Multi-agent Control System with Intelligent Optimization for Smart and Energy-efficient Buildings

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Abstract- **In this paper, a new control system with an intelligent optimizer is developed which can be applied to energy and comfort management in the smart and energy-efficient buildings. Hierarchical multi-agent theory is used to build this control system, which contains agent-controllers at two levels - a central coordinator-agent at the higher level and multiple local controller-agents at the lower level. Particle Swarm Optimization (PSO) is adopted to optimize the set points of the control system during system operations. This multi-agent intelligent control system is utilized to minimize the main conflict in smart and energy-efficient buildings in terms of power consumption and customers' comfort.**

I. INTRODUCTION

In a smart and energy-efficient building, an indoor environment control system needs to be developed to meet the demands of the building and its occupants [1]. The basic three factors which determine occupants' quality of lives in a building environment are thermal comfort, visual comfort and air quality [2]. The operation of a building requires high energy efficiency to save energy consumption. Most often, the improvement of the environment comfort demands more energy consumption. Thus, one of the most important issues on smart and energy-efficient buildings is to balance the requirements of the occupants' comfort and power consumption [3].

In the past decades, great progress has been made in energy saving and some useful energy management systems have been proposed. However, how to design an intelligent control system accounting for the two design objectives remains a challenging problem. In this paper, we intend to design an intelligent control system, which is capable of achieving the energy efficiency goal by maximizing customers' comfort while minimizing the total power consumption.

In our earlier study [4], temperature is used to indicate the thermal comfort in a building environment. The auxiliary heating/cooling system is applied to maintain the temperature in a comfortable region. The illumination level is used to indicate the visual comfort in a building environment, which is measured in lux [5]. The electrical lighting system is used to control the visual comfort. CO_2 concentration is used as an index to measure the air quality in the building environment, and the ventilation system is utilized to keep low CO_2 concentration [6].

A multi-agent intelligent system is developed for energy and comfort management by controlling the building temperature, illumination and ventilation. Hierarchical control architecture [7] is utilized to design such a control system, which includes a central coordinator-agent and three local controller-agents. The central coordinator-agent coordinates energy dispatch among the local controller-agents. The local agent-based subsystems use multiple fuzzy logic controllers to satisfy different comfort demands. Moreover, particle swarm optimization (PSO) algorithm is applied to optimize the overall control system by tuning set points adaptively during system operations.

II. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) algorithm was first described as a novel modern heuristic method in 1995 by Kennedy and Eberhart [8]. It is introduced as a stochastic, population-based and self-adaptive computer algorithm simulated based on animal social behaviors [9], [10]. PSO is being widely used for various engineering applications and has turned out to be a powerful optimizer [11], [12].

Similar to other evolutionary algorithms such as Genetic Algorithm (GA), PSO also randomly generates a number of solutions called population initially, and then finds the optimal solution by updating generations iteratively. Each potential solution in PSO is called a particle, which follows the current local best solution to fly through the whole solution space for approaching the global best solution [9]. An objective function is used to evaluate the quality of each candidate solution with respect to a given problem. In PSO, each particle represents a possible solution involving two vectors, which are the position vector ($l_i = [l_{i1}, l_{i2}, ..., l_{in}]$) and velocity vector ($V_i = [V_{i1}, V_{i2}, ..., V_{in}]$). Here an *n*-dimensional search space is assumed. The velocity of each particle is continuously adjusted to move towards its best particle (P_{best}) and memorizes its own best location (l_{best}) in each time step. Influenced by the randomly generated weights (α, r_1 and r_2) and acceleration constants (m_1 and m_2), the swarm moves towards the global best location [9], [11], [13]. The two updating rules of PSO are listed as follows:

$$V_i(k+1) = \alpha V_i(k) + m_1 r_1 [P_{best(i)}(k) - l_i(k)] + m_2 r_2 [G_{best}(k) - l_i(k)] \quad (1)$$

$$l_i(k+1) = l_i(k) + V_i(k+1) \quad (2)$$

where α is the inertia weight, which is usually slightly smaller than 1; m_1 and m_2 are two positive constants; r_1 and r_2 are two randomly generated numbers from $[0,1]$; $P_{best(i)}(k)$ is the best previous position of the i-th particle; $G_{best}(k)$ is the best previous position of all particles in the swarm; and k is the iteration index.

