Multi-agent control for integrated smart building and micro-grid systems

Zhu Wang
The University of Toledo

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A Dissertation

entitled

Multi-agent Control for Integrated Smart Building and Micro-grid Systems

by

Zhu Wang

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the

Doctor of Philosophy Degree in Engineering

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Dr. Lingfeng Wang, Committee Chair

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The University of Toledo

August 2013
An Abstract of

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Smart buildings are becoming a trend for the next-generation building industry, and micro-grids are a promising technology in the future power sector. Thus, it is beneficial to combine these two emerging technologies for building integrated smart building and micro-grid systems. Advantages of these micro-grid-enabled smart buildings include the improvements of indoor comfort, power efficiency, and environmental friendliness. Renewable energy resources are utilized as the primary power supply of smart buildings to meet the requirements on environmental friendliness. The higher comfort level and higher power efficiency should be obtained by developing an effective building energy management system for the integrated smart building and micro-grid systems. The major task of the building energy management is to minimize the power consumption without compromising the occupants’ comfort. For this purpose, a hierarchical multi-agent control system with intelligent optimizers for building applications is proposed in this dissertation.

Four major types of agents, which are the switch agent with negotiation capability, central coordinator-agent, local controller-agents, and load agent, cooperate
with each other to achieve the overall control goals. Particle swarm optimization is used to optimize the overall system and enhance its intelligence. A graphical user interface based platform is developed for customers to configure their preferences and monitor the operating conditions of the building. In addition, plug-in hybrid electric vehicles are integrated into the building energy management system as a distributed energy storage device.

Major contributions of this dissertation include the development of a multi-agent control system for building energy and comfort management, the formulation of multiple important control problems for the integrated building system, the deployment of computational intelligence based methods to optimize the overall system performance, the design of simulation models for various components and integrated systems, and the development of a comprehensive and user-friendly simulator.
This work is dedicated to my dearest father and mother,

*Chun Wang and Tianhui Zhu*
Acknowledgements

I owe a special acknowledgement to many people, who provide generous support to me throughout this work.

I would like to first express my deepest gratitude to my advisor, Dr. Lingfeng Wang. Thanks for his endless encouragement and support during these years. His distinguished professional guidance and insightful comments make this work possible. His enthusiasm in work is my inspiration. I have to say that having him as my advisor during the Ph.D. study is one of luckiest things happened in my life.

Next, many thanks to Dr. Jackson Carvalho, Dr. Richard Molyet, Dr. Weiqing Sun, and Dr. Hong Wang for serving on my committee. Thanks for their time and assistance in this work.

My special thanks go to the following individuals: Yi Zhao, Jiajia Lv, Nanke Jiang, Rui Yang and Zhaoning Song. The understanding and support that they gave to me strengthened me, and their friendship made my life wonderful.

Finally and most importantly, I would love to thank my parents. They have stood by me all the time and their deepest love makes me who I am. I dedicate this dissertation to them.
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<td>AABS</td>
<td>Adaptive Attitude Bidding Strategy</td>
</tr>
<tr>
<td>ACL</td>
<td>Agent Communication Language</td>
</tr>
<tr>
<td>AGO</td>
<td>Accumulated Generating Operations</td>
</tr>
<tr>
<td>ASHRAE</td>
<td>American Society of Heating, Refrigerating, and Air-Conditioning Engineers</td>
</tr>
<tr>
<td>BUM</td>
<td>Basic Unit-interval Monotonic</td>
</tr>
<tr>
<td>CC</td>
<td>Customer-Centered</td>
</tr>
<tr>
<td>CEN</td>
<td>European Committee for Standardization</td>
</tr>
<tr>
<td>CEUS</td>
<td>Commercial End-Use Survey</td>
</tr>
<tr>
<td>CI</td>
<td>Comfort Index</td>
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<tr>
<td>CIBSE</td>
<td>Chartered Institute of Building Engineers</td>
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<tr>
<td>CO$_2$</td>
<td>Carbon Dioxide</td>
</tr>
<tr>
<td>CO$_2$-SBDCV</td>
<td>Carbon Dioxide Sensor-based Demand Controlled Ventilation</td>
</tr>
<tr>
<td>DCV</td>
<td>Demand-controlled Ventilation</td>
</tr>
<tr>
<td>DG</td>
<td>Distributed Generator</td>
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<tr>
<td>DS</td>
<td>Distributed Storages</td>
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<td>FABS</td>
<td>Fixed Attitude Bidding Strategy</td>
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<td>FACT</td>
<td>Fuzzy Adaptive Comfort Temperature</td>
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<td>GA</td>
<td>Genetic Algorithm</td>
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<td>GM</td>
<td>Grey Model</td>
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<tr>
<td>GUI</td>
<td>Graphical User Interfaces</td>
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<tr>
<td>IEEE</td>
<td>Institute of Electrical and Electronics Engineers</td>
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<td>ILD</td>
<td>Interruptible Load Demands</td>
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<td>IPP</td>
<td>Independent Power Producers</td>
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<tr>
<td>LSEM</td>
<td>Least Square Error Method</td>
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<tr>
<td>MAS</td>
<td>Multi-agent System</td>
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<tr>
<td>MPG</td>
<td>Miles per Gallon</td>
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<tr>
<td>OH</td>
<td>Ohio</td>
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<tr>
<td>OWA</td>
<td>Ordered Weighted Averaging</td>
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<td>PHEV</td>
<td>Plug-in Hybrid Electric Vehicle</td>
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<td>PSO</td>
<td>Particle Swarm Optimization/Optimizer</td>
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<td>PSO-AABS</td>
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<td>Radio Frequency Identification</td>
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<td>Sensor-based demand controlled ventilation</td>
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<td>SOC</td>
<td>State of Charge</td>
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<tr>
<td>S-PSO</td>
<td>Set-point Particle Swarm Optimizer</td>
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US .......................... United States
V2G .......................... Vehicle-to-grid
W-PSO ...................... Weight Particle Swarm Optimizer
ZI ................................ Zero Intelligence
ZIP ...............................Zero-intelligence Plus
Chapter 1

Introduction

With the development of intelligent technologies and the maturity of renewable energy technologies, it is safe to say that the smart building is becoming more attractive as well as more viable in the current and next-generation building industry. Generally speaking, smart buildings are expected to address both intelligence and sustainability issues by utilizing advanced computing and intelligent technologies to achieve the optimal combinations of overall comfort level and energy consumption [1]. The utilization of renewable energy resources aids the smart building in reducing the detrimental effects on natural environment.

