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Design of a multiagent-based smart microgrid system for building energy and comfort management

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Abstract: Modern intelligent control system design methodology in the electric power industry and their features are considered when providing the required comfort in multizone buildings with the use of multiagent power consumption and comfort management systems. Such a control system covers all the monitored zones of a building and, if necessary, can provide the greatest possible overall comfort in the building while reducing the required electric power. The purpose of this study was to develop a comfort management system in a multizoned building that can provide comfort while reducing the required electric power.

Key words: Multiagents, energy efficiency, smart grid, smart building, microgrid

1. Introduction

The quality and productivity of people's lives in buildings depends on the level of comfort inside of it. These conditions include the visual and thermal comfort of the buildings. They provide lighting and heating/conditioning systems. Strategies to ensure sustainable work have become important. According to the California Commercial End-use Survey [1], up to 85% of energy consumption in commercial buildings is spent on heating and cooling facilities, lighting of the building, ventilation structures, and office equipment [2]. The construction of a building requires high energy efficiency to reduce energy consumption.

Heating equipment determines the thermal comfort inside a room, and auxiliary cooling and heating systems are used to maintain the temperature inside the building. The relative air humidity in a room depends on the weather and climate conditions, the time of year, the availability and operation of household appliances, and human life processes. The level of illumination describes visual comfort and an artificial lighting system is used with drives for lighting control. The concentration of carbon dioxide (CO_2) is used as an index to measure air quality and a ventilation system is used to achieve low CO_2 concentrations [1,3].

The main task of management is to how use multiagent technology efficiently. The aim of our work is to approach this problem using computational intelligence [4] for the optimization of multicriteria heating, ventilation, and air conditioning (HVAC) systems.

Multiagent systems can help in solving many problems. The purpose of the multiagent system is to optimize the functioning of the energy system, with each agent performing its tasks [5,6]. An agent is an open system located in some environment. This system has its own behavior, corresponding to some extreme

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principles [7]. Thus, the agent is considered capable of perceiving information from the external environment with limited permission, processing it based on its own resources, interacting with other agents, and influencing the environment for some time. The agent platform (AP) implements the basic mechanisms that support the operation of the multiagent system and thus facilitates the creation of agent systems. Multiagent systems work on top of the AP and use its services. The main functions of the AP are agent interaction, message passing between agents within the platform, message exchange between agents of different platforms, ontology support, agent management, search for agents and data about them in the system, agent life cycle management, and security [8,9].

The remainder of this paper is organized as follows. In Section 2, the architecture of the proposed multiagent system is explained. In Section 3, the model of the energy management system (EMS) agent and EMS multiagent system implementation are presented. Section 4 represents experiment results with brief discussions. Finally, we summarize the main contribution of this study and outline a number of recommendations for future research.

2. Proposed system architecture

Figure 1 illustrates the multiagent EMS architecture of our study. The architecture consists of three parts: the grid system, multiagent system, and management system. Grid systems are needed to supply a building with energy.

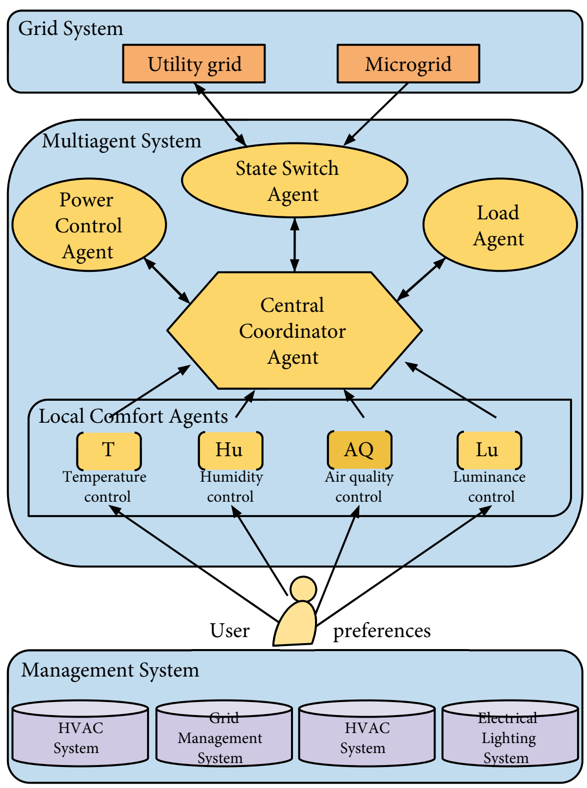

Figure 1. Architecture of the proposed multiagent control and management system.