III. Architecture of Multi-Agent Control System

As shown in Fig. 1, the proposed layered control system is made up of multiple agents, which are classified into two levels. The first level interacts with the power grid or micro source and is termed as central coordinator-agent; and the second level is more relevant to the customer which is termed local controller-agents. The users' comfort in the smart and energy-efficient buildings is mainly decided by three factors, which are environment temperature, indoor air quality (CO_2 concentration), and illumination. Therefore, the local controller-agents include the local temperature controller-agent, the local air quality controller-agent and the local lighting controller-agent. The overall control target is to achieve the maximum comfort with the minimum power consumption. The central coordinator-agent works with the intelligent optimizer to accomplish its control goal. The load agents are used to shed loads to keep the customers' comfort at a high level when the power is not sufficient in emergency mode. There are distributed energy resources in the control system to support the building operations, which are usually renewable energy sources such as solar panels and wind turbine generators [4].

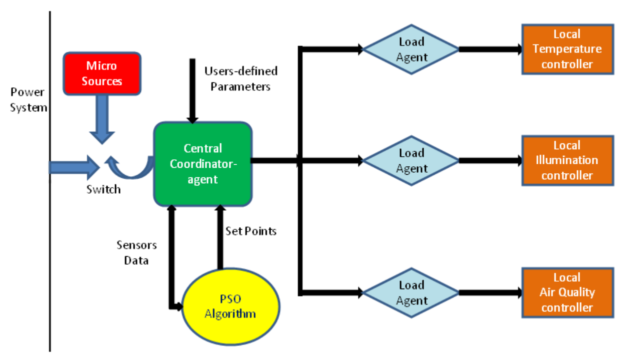


Fig.1. Structure of the proposed multi-agent intelligent control system

In this study, PSO is used to optimize and update the set points of central agent-controller and the local controller-agents. Users can define their own preferred ranges of each set point, which are $[T_{\min}, T_{\max}]$, $[L_{\min}, L_{\max}]$ and $[A_{\min}, A_{\max}]$. Here T, L and A represent the temperature, illumination level and CO_2 concentration, respectively. Different customers may have different preferences. This optimizer allows the customers to specify their preferred set points' ranges. It utilizes the outside environmental information to update the best set points in each step.

In the multi-agent intelligent control system, the optimization goal is to achieve the highest customers' comfort level using the minimum power consumption. Fuzzy controllers are applied to the multiple local subsystems. The errors between the measured values and the set points are used as input to the fuzzy controllers [13]. The output of the fuzzy controller is the required power to maintain high comfort by controlling the actuators of the subsystem. Users' comfort is related to the error between the measured real value and the set point. When the error decreases, the required power decreases and the comfort value increases. Thus, the selection of set points has impacts on both energy consumption and comfort level. Our proposed intelligent control system can realize simultaneous optimization of the comfort and energy consumption through tuning the set points using PSO.

The central coordinator-agent coordinates the power dispatch and maximizes the users' comfort. In the normal operating situation, the building is connected to the power grid. If power disturbance or failure occurs, or the electricity price is higher than the customers' expectations, the switch opens for disconnecting the building from the power grid and the building is re-connected to the local micro sources. The central coordinator-agent will operate in the emergency mode. When the energy is not adequate, for achieving the maximum comfort, the central coordinator will carry out load shedding through the load agents.