According to the results of the California Commercial End-Use Survey (CEUS), up to 85% of the energy usage in commercial buildings is consumed by heating and cooling, lighting, ventilation, and office equipment [2]. The operation of a building requires high energy efficiency to reduce the total energy consumption. Meanwhile, people spend most of their life time in buildings so that the environmental comfort conditions of a building are highly related to occupants’ health and productivity. However, the improvement of the indoor environment comfort usually demands higher energy consumption. Thus, one of the most important issues on building energy
management is to balance the requirements of the occupants’ comfort and total energy consumption.

In some sense, the building equipment which consumes energy can be classified into two broad types: comfort-related and non-comfort-related equipment. The three basic comfort factors which determine the occupants’ quality of lives in a building environment are thermal comfort, visual comfort and air quality [3]. Generally speaking, temperature is used to indicate the thermal comfort in a building environment, and 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. The electrical lighting system and the venetian blind system serve as actuators to control the illumination. CO$_2$ concentration is used as an index to measure the air quality in the building environment, and the ventilation system is utilized to achieve low CO$_2$ concentration [3]. The aforementioned equipment related to the three basic comfort factors is termed comfort-related equipment. Intelligent control of the thermal comfort, visual comfort and air quality comfort is important for both energy efficiency and occupant’s quality of living. Although the non-comfort related equipment has no direct impact on these three comfort factors, intelligent energy management of the equipment can not only enhance the energy efficiency but also help implement the optimal energy dispatch scheme for the comfort-related equipment. Thus, the basic control objectives for a smart building are to maintain the high comfort level while reducing total energy consumption by developing an intelligent energy control and management system.

Micro-grid is an important and promising technology for meeting the increasing
challenges faced by modern power systems such as environmental concerns, high requirements on power quality and reliability, growing social and industry demands, and aging infrastructure of the current power grid. A micro-grid system is usually made up of distributed generators (DGs), distributed storages (DSs) and controllable loads. Since generators and storage devices geographically locate close to the controllable loads, a variety of benefits can be achieved including improved reliability and reduced transmission losses. Furthermore, micro-grid employs renewable resources as energy supplies, which meet the requirement of environmental friendliness. The overall micro-grid system can be connected to and disconnected from the upstream utility grid according to the current condition in order to minimize the disruption to the loads [4]-[7].

Most, if not all, existing work in the field of energy and comfort management for building control and automation has been surveyed and discussed in [3]. However, little/no work has been done thus far to deal with the energy and comfort management for the integrated building and micro-grid systems including distributed renewable energy resources. In particular, the task for energy and comfort management becomes more difficult for such building systems since multiple distributed energy resources need to be effectively coordinated, which are usually intermittent. In this dissertation, the problem of energy and comfort management in an integrated building and micro-grid system will be formulated and the proposed control method will be discussed.

1.1 Structure of the dissertation

The remainder of this dissertation is organized as follows: Chapter 2 reviews two essential techniques which have been utilized throughout the entire dissertation. Chapter
3 describes the overall system architecture, including the detailed design of the multi-agent control system and the local controller agent. Chapter 4 discusses the central coordinator-agent including two possible mathematical models for representing the overall comfort index. Three local controller agents, which are the local temperature controller-agent, the local air-quality controller-agent and the local illumination controller-agent, are presented in details in Chapter 5. Chapters 6 and 7 illustrate the development of switch agent with negotiation agent and the load agent, respectively. Chapter 8 presents the integration of plug-in hybrid electric vehicles (PHEVs) into energy and comfort management for smart building. Concluding remarks and outlook are given in Chapter 9.
Chapter 2

Techniques review

This chapter reviews and summarizes two essential techniques applied throughout this dissertation, including the multi-agent system (MAS) technique and the particle swarm optimization (PSO) technique.

2.1 Multi-agent system technique

Multi-agent system (MAS) technology has been successfully utilized in various engineering fields, such as transportation, robotics, process control, and manufacturing. The fundamental element in MAS is the agent, which can be a software or physical entity. In this dissertation, all the proposed agents are pieces of software in this stage. Although different agents exhibit distinct behaviors, they share some common properties and all agents cooperate with one another to achieve the overall control goals [8]-[12]:

1) Agents have a certain degree of autonomy enabling them to work properly without human intervention;

2) Agents are able to communicate with each other through a special language called “agent communication language” (ACL);
3) Agents are capable of perceiving and reacting to the changes in the environment as well as determining the proper behaviors to achieve the final goal.

Taking advantages of the agents, the multi-agent system technology turns out to be effective and efficient in dealing with some extremely complicated situations. In this dissertation, the hierarchical MAS is applied to develop the control system for the energy and comfort management of the integrated smart building and micro-grid systems. All the agents can be classified into multiple layers based on their different functions, and the proper cooperation of different agents successfully achieves the control goal, which is to reduce the energy consumption without comprising customer comfort.

2.2 Particle swarm optimization technique

Particle swarm optimization (PSO) is inspired by the animal social behavior such as fish schooling and bird flocking, and it was first introduced as a novel stochastic, self-adaptive and population-based algorithm by Kennedy and Eberhart in 1995 [13]-[16]. As compared with other heuristic algorithms, PSO has several advantages. It has fewer parameters to adjust and it is easier to escape from the local optimal solutions. PSO has turned out to be an effective tool to solve highly complex problems such as large-scale non-linear optimization.

In PSO, each possible solution is seen as a particle, which follows the current local optimal solution to fly through the whole multi-dimensional search space for approaching the global optimal solution [16]. The particle includes location vector \( l \) and velocity vector \( v \). The particle moves towards its best local position \( p_{best} \) by continuously adjusting the velocity vector and memorizing its own current location. Influenced by the
randomly generated weights ($\alpha_{in}, r_1$ and $r_2$) and acceleration constants ($\varphi_1$ and $\varphi_2$), the swarm finally moves towards the global best location $g_{best}$. The updating rules are described as follows:

$$v^{k+1} = \alpha_{in}v^k + \varphi_1 r_1[p_{best}^k - l^k] + \varphi_2 r_2[g_{best}^k - l^k]$$  \hspace{1cm} (2.1)$$

$$l^{k+1} = l^k + v^{k+1}$$  \hspace{1cm} (2.2)$$

$$\alpha_{in} = \alpha_{max} - (\alpha_{max} - \alpha_{min}) \times \frac{k_n}{k_{max}}$$  \hspace{1cm} (2.3)$$

where $\alpha_{in}$ is the inertia weight, $\alpha_{max}$ and $\alpha_{min}$ are the maximum value and minimum value of the inertia weight which can be set by customers, respectively; $\varphi_1$ and $\varphi_2$ are two positive acceleration constants; $r_1$ and $r_2$ are two randomly generated numbers from $[0,1]$; $p_{best}^k$ is the local best position; $g_{best}^k$ is the best global position; $k$ is the iteration index, $k_n$ is the current number of iterations, and $k_{max}$ is the maximum number of iterations [17]-[20].