In our study, we consider two types of energy sources: the utility grid and microgrid. The utility grid takes energy from the main grid of a city. The microgrid is supplied by renewable energy sources. The second part of the system is the multiagent system. Since each agent assumes a high level of intelligence for making a local decision, the system requires new agent model architecture. The multiagent system takes data from sensors and residents as input data and makes decisions to implement control on the drives. Management systems are the systems that should be controlled and supply the inhabitants with comfort and energy.

The sensors are distributed throughout the building to monitor its operation. Three types of data, including environmental, user preferences, and energy data, can be obtained from the sensor network. Environmental data refers to the environmental parameters of the building, such as indoor and outdoor temperatures, light levels, CO_2 concentration, or even the detection of intrusion or fire alarm signals. Energy data are mainly focused on the status of the energy supply, such as the state of the utility network, the price of electricity, and the availability of renewable resources. These measured data will be used by various local agents to determine their behavior.

3. The system implementation for building energy and comfort management

3.1. State switch agent

The switch agent receives data from the central coordinator about the energy consumed and generated. According to this information, the switch agent receives power from the power grid when there is not enough power from renewable sources and batteries to satisfy the demand of the required load. In addition, the switch agent can deliver excess energy back into the network when the renewable energy is more than the building's needs, which can then be stored in the batteries.

The total integrated building and microgrid system has two modes of operation: grid connection mode and isolated mode. The state switch agent communicates with the central coordinator agent to determine the status of the switch for connecting/disconnecting the microgrid to/from the utility grid is considered.

Figure 2 illustrates the procedure for selecting a particular operating mode in different scenarios. If there is any damage to the power system or if the rate of power consumption is not acceptable to consumers, the microgrid will be disconnected from the main grid. The switch in these scenarios will be opened and appropriate optimization or mitigation schemes will be adopted to maximize the overall comfort level using available renewable energy sources. Otherwise, the microgrid is connected to the power system.

Nevertheless, the building will always consume available renewable energy in the first place. If there is excess energy from renewable resources, the batteries will be charged. If there is still energy, the excess energy will be sold back to the energy system.

3.2. Central coordinator agent

The central coordinating agent is one of the key elements in the management system. It interacts with all agents based on external data (information about weather conditions) and user preferences for thermal, visual comfort, and air quality, as well as based on electrical load data of the building. The central coordinator determines the amount of energy and the energy needed to cover it, and manages it accordingly. Based on this information, the central agent manages local agents to distribute the available power in the region of the building in which comfort is assured.

Consider the evaluation of the comfort in buildings and areas based on its comfort index (CI) and overall comfort (OC) [4]. Mathematically, CI can be written as

$$Comfort\ Level = \delta_T\left(1-\left(\frac{e_T}{T_{set}}\right)^2\right)+\delta_H\left(1-\left(\frac{e_H}{H_{set}}\right)^2\right)+\delta_L\left(1-\left(\frac{e_L}{L_{set}}\right)^2\right)+\delta_A\left(1-\left(\frac{e_A}{A_{set}}\right)^2\right) \quad (1)$$