Fig. 2 illustrates the structure of the subsystems. The fuzzy controller takes the error between actual value and set point as input. Real values refer to the measured values of the environmental parameters obtained from sensors, including temperature, illumination level, and CO_2 concentration. The output of the fuzzy controller is the required power for achieving high comfort level. Comparison is carried out between the required power and the power given by the central coordinator (i.e., adjusted power) in order to determine the real power needed. The power needed will be applied to the building model to calculate the variation of the environmental parameters. The subsystems feed back the value of required power to the central coordinator to determine the future adjusted power.

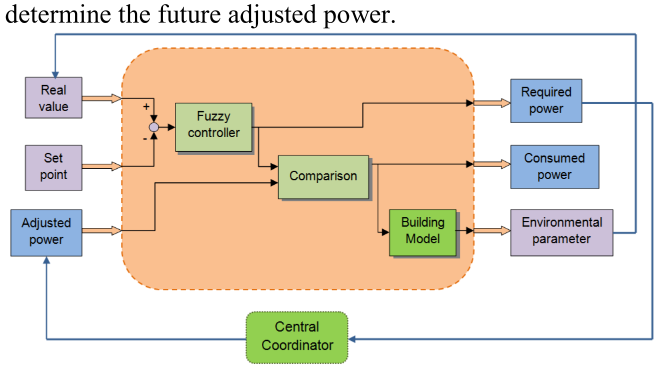


Fig.2. Structure of the subsystems for local control

IV. MATHEMATICAL DESCRIPTION OF CONTROL DESIGN

A. Central Coordinator-Agent

The control strategy for the central coordinator-agent is defined as follows:

$$Comfort = \delta_1[1-(e_T / T_{set})^2] + \delta_2[1-(e_L / L_{set})^2] + \delta_3[1-(e_A / A_{set})^2] \quad (3)$$

$$P_T(k+1) = P_T(k) + M_1 \quad (4)$$

$$P_L(k+1) = P_L(k) + M_2 \quad (5)$$

$$P_A(k+1) = P_A(k) + M_3 \quad (6)$$

$$P_T(k) + P_L(k) + P_A(k) = P_{in}(k) \quad (7)$$

$$P_{in}(k) \le P_{\max}(k) \quad (8)$$

where,

Comfort represents the overall customer comfort level, which falls into $[0,1]$. It is the control goal to be maximized;

δ_1, δ_2 and δ_3 are the users-defined factors, which indicate the importance of three comfort factors as well as solve the possible equipment conflicts. δ_1, δ_2 and δ_3 fall into $[0,1]$, and $\delta_1 + \delta_2 + \delta_3 = 1$;

e is the difference between set point and actual sensor measurement;

T_{set} , L_{set} and A_{set} are the set points of temperature, illumination and air quality, respectively.

$P(k)$ is the required power, which is the sum of power demands from all online devices for each control task and is obtained from the local controller- agents;

$P_{in}(k)$ is the total energy from the source which can be either electrical grid or micro sources;

$P_{\max}(k)$ is the maximum power that the power grid or the micro sources can supply;

M_1 , M_2 and M_3 are small values for compensating for the power losses in distribution;

k is the time instant.

B. Optimizer

Here the optimization goal is to maximize the objective function defined in (3), which is in actuality the overall comfort. There are three dimensions for particle flight, which represent three primary factors impacting the overall comfort. The PSO algorithm is described as follows:

1) Randomly generate the initial particles, The initial location in each dimension for each particle should be within the users-defined ranges.

2) Evaluate each particle based on (3).

3) Each particle chooses and remembers its best location, based on which P_{Tbest} , P_{Lbest} and P_{Abest} can be determined. P_{best} is set as G_{best} in the first iteration.

4) Base on (1) and (2), the velocity and position of all particles are updated.

5) Repeat steps *1)-4)* until any stopping rule is fulfilled. In our simulation, the stopping rule is whether or not the number of generations has reached 100 or the maximum comfort value 1 has been achieved.

Following the steps above, the optimum set points of temperature, illumination and CO_2 concentration can be found out. Since PSO has no guarantee to achieve the optimum solution within 100 iterations, the PSO program is run 10 times in each time period to ensure that there is a higher chance to obtain the highest comfort [9], [10], [14].