The general implementation of PSO is described as Fig. 2-1 [16].

PSO has been widely used throughout this dissertation. That is because most of the mathematical models developed for the integrated smart building and micro-grid systems are extremely non-linear with high complexity. PSO has been approved as a powerful tool to find the solution accurately and time-effectively in this kind of high dimensional and complicated search space.
Figure 2-1 Flow chart of the implementation of PSO
Chapter 3

System architecture and description

In this chapter, the proposed architectures including the integrated smart building micro-grid systems, the multi-agent control system and the local controller-agent are introduced and discussed in details.

3.1 Overall micro-grid system architecture

As shown in Fig. 3-1, the overall micro-grid system includes the distributed renewable power supply, the distributed storage and controllable loads. Considering the environmental friendliness, solar panels and wind generators are used for the distributed renewable power supply in this research, which are green energy with zero CO₂ emission. Batteries and PHEVs can be used as the distributed storage for enhancing the power supply reliability through storing the surplus energy in low demand periods and releasing the stored energy in high demand periods. The smart building is integrated into the micro-grid system and it can be seen as the controllable load. The operation mode for the smart building includes grid-connected mode and islanded mode. Due to the requirements of environmental friendliness in sustainable buildings, distributed renewable energy resources are considered as the primary energy supply and the utility grid is the backup
energy supply in this study. All the devices in the building prefer consumption of renewable energy over utility power. The utility grid can be connected to the building in order to supply power when the available renewable energy cannot satisfy the building demands [21].

![Figure 3-1 The overall system architecture for micro-grid](image)

3.2 Configuration of multi-agent control system for smart building

Multi-agent system (MAS) technology described in Chapter 2 has been utilized to design our control system for smart building.

Based on their distinct functions, all the agents are classified into four different layers as shown in Fig. 3-2. The first-layer agent is a switch agent including negotiation agent, which is used to determine and monitor the energy exchange between the utility
grid and the smart building system according to customer preferences and other relevant information. The central coordinator-agent and the multiple local controller-agents are considered to be the primary agents and locate in the second layer and the third layer, respectively. Multiple particle swarm optimizers (PSOs) are embedded in the central coordinator-agent to optimize parameters such as set points. Multiple local controller-agents are used to control all the comfort-related devices. The structure of local controller-agent is presented in the next section. The three main comfort factors considered in this research include environmental temperature, illumination level, and indoor air quality (CO\textsubscript{2} concentration). Accordingly, the local controller-agents are classified into the temperature controller-agent, the illumination controller-agent, and the air-quality controller-agent. The fourth layer is the load agent, which controls all the interruptible loads and plug-in loads. In this study, interruptible loads are those non-critical devices that have no direct connection with the three main comfort factors, while plug-in loads are the non-comfort-related and uninterruptible appliances. When necessary, the load agent decides the amount and the order of the interruptible load shedding according to the customer preference to maintain the high-level comfort. Through the cooperation of these multi-layered agents, the control goal, which is to maximize the customer comfort and minimize the energy consumption simultaneously, can be achieved [22].

Two communication modes in terms of direct communication and indirect communication are used for facilitating the communications between various agents in the proposed control framework. Direct communication mode can be utilized for the inter-agent communications in the same layer. This is accomplished through a direct
information exchange between agents based on the Agent Communication Language (ACL). The indirect communication mode is used for enabling an information exchange between agents in different layers. A global database maintained by the coordinator-agent is needed for storing the incoming information from other agents including the local controller-agents, the switch agent, and the load agent. After the data is manipulated, the processed data or the resultant decisions will be sent back to the corresponding agents. By utilizing these two communication modes, each agent in the proposed control system will have sufficient real-time information to make correct decisions and thus exhibit the desired behaviors [23].

Figure 3-2 The configuration of multi-agent control system in smart building
3.3 Structure of local controller-agents

Local controller-agents are implemented in three local subsystems to control thermal comfort, visual comfort and air quality, respectively. Fig. 3-3 shows the structure of the local subsystems. In the proposed building model, it is supposed that the indoor environment of the building under consideration is quite sensitive to the variation of the outdoor environment. It means that the indoor building environment will closely follow the change of outdoor environment if no control is applied. The local controller-agent takes the adjusted power from the central coordinator-agent and the error between real environmental parameters and the set points as inputs to the fuzzy controllers. Fuzzy rules are applied to calculate the required power in uncertain circumstances [24]. Comparison is carried out between the required power calculated and the adjusted power from the central coordinator-agent to determine the actual power to be used. It is used to drive the actuators to control indoor environmental parameters which decide the users’ overall comfort level. The actuators are auxiliary heating/cooling, electrical lighting and

Figure 3-3 Structure of local controller-agents
ventilating for controlling the thermal comfort, visual comfort and air quality, respectively. Thus, the indoor environmental parameters can be controlled by the corresponding actuators in local subsystems [23].
Chapter 4

Central coordinator-agent

For the central coordinator-agent, the primary task is to coordinate the power allocation and maximize the customer comfort. The central coordinator-agent bridges the energy sources and all other agents. Cooperating with other agents and based on the customer preference, the online energy production and the environmental information, it is responsible for improving the customer comfort index as well as efficiently dispatching the power to the lower-level agents.

The composite comfort index can be defined in multiple ways based on specific customer needs. Two possible comfort indexes are proposed in this chapter, which are in terms of customer-centered comfort index and information fusion based comfort index, respectively. In addition, embedded particle swarm optimizers are presented in details in this chapter.

4.1 Customer-centered comfort index

For simplicity, a basic customer-centered comfort index model is proposed. The general idea is to provide the customers flexibility to set their own preferences. And the mathematical model for the customer-centered comfort index is shown as follows:
\[ CI = \mu_1[1-(e_T / T_{set})^2] + \mu_2[1-(e_L / L_{set})^2] + \mu_3[1-(e_A / A_{set})^2] \] (4.1)

where

\( CI \) is the overall customer comfort, which falls in the range of [0,1] and the control goal is to maximize its value.

\( \mu_1, \mu_2 \) and \( \mu_3 \) are the user-defined weighting factors, which indicate the importance of three comfort factors and resolve the possible equipment conflicts as well.

Customers can set their own preferred values in different situations through Graphical User Interfaces (GUIs). All the user-defined weighting factors fall into [0,1] and \( \mu_1 + \mu_2 + \mu_3 = 1 \). In some cases, a weighting factor can be zero. For example, \( \mu_2 \) can be set zero if the users do not care about the indoor illumination level in certain conditions. Also a range can be imposed on any weighting factor if needed.

\( T_{set}, L_{set} \) and \( A_{set} \) represent the set points of the temperature, the illumination, and the indoor air quality, respectively.