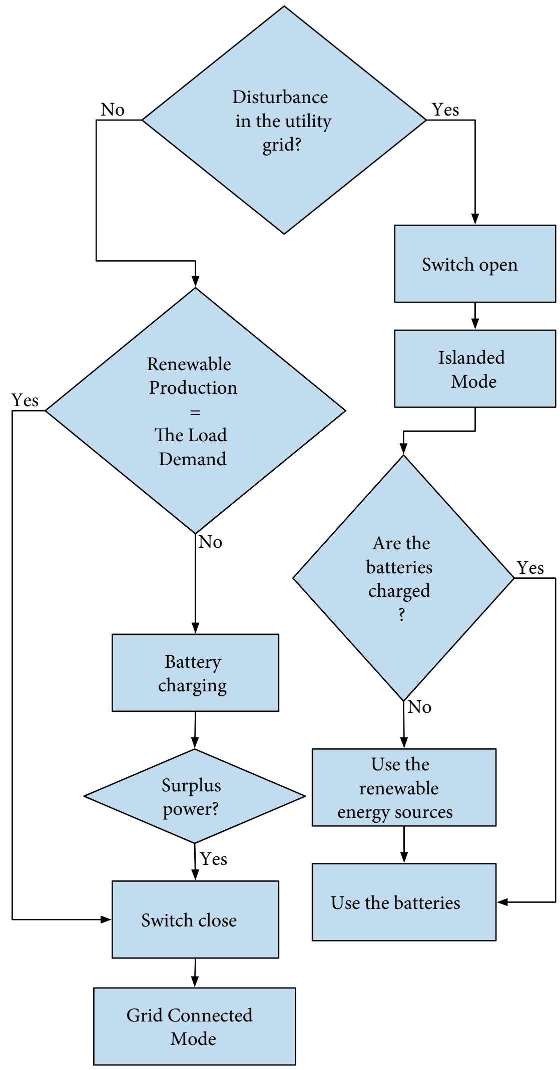

Figure 2. Structure of the state switch agent.

All user-defined weighting factors belongs to the segment [0, 1], and their sum equal to 1. If we use a power supply with an output insufficient to cover all the needs of the building, the general comfort in the building is less than 1. In this case, the central agent must solve the optimization problem: knowing the required power, weights, and areas' available power, capacity values are determined for each zone, at which the overall comfort is maximized. In our case, we apply a multiobjective optimization algorithm (MOOA) to minimize the conflict in negotiation of agents and its optimization process [10].

A general multiobjective optimization problem can be mathematically represented in Eqs. (2) and (3) [11].

$$MOOP \min_{x \in C} F(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \dots \\ f_n(x) \end{bmatrix} \quad n \geq 2 \tag{2}$$

subject to

$$C = \{x : h(x) = 0,\ g(x) \leq 0,\ a \leq x \leq b\}, \tag{3}$$

where $x^* \in C$ is Pareto optimal (or nondominated) for a multiobjective optimization problem if and only if there is no $x \in C$ such that $f_i(x) \leq f_i(x^*)$ for every instance where there is no $i \in 1, 2, 3, \ldots, n$ with at least one strict inequality. $f(x)$ is the objective vector, C represents the constraints, and x is a P-dimensional vector representing the decision variables within a parameter space X. The space spanned by the objective vectors is called the objective space. The subspace of the objective vectors that fulfills the constraints has been called the feasible space.

3.3. Local controller agents

Local controller agents are implemented in four local subsystems to control thermal comfort, visual comfort, and air quality.

Figure 3 shows the structure of local subsystems. In the proposed model of the building, it is assumed that the internal environment of the building in question is sensitive to changes in the external environment. This means that conditions inside the building will closely track changes in the external environment if the control is not applied. Fuzzy rules are applied to calculate the required capacity under uncertain circumstances.

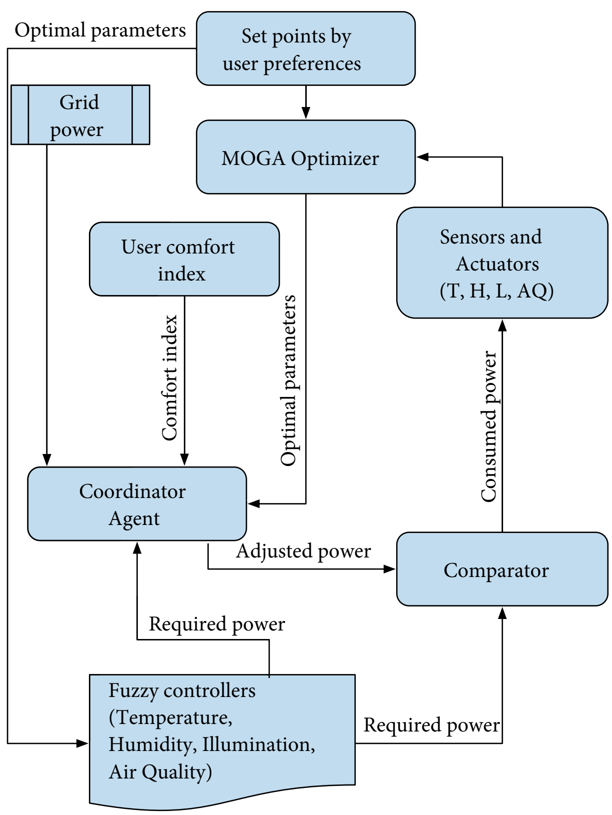

Figure 3. Structure of local controller agents.