C. Local Controller-Agents

Fuzzy controllers are utilized in the subsystems to calculate the required power. The error between actual environmental parameters and set values obtained from central controller is used as input to the fuzzy controller. The output of the fuzzy controller is applied to the building model to derive the variation of the environmental parameters.

1. Auxiliary heating/cooling subsystem

A fuzzy PD controller is developed for this subsystem. The input of this fuzzy controller includes the error e_T and the change of error ce_T . The change of error ce_T represents the difference between the previous and present errors. The membership function of the inputs and output of the local temperature controller is shown in Fig. 3 [16].

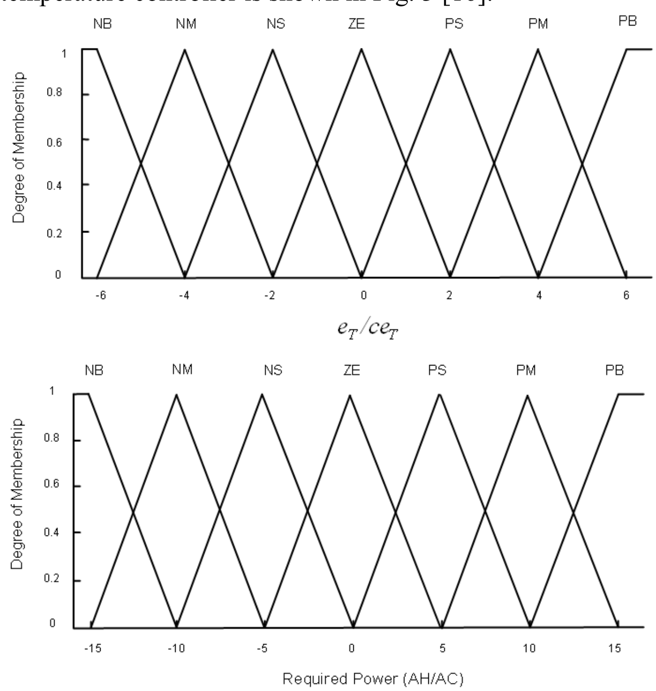


Fig.3. Membership functions of local temperature controller

The rules of the local temperature controller are shown in Table I. The membership functions of the inputs and outputs include the following values: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM) and Positive Big (PB).

TABLE I
FUZZY CONTROL RULES FOR LOCAL TEMPERATURE CONTROLLER

Required Power		e_T						
		NB	NM	NS	ZE	PS	PM	PB
ce_T	NB	NB	NS	PS	PB	PB	PB	PB
	NM	NB	NM	ZE	PM	PM	PB	PB
	NS	NB	NM	NS	PS	PM	PB	PB
	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NB	NB	NM	NS	PS	PM	PB
	PM	NB	NB	NM	NM	ZE	PM	PB
	PB	NB	NB	NB	NB	NS	PS	PB

The output of the fuzzy controller indicates the required power for temperature control. If its value is negative, it indicates the heating system is working; if the value of required power is positive, it means the cooling system is working.

The temperature increment ω_T has the following relationship with the consumed power P_T and time t :

$$\omega_T = 0.05 * P_T * t \tag{9}$$

2. Electrical lighting subsystem

The input of the local illumination fuzzy controller is the error between the current illumination level and the set point. The output is the required added power based on current power used in the lighting system. The membership function of the input and output of the local illumination controller is shown in Fig. 4. The rules of the local illumination controller are shown in Table II.