\( e_T, e_L \) and \( e_A \) are the errors between the measured values and set points of the temperature, the illumination, and the indoor air quality, respectively.

Here in the definition of the overall comfort level, all three major environmental parameters are included. It is also possible that the air quality level is used as a constraint in the optimization problem. Here it is assumed that the set point of the air quality has been carefully selected by the users who are aware that the achievement of a lower CO\(_2\) concentration level is at the expense of higher power consumption. Thus, in this optimization problem, the proposed control system is also designed to drive the CO\(_2\) concentration to the set point.
4.2 Information Fusion Based Comfort Index

4.2.1 Background introduction

From the perspective of system control, the smart building is a large-scale dynamic system with high complexity and huge amount of information. Proper combination of the available information and effective control of the overall building system turn out to be a big challenge. Thus, in order to meet the challenge, the proposed system designs a suitable and representative overall comfort index model to make a rational and optimal combination for the information of the temperature, the illumination level and the CO$_2$ concentration.

The overall comfort index is an aggregation of information from these three comfort factors. Considering the information from the three factors is time-varying and enormous in the building system, the information fusion is applied. The definition of the information fusion is a process to utilize a proper aggregation operator to merge different data from various sources. Aggregation operators are one of the tools for information fusion which are used to combine the inputs information into a single representative value to be used in the decision making process [25] [26].

The ordered weighted averaging (OWA) aggregation operator is introduced to determine a representative comfort index value [27]. A mapping from $R^n \rightarrow R$ is termed an OWA aggregation operator of dimension $n$, and the OWA weighting vector is defined as $\omega = [\omega_1, \omega_2, ..., \omega_n]$, $\omega_i \in [0,1]$ and $\sum_{i=1}^{n} \omega_i = 1$. The OWA aggregation operator should satisfy the following relations:
\[
OWA(a_1, a_2, \ldots, a_n) = \omega_1 b_1 + \omega_2 b_2 + \ldots + \omega_n b_n \tag{4.2}
\]
\[
MAX(a_1, a_2, \ldots, a_n) = 1 \times b_1 + 0 \times b_2 + \ldots + 0 \times b_n \tag{4.3}
\]
\[
MIN(a_1, a_2, \ldots, a_n) = 0 \times b_1 + 0 \times b_2 + \ldots + 1 \times b_n \tag{4.4}
\]
\[
MIN(a_1, \ldots, a_n) \leq OWA(a_1, \ldots, a_n) \leq MAX(a_1, \ldots, a_n) \tag{4.5}
\]

where \( b_i \) is the \( i \)th largest number of \( a_1, a_2, \ldots, a_n \).

From (4.5), it is easy to conclude that OWA operator lies somewhere between the MAX operator and the MIN operator, and OWA can adjust the degree of “and” and “or” in aggregation. The implementation of the OWA operator is described as below:

1) Reorder the inputs \( a_1, a_2, \ldots, a_n \) in a descending order.
2) Find a proper method to determine weights associated with the OWA operator.
3) Aggregate the reordered objects with the OWA weights.

For step 2), and considering the richness and diversity of human language, a proportional quantifier \( Q \) is introduced to use to represent the amounts that are correlative in nature. It is proved the weighting vector \( \omega = [\omega_1, \omega_2, \ldots, \omega_n] \) is a manifestation of the quantifier in the aggregation process [26]-[28].

In this research, a proper quantifier called basic unit-interval monotonic (BUM) function is applied to obtain the associated OWA weights, which can change continuously between AND-type and OR-type [28]. The BUM function has the following characteristics:

1) \( Q(0)=0 \)
2) \( Q(1)=1 \)
3) If \( r_1 > r_2 \) then \( Q(r_1) > Q(r_2) \)
4.2.2 Comfort index design using information fusion

The comfort index value, which represents indoor environment of the building system, is determined by the information fusion technique using the ordered weighted averaging (OWA) aggregation operator [26] [29]. Primary comfort impact factors are the temperature, the illumination and the air quality, and the combination of those comfort factors constitutes the overall comfort index. Then the mathematical model of the comfort index, which utilizes the information fusion with the aggregation operator to obtain the comfort value, is shown as follows [30]:

\[ CI = OWA(C) = OWA(\mu_T, \mu_L, \mu_A) = \sum_{j=1}^{3} \omega_j b_j \]  (4.6)

where:

- \( CI \) is the comfort index value. It falls in the range of \([0,1]\).
- \( \mu \) is the aggregated object which represents the individual comfort value of the three comfort factors.
- \( \omega_j \) is the OWA weight of the \( j \)th factor. It represents the importance of each comfort factor. \( \omega_j \in [0,1] \) and \( \sum_{j=1}^{3} \omega_j = 1 \).
- \( b_j \) is the \( j \)th largest of the collection of the three aggregated objects \( \mu_T, \mu_L, \mu_A \).

Two different individual comfort models are proposed. Similar to the customer-centered model, the first model utilizes the discomfort function which considered the error between the real measured value and the customer set point. Following are the mathematical formulae of the first individual comfort model

\[ \mu_N = 1 - discomfort_N \]  (4.7)
\[
\text{discomfort}_N = ((N - N_{\text{set}})/N_{\text{set}})^2, N = T, L, A
\]  

where:

\(T, L, A\) are the real measured values of the comfort factors, which are temperature (°F), the illumination (lux) and the air quality (ppm), respectively. They can be obtained from the multiple local controller-agents.

\(N_{\text{set}}\) is the set point of each comfort factor. It can be set by the customers directly or be optimized by the set-point particle swarm optimizer (S-PSO) according to the comfort range.

The second individual comfort model uses a trapezoidal membership function of user’s preferences to represent the individual comfort level [29]. The model is illustrated as follows

\[
\mu_N = \max\left(\min\left(\frac{N - a_{N_1}}{a_{N_2} - a_{N_1}}, 1, \frac{a_{N_4} - N}{a_{N_4} - a_{N_3}}\right), 0\right)
\]  

\[a_{N_1} = a_{N_2}/1.05\]  

\[a_{N_4} = a_{N_3}/0.95, \ N = T, L, A\]

where \([a_{N_2}, a_{N_3}]\) is the comfort range which can be defined by the customers.

Unlike the customer-centered comfort index model which provides the flexibility to define the weights to customers, the information fusion based comfort index model with OWA aggregation operator can autonomously achieve the optimal weight \(\omega\) to maximize the comfort index value. A basic unit-interval monotonic (BUM) function \(Q(r)\) is introduced to obtain the OWA weight \(\omega\).

\[
Q(r) = r^\lambda, \ 0 \leq \lambda \leq 10
\]
\[ \omega_j = Q(j/3) - Q((j-1)/3), \quad j = 1, 2, 3 \] (4.13)

Considering the non-linear function (4.13), PSO introduced in Chapter 2 is utilized to determine the \( \lambda \) and it is named weight particle swarm optimizer (W-PSO). The objective function is the comfort index function (4.6) and the optimization goal is to maximize this comfort index function. The implementation of the central coordinator-agent with the proposed information fusion based comfort index function is illustrated in Fig. 4-1.