3.4. Local temperature agent

To calculate the required power to maintain internal thermal comfort, a controller with fuzzy proportional–derivative (PD) is designed for this subsystem. The input of this fuzzy controller includes error and changing error. The changing error is the difference between the previous and current errors. The problem is to determine the temperature corresponding to the level of control to the digital-to-analogue converter regulator, the input variables of which are as follows: e (difference between the desired and actual temperature; the first derivative of temperature change during the computing cycle)

$$\Delta e = T_{desired}(t) - T_{current}(t), \tag{4}$$

where $T_{desired}(t)$, $T_{current}(t)$ are the desired and current temperatures and t is the time.

Membership functions $\mu(e)$ and $\mu(\Delta e)$ determine the linguistic fuzzy variables e and Δe fuzzy sets with corresponding identifiers. We construct two membership functions. In one case, the argument is a temperature difference ( ); in the second, it is the rate of temperature change (Δe) (Figure 4). The identifiers are as follows: large positive deviation, average positive deviation, small positive deviation, zero deviation, small negative deviation, average negative deviation, and large negative deviation. With the help of the membership functions, the desired operating mode of the HVAC system is chosen.

3.5. Local humidity agent

To identify the required power for humidity comfort, we apply fuzzy PD design. The fuzzy humidity control has a set of fuzzy variables, including very dry, dry, normal, humid, and very humid. Depending on each mode, power requirement is changed.

3.6. Local illumination agent

Factors that affect illumination level are outdoor and indoor luminance as well as room occupancy. Figure 5 shows these factors and their relations.

The membership functions of the input and output of the local lighting controller are shown in Figure 6.

Curtain status and occupied status is defined in crisp logic (0 or 1). Here 1 means the curtain is open and a person is in the room.

In local lighting, illumination level is used as measured parameters to indicate visual comfort, which is measured in lux. The input of the local fuzzy light controller is an error between the ambient light level and the internal set point. The output power is the required power consumed by the lighting system. The rules of the local illumination controller are shown in Figure 7.

3.7. Local air quality agent

Local air quality agent controls CO_2 concentration level in the building based on air quality sensors data. A schematic representation of a building envelope with a forced fresh air filtration is shown in Figure 8.

The relevant quantities describing the volume flow rates in and out, as well as CO_2 concentrations, are as follows: q_i, the volumetric flow rate of fresh air through the filter; q_0, the volumetric air flow rate leaked from the building; V, the volume of air inside the building; C, the concentration of CO_2 inside building at time t; C_0, the concentration of CO_2 inside the building at time t_0; and S, the generation rate of CO_2 mass per unit time from high occupancy or other source.

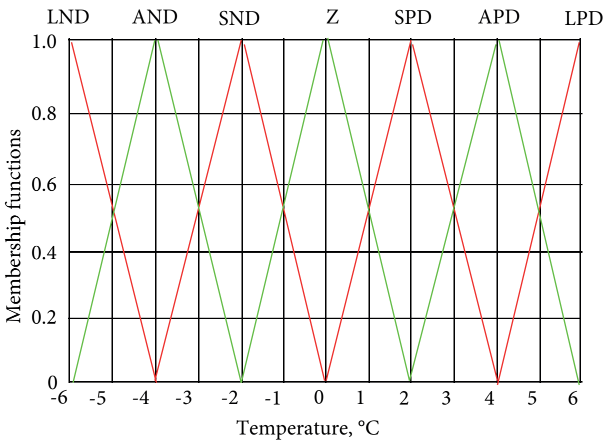

Figure 4. Linguistic membership functions by input parameter.