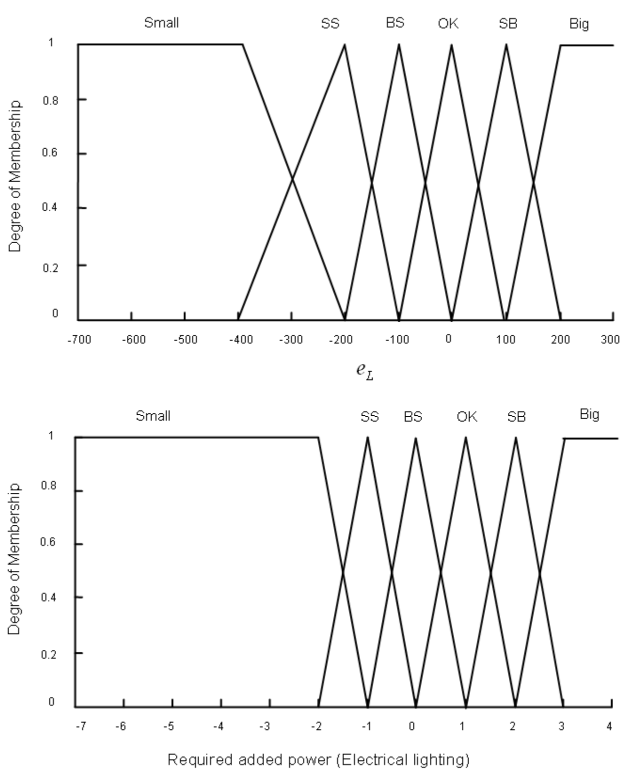


Fig.4. Membership functions of local illumination controller

TABLE II
FUZZY CONTROL RULES FOR LOCAL ILLUMINATION CONTROLLER

Error	Small	SS	BS	OK	SB	Big
Required added Power	Small	SS	BS	OK	SB	Big

As the output of the fuzzy controller is the required added power, the total required power is the sum of current power and the required added power. The consumed power P_L has the following relationship with the increment of the illumination level ω_L :

$$\omega_L = 30 * P_L \tag{10}$$

3. Ventilation subsystem

The membership function of the input and output of the local temperature controller is shown in Fig. 5. The rules of the local ventilation controller are shown in Table III.

The increment of the CO_2 concentration ω_A has the following relationship with the consumed power P_A and time t :

$$\omega_A = 2 * (P_A - c) \tag{11}$$

where the constant c is the basic operation power of ventilator.

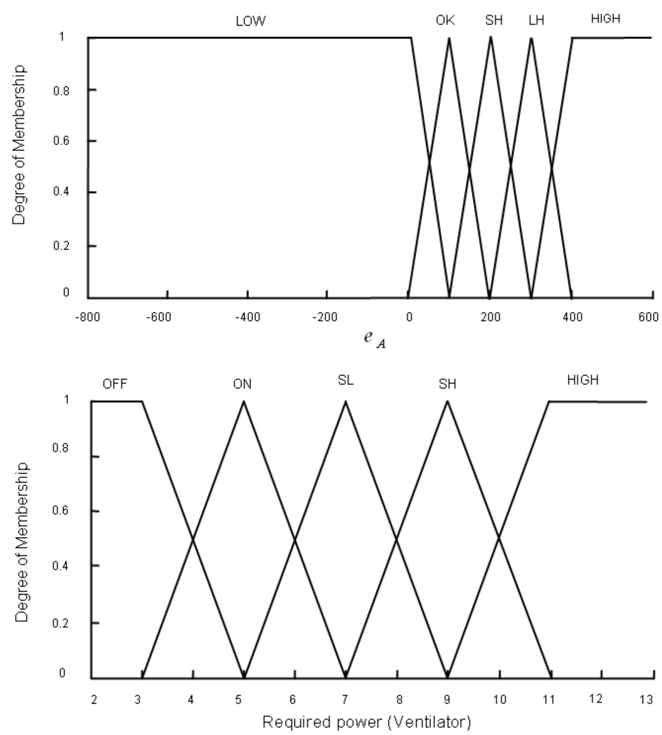


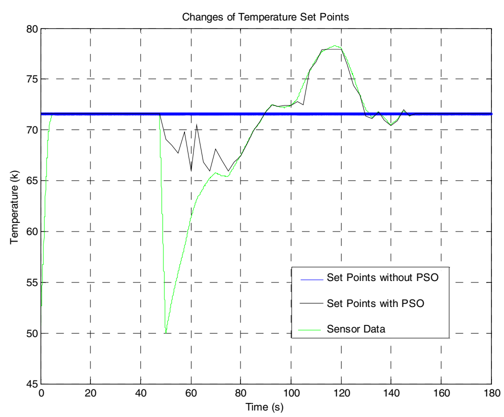
Fig.5. Membership functions of local ventilation controller