![Figure 4-1 The flow chart of the implementation of the central coordinator-agent](image)

4.3 **Particle Swarm Optimizer**

The optimizers embedded in the central coordinator-agent are applied the particle swarm optimization (PSO) described in Chapter 2 in this dissertation. Two optimizers
termed S-PSO and W-PSO are introduced to optimize the set points and OWA weights, respectively.

The implementation of the W-PSO to obtain the optimal OWA weight has been discussed in the previous part. For the S-PSO, that is utilized to tune the set points according to the outdoor environmental information and the customer preference. As different customers have different preferences, a GUI simulation platform has been developed as Fig. 4-2 shown, which offers the flexibility to customers to set their different comfort zones $[T_{\min}, T_{\max}]$, $[L_{\min}, L_{\max}]$ and $[A_{\min}, A_{\max}]$ for the temperature, the illumination, and the CO$_2$ concentration, respectively. In addition, the GUI platform [31] provides monitoring for the essential parameters, including the building demands, the renewable production, the overall comfort level, etc. In the detailed encoding scheme, each particle has three dimensions, which indicate the set point values of temperature, illumination, and air quality, respectively. Thus, there are three flight directions for each particle. This three-dimensional search space is restricted by the three corresponding comfort zones defined by the customers. The objective function is defined in equation (4.1), and the optimization goal is to maximize the objective function. Since the error between the measured value and set value determines the customer comfort level and power consumption, optimization of the set points plays an important role in achieving the control goal.

Since heuristic algorithms such as PSO have no guarantee to find the global optimal solution within the limited iterations, in this research PSO runs 10 times in each time step to increase the possibility of achieving the global optimization [18], [19]. In principle, more runs of the optimization algorithm will lead to a higher probability of
achieving better results, but it will inevitably take more computational time. After many trials, it was found that 10 is a reasonable number of runs for balancing the solution quality and computational cost.

4.4 Case studies and simulation results

In this section, two case studies will be conducted and discussed. In the first case study, the impacts of different user-defined weighting factors and S-PSO are examined based on the customer-centered comfort index. The second case uses the information
fusion based comfort index function. Both individual comfort models as well as the W-PSO are examined. It demonstrates that the control goal, which is to maximize the comfort index value and minimize the power consumption, can be achieved through the cooperation of all the agents and optimizers.

4.4.1 Case study one

This case study is concerned about the islanded mode, which indicates the smart building is disconnected from the utility grid. Here three 4.5-kilowatt solar panels and four 5-kilowatt wind turbines are used for the renewable energy supply, and the simulation is carried out on a 24-hour time scale [32], [33]. The batteries with total

![Figure 4-3 Energy production from the distributed renewable supply](image-url)
storable energy of 35 kilowatt-hours and a minimum storage threshold of 5 kilowatt-hours are selected for distributed energy storage. Fig. 4-3 shows the total power production from the distributed renewable energy resources.

4.4.1.1 Impact of users defined weighting factors

To illustrate the impact of user-defined weighting factors, two sets of weighting factors have been chosen. In the first group, $\mu_1 = 1/3, \mu_2 = 1/3, \mu_3 = 1/3$, and in the second one $\mu_1 = 0.3, \mu_2 = 0.5, \mu_3 = 0.2$. Here PSO is not applied, and the set points are $T_{set} = 71.6 (^\circ F), L_{set} = 800$ (lux), $A_{set} = 800$ (ppm). Figs. 4-4 and 4-5 show the differences of the power consumption of each comfort demand using these two sets of weighting factors. The differences of the resultant indoor environmental parameters can be seen by comparing Figs. 4-6 and 4-7.

Figure 4-4 Power consumption for each comfort demand using the first set of weighting factors without PSO
Figure 4-5 Power consumption for each comfort demand using the second set of weighting factors without PSO

Figure 4-6 Indoor environment parameters using the first set of weighting factors without PSO
Figure 4-7 Indoor environmental parameters using the second set of weighting factors without PSO

Figure 4-8 Comfort values using different sets of weighting factors without PSO
Based on the online power production and user-defined weighting factors, the final power assigned to each local controller-agent is derived by the central coordinator-agent for controlling the corresponding indoor environmental parameter. The overall users’ comfort is determined by all of the associated indoor environmental parameters. Fig. 4-8 illustrates the different overall user comfort levels based on the customer-centered comfort index using these two sets of different weighting factors.

### 4.4.1.2 Effect of applying S-PSO

In the islanded mode, because of the possibility of power shortage in some time periods, the overall comfort cannot be maintained at the maximum value at all times. To enhance the comfort level and reduce the power consumption, PSO is applied to optimize the set points. The control system is tested using two scenarios with different comfort zones. The comfort zones of the first scenario are set as $[T_{\text{min}}, T_{\text{max}}] = [67.76, 2] ^\circ\text{F}$, $[L_{\text{min}}, L_{\text{max}}] = [750, 850]$ (lux) and $[A_{\text{min}}, A_{\text{max}}] = [700, 850]$ (ppm). The comfort zones of the second scenario are $[T_{\text{min}}, T_{\text{max}}] = [64.79, 2] ^\circ\text{F}$, $[L_{\text{min}}, L_{\text{max}}] = [720, 880]$ (lux) and $[A_{\text{min}}, A_{\text{max}}] = [700, 880]$ (ppm). These parameters are configured through the GUI of the simulation platform. The variations of the set points in the two scenarios, which can be monitored from the GUI-based platform, are shown in Figs. 4-9 and 4-10, respectively. Figs. 4-11 and 4-12 indicate the effects of the PSO. The variation pattern of the set points becomes different, and the overall comfort level is improved with the reduced total power consumption. It can also be seen that different comfort zones have different impacts on the system behaviors. Larger comfort zones lead to lower power consumption and higher comfort values if other conditions are identical.
Figure 4-9 The variation of set points in the first scenario

Figure 4-10 The variation of set points in the second scenario
Figure 4-11 Changes of total power consumption without and with PSO using different comfort zones

Figure 4-12 Changes of overall user comfort without and with PSO in different comfort ranges
4.4.2 Case study two

Similar to the previous case study, the system is operated in the islanded mode and the simulation is carried out on a 24-hour time scale. However, five 4.5-kilowatt solar panels and four 5-kilowatt wind turbines are chosen as the renewable energy sources [32], [33]. The distribution storage system is the same as the case study one. Fig. 4-13 shows the renewable energy production in a 24-hour time period. Fig. 4-14 shows the total power consumption of the building system without any optimization. It includes the load demands and the comfort energy demands which can be obtained from multiple local controller-agents [34].