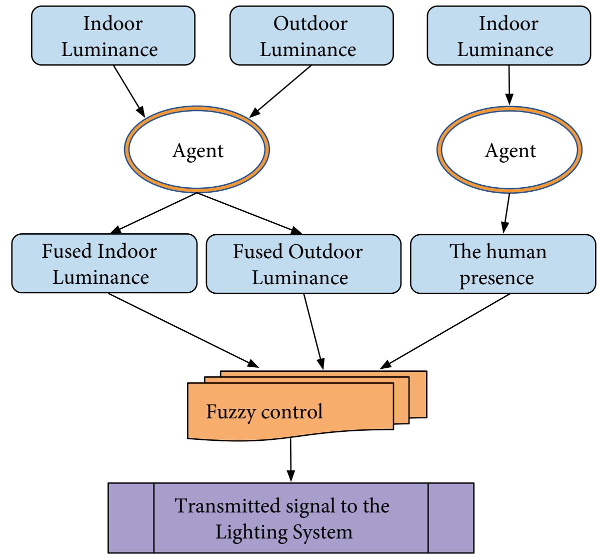

Figure 5. Fuzzy controller for the illumination system.

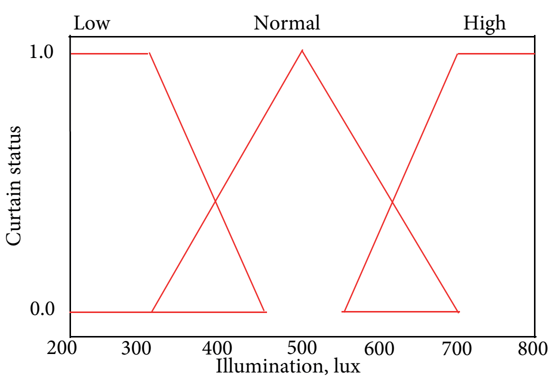

Figure 6. Membership function for indoor luminance.

error	VS	Small	LS	SS	OK	Large
Required power	VL	Large	LL	SL	OK	Small

Figure 7. Fuzzy control rules for local illumination control.

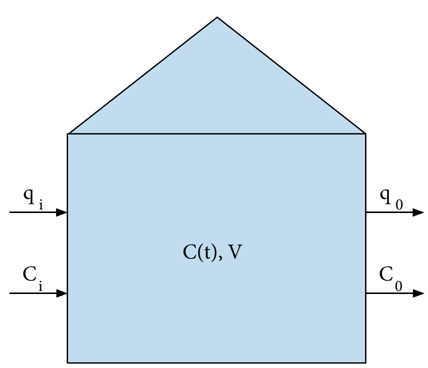

Figure 8. Mass balance representation for air quality control.

CO_2 was considered an air contaminant detector as, by managing the CO_2 to an acceptable level, it is also possible to bring other air pollutants to acceptable levels. A schematic representation of a building envelope with a forced fresh air filtration system is presented. In order to determine the concentration of indoor air quality necessary to keep indoor air quality level in an acceptable range, Eq. (5) was applied.

$$C = \left(C_i + \frac{S}{q_0}\right) - \left(\left(C_i + \frac{S}{q_0} - C_0\right) - C_0\right) e^{-\frac{q_0}{V}(t-t_0)} \tag{5}$$

3.8. Local power management agent

The role of a power management agent is adapting power consumption to the available power resources, taking into account the user comfort criteria. It allows the use of supplementary resources, which require additional investment, to be limited and avoids the expensive need for storage. Local power management agent controls energy level in the grid management system (Figure 1).

3.9. Load agent

The load agent controls all equipment that does not have a direct connection to the three main comfort factors. The load agent controls all electrical loads that can be turned off during a power shortage. Consumers are given the opportunity to select preferred load disconnections and prioritize each load through this agent. Some load profiles are created, and a graphical user interface is designed to configure the appropriate parameters. Using a graphical platform, customers can not only determine the characteristics of the load, but also control the amount and order of load shedding.

4. Experiment results

In the experimental part, as a case study, we consider the utilized mode. By performing experiments with utilized mode and measuring the required power, we can predict the capacity of the microgrid to supply the building with energy. In the simulation, the inhabitants' comfort ranges for the various control tasks are set as follows: illumination ranges between 750 and 880 (lux) [11], air quality ranges between 400 and 8800 ppm, and temperature and humidity ranges are based on international standards and recommendations ISO/FDIS 7730 [11] (Figure 9).

These comfort ranges serve as the bound constraints in the stochastic multiobject genetic optimization algorithm to drive out the optimal set points tuning in each time step. The set points targeted for each comfort parameter are set at Tset = 22 °C, RH = 50%, Lset = 800 lux, and AQset = 800 ppm with a one-fourth (1/4) equal weighting coefficient for each comfort parameter.