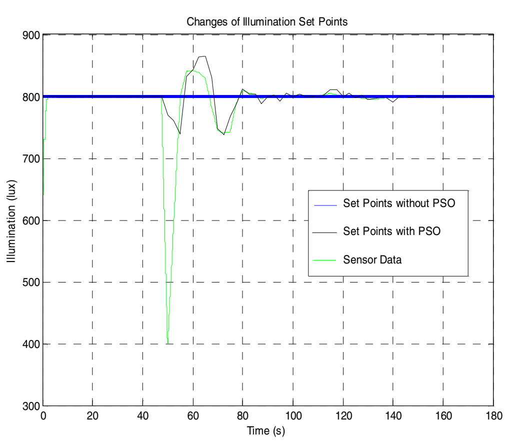
TABLE III
FUZZY CONTROL RULES FOR LOCAL VENTILATION CONTROLLER

Error	LOW	OK	SH	LH	HIGH
Required Power	OFF	ON	SL	SH	HIGH

V. SIMULATION RESULTS

Matlab/Simulink is used to simulate the proposed multi-agent control system. In the simulations, the occupants' comfort ranges for different control tasks are set as $T=[66,78]$ (k), $L=[720,880]$ (lux) and $A=[400,880]$ (ppm), which serve as constraints in the PSO to derive out the optimal set points in each time step. Fig. 6 shows the comparison of set points before and after PSO is applied in the simulations. Sensor data from the local controller-agents are provided in Fig. 6, where an environmental disturbance occurs in 50s-150s. In this period of disturbance, PSO is applied to optimize the set points. Overall, the errors between the set points and the measured environmental parameters become smaller than those without PSO. Although the extents of result improvement due to PSO somehow vary in each simulation run, the errors are consistently shown to be smaller than those without PSO.





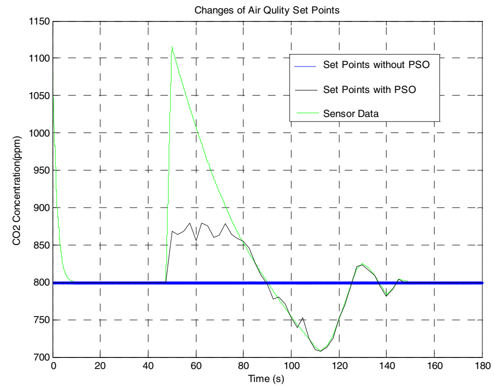


Fig.6. The changes of set points and the sensor data

Fig. 7 and Fig. 8 show the comfort values before and after PSO is applied, respectively. Here the users-defined weighting factors are set as $\delta_1=\delta_2=\delta_3=1/3$.