Figure 4-13 The energy production from the renewable source
4.4.2.1 Test based on the first individual comfort model

In this test, the first individual comfort model is applied to the information fusion based comfort index function. According to Figs. 4-13 and 4-14, the comfort index value is impossible to be maintained at the maximum value all the 24 hours. The comfort index value is reduced because of power shortage at some time periods. For comparison, in the control design the customer will be offered the flexibility to set the OWA weights. Here the OWA weights are defined as $\omega_1 = \omega_2 = \omega_3 = 1/3$. The set points for three comfort factors are $T_{set} = 71.6^\circ F$, $L_{set} = 800$ lux and $A_{set} = 800$ ppm, respectively. Fig. 4-15 shows the comfort index value in this situation.

The new control system is proposed as a fully optimized system, which means that the OWA weights will be optimized using intelligent search to meet the requirement of the high comfort level. Then the W-PSO is applied to optimize the OWA weights
through tuning the BUM function parameter $\lambda$. A significant improvement in system performance is illustrated in Fig.4-16. The comfort index value is obviously enhanced and the deficient time is markedly reduced.

Figure 4-15 Comfort index value without any optimization

Figure 4-16 Comfort index value with the W-PSO only
Then the S-PSO is added to tune the set points. The comfort ranges are set as 
$[T_{\text{min}}, T_{\text{max}}] = [67.76, 76.2]$ ($^\circ$F), $[L_{\text{min}}, L_{\text{max}}] = [750, 850]$ (lux) and $[A_{\text{min}}, A_{\text{max}}] = [750, 850]$ (ppm). After optimizing the set points, the errors of the set points and the measured values will be minimized and the comfort index value will be increased. Fig. 4-17 shows the result by applying two optimizers to the control system.

![Graph showing comfort index value with W-PSO and S-PSO](image)

Figure 4-17 Comfort index value with W-PSO and S-PSO

Table 4.1 illustrates the statistical results of Figs. 4-15 to 4-17. The time period where the comfort index value is smaller than 1 is termed as the uncomfortable period. The comparison of the total uncomfortable time and the minimum comfort index value for a day is shown in table. It can be found that the deployment of heuristic optimization technique significantly improves the comfort index value and provides more comfortable time to the customers.
From the simulation results in the first test, those two particle swarm optimizers have turned out to be effective. Through the coordination of all the agents and optimizers, the comfort index value is maintained at a very high level even in the energy shortage condition.

Table 4.1 Comparison for the system with and without optimization

<table>
<thead>
<tr>
<th></th>
<th>Accumulative uncomfortable period (hrs/day)</th>
<th>Minimum comfort index value(/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>System without optimization</td>
<td>8.33</td>
<td>0.9838</td>
</tr>
<tr>
<td>System with W-PSO only</td>
<td>2.38</td>
<td>0.9935</td>
</tr>
<tr>
<td>System with W-PSO and S-PSO</td>
<td>0.59</td>
<td>0.9997</td>
</tr>
</tbody>
</table>

4.4.2.2 Test based on the second individual comfort model

Information fusion based comfort index with the second individual comfort model has been chosen to conduct this test. Two distinct groups of comfort range \([a_{N2}, a_{N3}]\) are simulated, which are named group 1 and group 2, respectively.

The comfort ranges of the group 1 are \([a_{T2}, a_{T3}] = [69, 74.2] (^\circ F)\), \([a_{L2}, a_{L3}] = [780, 820] (\text{lux})\) and \([a_{A2}, a_{A3}] = [780, 820] (\text{ppm})\). From (4.9) and (4.10), the calculated results are \(a_{T1} = 65.7 (^\circ F)\), \(a_{T4} = 78.1 (^\circ F)\), \(a_{L1} = 742.9 (\text{lux})\), \(a_{L4} = 863.2 (\text{lux})\), \(a_{A1} = 742.9 (\text{ppm})\) and \(a_{A4} = 863.2 (\text{ppm})\). W-PSO and S-PSO cooperate with multiple agents to achieve the control goal. Figs 4-18 and 4-19 illustrate the comfort index and the total power consumption of the building system using data of group 1, respectively.
Figure 4-18 Comfort index value with data of group 1

Figure 4-19 Total power consumption with data of group 1 and PSO
By comparing Fig. 4-14 to Fig. 4-19, it is easy to observe the reduction of the total power consumption after the optimizers are applied. The control goal, which is to maximize the comfort index value with the minimum power consumption, has been achieved.

The data of group 2 are: $a_{T_1} = 63.8 (^\circ\text{F})$, $a_{T_2} = 67 (^\circ\text{F})$, $a_{T_3} = 76.2 (^\circ\text{F})$, $a_{T_4} = 80.2 (^\circ\text{F})$; $a_{L_1} = 714.3$ (lux), $a_{L_2} = 750$ (lux), $a_{L_3} = 850$ (lux), $a_{L_4} = 894.7$ (lux) and $a_{A_1} = 714.3$ (ppm), $a_{A_2} = 750$ (ppm), $a_{A_3} = 850$ (ppm), $a_{A_4} = 894.7$ (ppm). The $[a_{T_2}, a_{T_3}]$, $[a_{L_2}, a_{L_3}]$ and $[a_{A_2}, a_{A_3}]$ are the comfort ranges defined by the customers, and the other parameters are calculated from the mathematical model. The comfort index value and the total power consumption are illustrated in Figs. 4-20 and 4-21, respectively. Under this condition, although the comfort index is somewhat varying because of the stochastic PSO characteristic, it is evident that the comfort level has been improved while consuming less power.

The results demonstrate that the system can be optimized by adjusting the comfort ranges, and they also prove the effectiveness of the multi-agent control system and particle swarm optimizers. Table 4.2 shows the average overall comfort and the energy consumption for those two groups. It can be observed that the average overall comfort is increased by 3%, while the energy is saved by around 9% after adjusting the comfort ranges.