Figure 10 illustrates a comparison of the temperature set points using our system and a conventional heating system in one day with 24-h precision (from 0000 to 2359 hours). The green dotted line demonstrates temperature changes when a conventional system was used and the blue line indicates temperature changes when our proposed system was applied. The experiment was conducted on 16 January 2017, when outside air temperature varied between −11 °C and −6 °C at night and between −6 °C and 3 °C in the day time; the outside humidity, on the other hand, varied between 34% and 67% at night and between 17% and 45% in the day time.

A conventional system provides much more energy during work hours without considering the preferences of employers, which leads to open doors and windows for a more comfortable temperature, leading to more energy expenditure. As illustrated in the graph, when we use our proposed multiagent energy management system, temperature varies between 21 °C and 26 °C, which coincides with the comfort level of temperature that does

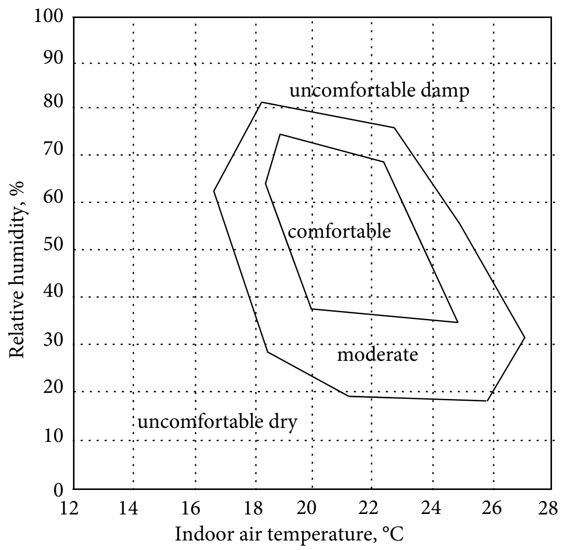

Figure 9. Comfort data of the premises, given based on ISO 7730 standard [11].

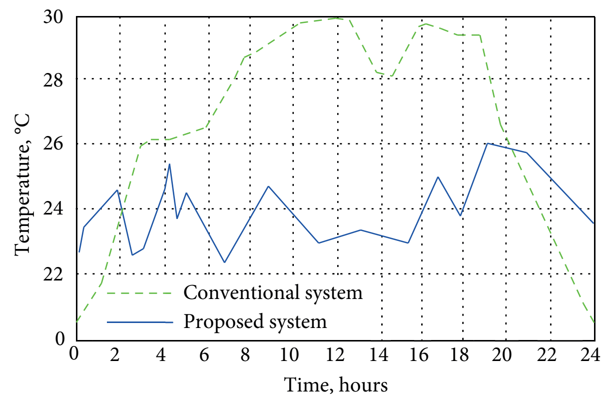

Figure 10. Temperature set points comparison.

not allow for additional energy expenditure. For comparison, a conventional heating system goes beyond the comfort level border most of the time.

When we use the multiagent-based smart grid system, the relative humidity rate changes between 30% and 40%, as illustrated in Figure 11, which coincides with the comfort level standard [11]. For comparison, the relative humidity rate of a conventional system gives a low-level humidity result (between 14% and 25%) because humidity control was not considered in the system concept. That is why humidity level indices less than 20% during work hours do not coincide with the comfort level. Due to the low level of outside humidity and overheating, there is a low level of humidity in the experimental indoor environment.

The illumination set points give 100% comfort level, as its work depends on human presence. The resulting rate of illumination with a multiagent-based controller illumination level coincides with comfort level. The illumination level at nighttime is low, which is nonworking time. During work hours, the illumination changes depending on the natural illumination level. The illumination levels of both systems are given in Figure 12.

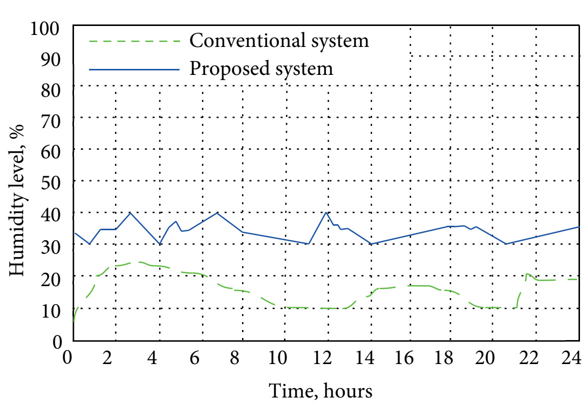

Figure 11. Humidity set points comparison.