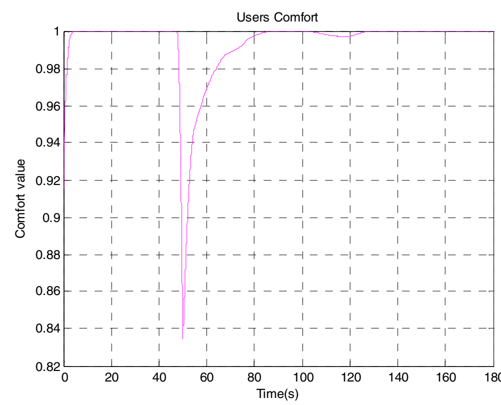


Fig.7. Control of comfort level without PSO

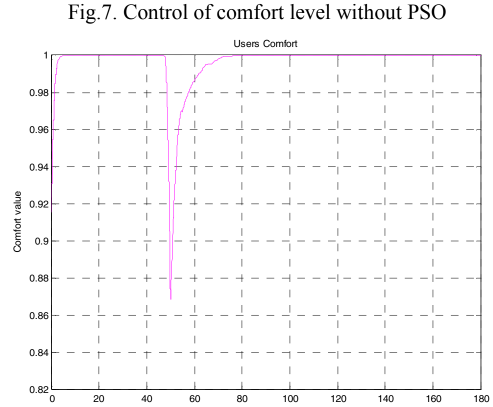


Fig.8. Control of comfort level with PSO

Based on the simulation results, the comfort value is improved due to the continuous tuning of set points by PSO. Meanwhile, the maximum comfort value can be derived in a shorter time.

The power consumptions with and without PSO are shown in Fig. 9. In each plot, the area that each curve covers is the energy consumption of its corresponding sub-control-system with or without PSO. The total energy consumption is the sum of energy consumption of each subsystem. From the simulation results, it is obvious that the total power consumption is reduced significantly by using PSO to adjust the set points adaptively.

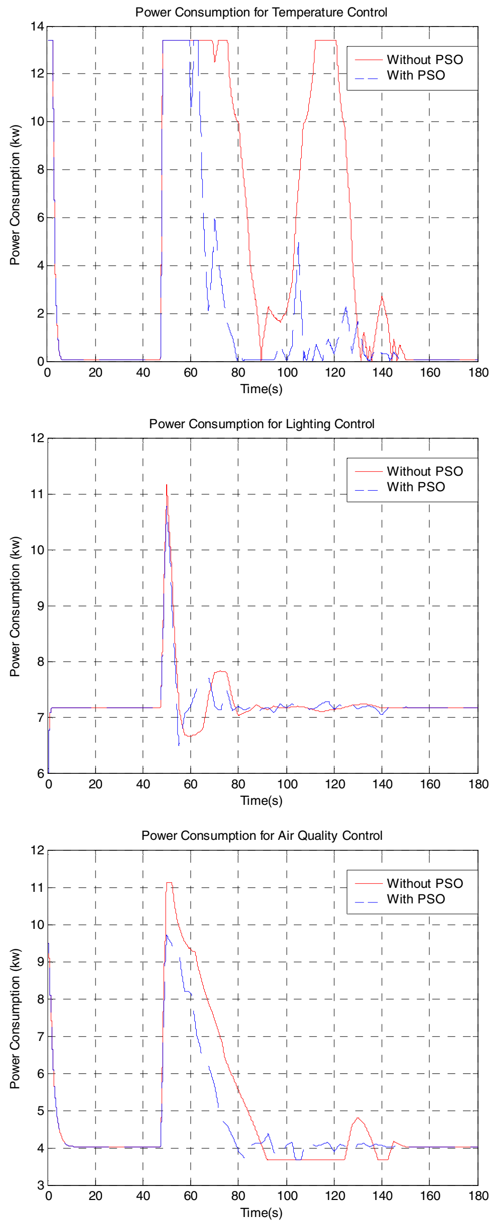


Fig.9. The power consumption for the system without and with PSO

Based on the simulation results, PSO has successfully achieved the reduction of energy consumption without compromising customers' comfort level. The multi-agent control system optimized by PSO has turned out to be effective for energy and comfort management in implementing smart and energy-efficient buildings.

VI. CONCLUDING REMARKS

In this study, an intelligent control system is designed which considers both the energy efficiency and occupants' comfort. Meanwhile, the customers' preference is also taken into consideration in deciding the overall comfort. Furthermore, using renewable energy units as the backup micro sources makes the building more environmentally friendly. The proposed building control system can be integrated with the existing SCADA software of buildings for practical applications.

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