Table 4.2. Comparison for different comfort ranges

<table>
<thead>
<tr>
<th>Groups</th>
<th>Average Overall Comfort Index Value (/day)</th>
<th>Power Consumption (kWh/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.962</td>
<td>398.323</td>
</tr>
<tr>
<td>2</td>
<td>0.997</td>
<td>362.056</td>
</tr>
</tbody>
</table>
Figure 4-20 Comfort index value with data of group 2

Figure 4-21 Total power consumption with data of group 2 and PSO
4.5 Conclusion

In this chapter, two possible mathematical models embedded in the central coordinator-agent have been proposed to represent the indoor comfort index. PSO has been implemented to tune the set points of three major comfort impact factors (temperature, illumination level, air quality) as well as the weights of the information fusion based comfort index. Various case studies have been conducted, and simulation results validate the proposed models and verify the effectiveness of the application of PSO.
Chapter 5

Local controller-agents

Local controller agents are critical elements for managing the comfort-related devices energy-efficiently. The detailed designs of three local controller-agents are presented in this chapter, including the local temperature controller-agent, the local air quality controller-agent and the local illumination controller-agent. Different simulation case studies are conducted for each local controller-agent in order to validate the effectiveness of proposed designs.

5.1 Local temperature controller-agent

The local temperature controller is used to control the heating and air-conditioner system to provide high level of thermal comfort. Based on the work proposed in chapters 3 and 4 which offers flexibility to customers to set their own comfortable thermal range \([T_{\text{min}}, T_{\text{max}}]\), a novel fuzzy adaptive comfort temperature (FACT) model embedded in the local temperature controller-agent has been developed in this section to achieve more rational comfort range systematically without the intervention of users [35].
5.1.1 Background introduction

Nicol and Humphreys first introduced the adaptive comfort theory in 1970s, and it hypothesized that the customer thermal expectations and preferences can be adjusted by the outside temperature and the past thermal history [36], [37]. Considering the variation and uncertainty of the temperature information, in this work we introduce a fuzzy adaptive comfort temperature (FACT) model integrated with a grey predictor that enables the prediction of outdoor temperatures. When applying the FACT model one important issue is the prediction of meteorological parameters. This is an interesting and challenging issue since the weather data is typically complicated and disordered. Short-term prediction is used to make use of the most recent data to forecast the future. This is termed local prediction. A grey predictor is employed in this model due to its good performance in local predictions despite requiring a limited amount of past data to make these predictions. As compared to the customer-centered (CC) model which needs customer to define the thermal comfort zones $[T_{\text{min}}, T_{\text{max}}]$ proposed in chapter 4, the FACT model improves the determination of the temperature limits systematically without the intervention of users, achieves energy savings, and enhances the intelligence of the building management system. Managers are also provided an upper level of overreaching controls in order to simplify the control process.

Our primary objective here is to combine the multi-agent technology, FACT model, grey predictor and heuristic optimization to build a more intelligent control system with better performances. It should be capable of maintaining the maximum thermal comfort level and achieving energy saving. Instead of defining a single-valued set point, the proposed control system is capable of determining the rational comfort zone
systematically and finding the optimal set point autonomously according to the ambient information and customer preferences.

5.1.2 FACT model with grey predictor

5.1.2.1 Adaptive comfort temperature model

Beyond a simple logical algorithm, adaptive control is an artificial intelligence technology which can be used for empirical and judgmental information [38], [39]. The adaptive models have recently been applied to define the indoor comfort temperature as a linear regression which is related to outdoor information. This can be expressed by an equation of the form:

$$ T_c = C_T + K T_o $$

(5.1)

where $T_c$ is the indoor comfort temperature ($^\circ C$), $T_o$ is the outdoor temperature ($^\circ C$) and $C_T$ and $K$ are constants. For different buildings the constants $C_T$ and $K$ are found to be distinct. For naturally ventilated buildings, which have heating in the winter and are free-running (no cooling or mechanical ventilation) in summer, the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) standard (55-2004) [40] adapts the model as follows:

$$ T_c = 17.8 + 0.31 T_o $$

(5.2)

Adaptive comfort temperature models are now included in the Chartered Institute of Building Engineers (CIBSE) (2006) guidelines [41] and most recently the European Committee for Standardization (CEN) standard EN 15251 [42] has adopted the following model:
Considering the effect of both heating and free-running situations, the equations for indoor comfort temperature models are different because the indoor temperature is decoupled from the outdoor temperature by the heating control when the heating is turned on. It has been shown that heating systems are more likely to be on than off when running mean outdoor temperature \( T_{mr} \) is less than 10°C. In CIBSE 2006 [41] and CEN Standard EN 15252-2007 [42] the equations linking comfort temperature to outdoor temperature are:

\[
T_c = 18.8 + 0.33T_o \quad (5.3)
\]

\[
T_c = 18.8 + 0.33T_{mr}, \quad T_{mr} \geq 10^\circ C \quad \text{(free-running)} \quad (5.4)
\]

\[
T_c = 22.6 + 0.09T_{mr}, \quad T_{mr} < 10^\circ C \quad \text{(heating on)} \quad (5.5)
\]

In [39], Peeters uses a new parameter named \( T_{o,ref} \) to define the comfort temperature. The modified set of equations is shown as:

\[
T_{o,ref} = \frac{T_k + 0.8T_{k-1} + 0.4T_{k-2} + 0.2T_{k-3}}{2.4} \quad (5.6)
\]

\[
T_c = 16.63 + 0.36T_{o,ref}, \quad T_{o,ref} \geq 12.5^\circ C \quad \text{(free-running)} \quad (5.7)
\]

\[
T_c = 20.4 + 0.06T_{o,ref}, \quad T_{o,ref} < 12.5^\circ C \quad \text{(heating on)} \quad (5.8)
\]

where \( T_{o,ref} \) is the reference outdoor temperature (°C), \( T_k \) is the arithmetic average of today’s maximum and minimum outdoor temperature (°C), \( T_{k-1} \) is the arithmetic average of yesterday’s maximum and minimum outdoor temperature (°C), \( T_{k-2} \) is the arithmetic average of the day before yesterday’s maximum and minimum outdoor temperature (°C), and \( T_{k-3} \) is the arithmetic average of maximum and minimum outdoor temperature of three days ago (°C).
For air-conditioned buildings the correlation between the comfort temperature and outdoor temperature is given by [43]:

\[ T_c = 18.6 + 0.16T_o \]  \hspace{1cm} (5.9)

As the primary goal of the smart building is to provide a high comfort level to customers, a naturally ventilated building cannot be the best choice for a smart building. We propose a mixed building model which provides heat to the building in the winter and cooling in the summer. The comfort temperature correlated to the outdoor temperature for smart buildings has been proposed using the following equations:

\[ T_c = 18.6 + 0.16T_{o,\text{ref}}, \quad T_{o,\text{ref}} \geq 18^\circ C \hspace{0.5cm} \text{(air-conditioner on)} \]  \hspace{1cm} (5.10)

\[ T_c = 20.4 + 0.06T_{o,\text{ref}}, \quad T_{o,\text{ref}} < 18^\circ C \hspace{0.5cm} \text{(heating on)} \]  \hspace{1cm} (5.11)

