -GA is intended to facilitate interactions between the inhabitants and the environment. The suggested SMA-GA can efficiently manage, regulate, and control the building to satisfy occupant comfort needs and optimize energy usage, according to case studies and simulation results.

4 Conclusion

An SMA-GA is created in this work to manage, govern, and regulate the internal space of the building using cutting-edge technologies like genetic algorithms and multi-agent systems. A genetic algorithm has been included into the multi-agent system to optimize building energy usage and boost occupant comfort. The agent building simulator may run a simulation that enables the discovery of the best plan for reducing the use of energy resources in buildings while enhancing their performance. Additionally, the building's occupants can express their preferences, and a high level of intelligence improves the control system's operability via the graphical interface. Our suggested method offers a robust and open architecture that enables simple agent configuration and allows for the addition of new agents without altering the overall architecture. As a result, the suggested strategy achieves a balance between energy usage and occupant comfort. The genetic process's key issue is consumption time. Analyzing the duration of the many tasks involved in the genetic process will be crucial in future research. We may also suggest using the same strategy to water consumption, which is a major issue for citizens in smart cities.

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