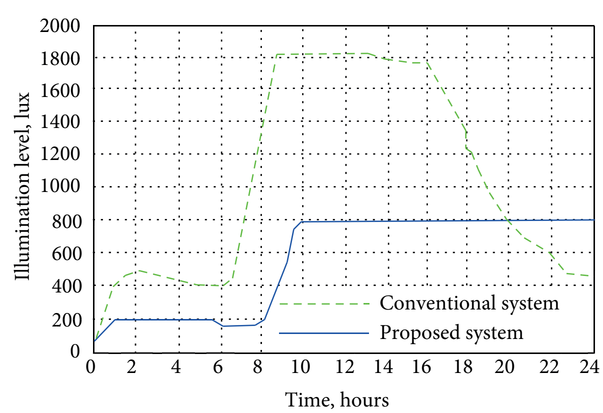

Figure 12. Illumination set points comparison.

Figure 13 shows the air-quality measurement results. The conventional system does not control air quality level. CO_2 is a type of occupant-related indoor air pollutant and it is only generated by human beings in an office area.

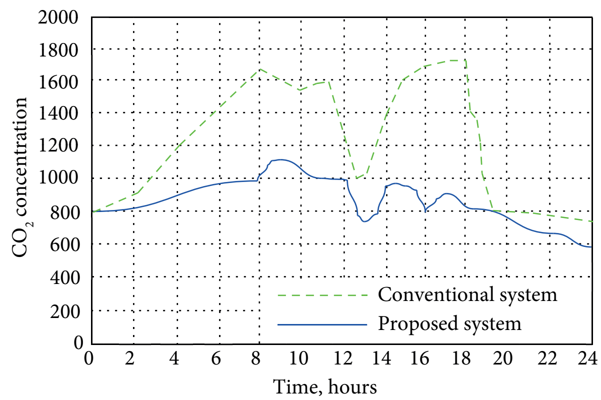

Figure 13. Air quality set points comparison.

Hence, when the air-conditioned space is unoccupied, there is no CO_2 generated. This means that the indoor CO_2 level should be similar to the outdoor CO_2 level at the beginning of each day. Then, when people come to work and the office is reoccupied, the CO_2 starts to increase, mainly based on the indoor occupancy level.

In Figure 13, when the conventional system is used, the CO_2 concentration level is at a much more than appropriate level during work hours because it increases depending on indoor occupancy. Attempts to improve indoor air quality by opening the door or windows lead to a decrease in the indoor air temperature, which leads to an imbalance between indoor comfort and energy consumption. When the proposed system was applied, the CO_2 concentration level did not exceed 1040 ppm, which is a level appropriate for the air quality in the room.

Figure 14 compares the overall comfort level, considering all the comfort parameters when using our approach and casual energy consumption. Comparing the cases, using the proposed approach, we achieved a higher comfort level without any fluctuations during the entire experimental period. In our research, comfort level depends on four factors: temperature, humidity, luminance, and air quality. All these factors were controlled in the proposed system. In our case, the CO_2 concentration level cannot be regulated and humidity was not considered in the conventional system.

Figure 15 shows the comparison in the total energy consumption over 24 h. During the off hours (except between 0900 hours and 1800 hours), there is more economy in energy consumption. During work hours, energy consumption is also lower than for a conventional system. Within the period that the proposed system was in use (0000 to 0700 hours) there was a decrease in the power consumption because all HVAC systems entered the energy-saving mode.

Maximum energy consumption occurred between 0800 and 1000 hours, because before work hours, the HVAC system prepares to provide a comfortable microclimate. From 1200 to 1300 hours, there was decline in energy use, as that is the lunch break period, and HVAC system enters the energy-saving mode. In the afternoon, energy use was stabilized and after 1800 hours, energy consumption decreased. In the case of the conventional system, there is leap in energy consumption from time to time because, periodically, a heater gets turned on and operates with maximum working power.

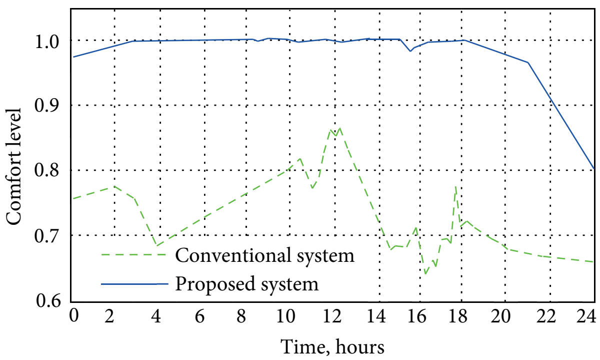

Figure 14. Overall comfort level comparison.

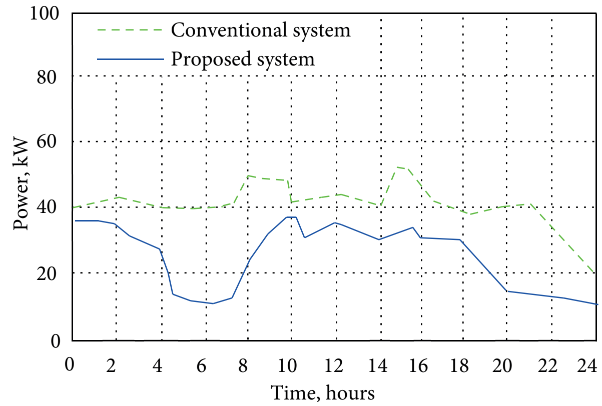

Figure 15. Overall power consumption comparison.

On average, the total actual comfort was 54.38%, and the optimized comfort, after applying the proposed system, rose to 98.53%, with 30% energy conservation. The intelligent optimized energy distribution system demonstrated its ability to achieve a better level of comfort in the room by saving energy. These results make it clear that the system can be optimized by adjusting comfort intervals and at the same time demonstrate the effectiveness of the multiagent system coordinator and the optimizer based on the multiobjective genetic optimization and fuzzy PD algorithm.

5. Conclusion

In this research, an intelligent multiagent energy management and control system with heuristic optimization was designed, and it has been shown to be capable of achieving the control goals by coordinating multiple agents and the optimizer. The proposed system structure, using a genetic algorithm, can optimize basic tools to achieve energy efficiency by providing thermal comfort in an indoor environment. In the future, we are going to improve the proposed model by applying machine learning algorithms and using learning agents and dynamically changed agents.

References

[1] Pigeon-Bergmann A, Abrishami M, Bender S, Hall V, Blevins B. California commercial end-use survey. Sacramento, CA, USA: California Energy Commission, 2006.

[2] Fu R, Wu Y, Wang H, Xie J. A distributed control strategy for frequency regulation in smart grids based on the consensus protocol. Energies 2015; 8: 7930-7944.

[3] Klein L. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. Automat Constr 2012; 22: 525-536.

[4] Kang D, Ou D, Ming C. The impact of indoor environmental quality on work productivity in university open-plan research offices. Build Environ 2017; 124: 78-89.

[5] Trinh P, Hector C, Chung I, Kang H, Cho J, Kim J. A novel voltage control scheme for low-voltage DC distribution systems using multi-agent systems. Energies 2017; 10: 41-55.

[6] Dehghanpour K, Colson C, Nehrir H. A survey on smart agent-based microgrids for resilient/self-healing grids. Energies 2017; 10: 1-25.

[7] Zhao H, Wang Y, Guo S, Zhao M, Zhang C. Application of a gradient descent continuous actor-critic algorithm for double-side day-ahead electricity market modeling. Energies 2016; 9: 1-20.

[8] Foo Y, Eddy H, Gooi S. Multi-agent system for distributed management of microgrids. IEEE T Power Syst 2015; 30: 24-34.

[9] Khan B, Jidin R, Pasupuleti J. Multi-agent based distributed control architecture for microgrid energy management and optimization. Energ Convers Manage 2016; 112: 288-307.

[10] Omarov B, Altayeva A, Cho Y. Smart building climate control considering indoor and outdoor parameters. Lect Notes Comput Sc 2017; 10244: 412-422.

[11] International Standard ISO/FDIS 7730:2005. Ergonomics of the thermal environment—Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria. Vernier, Switzerland: International Standards Organization, 2005.