5.1.2.2 FACT model

Changing outdoor weather conditions, internal heat gains, ventilation, and the preferences of users all influence the indoor environment of a smart building leading to different comfort profiles for different persons. The acceptable comfort temperature regions are formulated by an upper and a lower limit which defines the comfort temperature band. In this section a new method to determine the upper \((T_{\max})\) and the lower \((T_{\min})\) bounds of the temperature band based on Equations (5.10) and (5.11) is proposed. This method can be implemented using the following fuzzy equations:

\[ \tilde{T}_c = \tilde{\alpha}_1 + \tilde{\beta}_1 \times \tilde{T}_{o,\text{ref}}, \quad T_{o,\text{ref}} \geq 18^\circ C \hspace{0.5cm} \text{(air-conditioner on)} \]  \hspace{1cm} (5.12)

\[ \tilde{T}_c = \tilde{\alpha}_2 + \tilde{\beta}_2 \times \tilde{T}_{o,\text{ref}}, \quad T_{o,\text{ref}} < 18^\circ C \hspace{0.5cm} \text{(heating on)} \]  \hspace{1cm} (5.13)
where $\tilde{\alpha}, \tilde{\beta}$ and $\tilde{T}$ are fuzzy numbers, which respectively represent the constant values $C_T, K$ of the adaptive model and the temperature $T$.

\[
\tilde{\alpha}_1 = (l_{\alpha 1}, m_{\alpha 1}, r_{\alpha 1}) \\
\tilde{\beta}_1 = (l_{\beta 1}, m_{\beta 1}, r_{\beta 1}) \\
\tilde{\alpha}_2 = (l_{\alpha 2}, m_{\alpha 2}, r_{\alpha 2}) \\
\tilde{\beta}_2 = (l_{\beta 2}, m_{\beta 2}, r_{\beta 2}) \\
\tilde{T}_{o,\text{ref}} = (l_o, m_o, r_o) \\
\tilde{T}_c = (l_c, m_c, r_c)
\]

where $l, m$ and $r$ are the real numbers.

Equations (5.12) and (5.13) above are combined with Equation (5.6) to form the FACT model used in the local temperature controller-agent.

### 5.1.2.3 Fuzzy arithmetic operations

Assume two generalized triangular fuzzy numbers $\tilde{X}_1$ and $\tilde{X}_2$ where $\tilde{X}_1 = (a_1, b_1, c_1)$ and $\tilde{X}_2 = (a_2, b_2, c_2)$. Using the fuzzy arithmetic operators from [44] and [45] the following equations can be given:

1) Fuzzy Numbers Addition $\oplus$

\[
\tilde{X}_1 \oplus \tilde{X}_2 = (a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2)
\]

2) Fuzzy Numbers Multiplication $\otimes$

\[
\tilde{X}_1 \otimes \tilde{X}_2 = (a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2)
\]
We consider three fuzzy numbers \( \tilde{\alpha} = (l_{\alpha}, m_{\alpha}, r_{\alpha}) \), \( \tilde{\beta} = (l_{\beta}, m_{\beta}, r_{\beta}) \) and \( \tilde{T}_{o,\text{ref}} = (l_o, m_o, r_o) \), where \( l \), \( m \), and \( r \) are real numbers.

Utilizing the fuzzy arithmetic operators \( \bigoplus \) and \( \bigotimes \), the following fuzzy adaptive comfort temperature model is developed:

\[
\tilde{T}_c = (l_c, m_c, r_c) = \tilde{\alpha} \bigoplus \tilde{\beta} \bigotimes \tilde{T}_{o,\text{ref}} = (l_{\alpha} + l_{\beta} l_o, m_{\alpha} + m_{\beta} m_o, r_{\alpha} + r_{\beta} r_o) \tag{5.22}
\]

The relationship of these fuzzy numbers is

\[
l_c = l_{\alpha} + l_{\beta} l_o, \quad m_c = m_{\alpha} + m_{\beta} m_o \quad \text{and} \quad r_c = r_{\alpha} + r_{\beta} r_o.
\]

The user participates in the control process by defining the “\( \alpha \)” that is the acceptability degree of comfort temperature. The \( \alpha \) level determines the crisp set, that is, the lower \( \tilde{T}_{c,\text{min}}^\alpha \) and the upper \( \tilde{T}_{c,\text{max}}^\alpha \) comfort temperatures in Equations (5.23) and (5.24). Fig. 5-1 indicates this generalized triangular fuzzy number \( \tilde{T}_c \) with acceptability \( \alpha \).

\[
\tilde{T}_{c,\text{min}}^\alpha = m_c - \alpha (m_c - l_c) \tag{5.23}
\]

\[
\tilde{T}_{c,\text{max}}^\alpha = m_c + \alpha (r_c - m_c) \tag{5.24}
\]

Figure 5-1 The generalized triangular number with acceptability
The acceptability degree, \( \alpha \), will substantially change the acceptance comfort zone. It is obvious that the bandwidth of the comfort zone will extend when the acceptable degree, \( \alpha \), is changed.

### 5.1.2.4 Grey predictor

Generally, a grey system means that the information regarding the system is incomplete or uncertain. By using a grey model that requires little previous data to perform a real-time forecast, the grey predictor has been successfully employed in many areas. A first order linear dynamic grey model, GM(1,1), is applied to make short-term predictions of the future average outdoor temperature on a daily basis [46].

Local forecasts of the future based on the most recent data set are a type of time series. Suppose we have the previous values of \( x \) from the time \( k-m \) to \( k-l \), that is \( x(k-1), x(k-2), \ldots, x(k-m) \). The next time interval values, \( x(k) \), can be predicted by a grey model. The algorithm of this first order grey model GM(1,1) is as follows [47].

Assume the original raw data series \( x^{(0)} \) with \( n \) samples is defined as \( x^{(0)} = \left[ x^{(0)}(1), x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \right] \). All values in this data sequence are required to be positive. When negative values appear in this sequence the absolute value of the maximum negative data is added to all the data in the sequence to make the data sequence positive.

To weaken the randomness of the original raw data, the original raw data \( x^{(0)} \) is pre-processed and transformed into a new sequence \( x^{(1)} \) using the accumulated generating operations (AGO).

\[
x^{(1)}(i) = AGO(x^{(0)}(i)) = \sum_{k=1}^{i} x^{(0)}(k), \quad i = 1, \ldots, n
\]  

(5.25)
Therefore, the new raw data series is defined as \( x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)] \). The \( x^{(1)} \) sequence can be modeled by a first-order differential equation that is defined as

\[
\frac{dx^{(1)}}{dt} + ax^{(1)} = b
\]  

(5.26)

where \( a \) is the development coefficient and \( b \) is the grey control variable. We now define \( y^{(1)}(i) \) as the sequence obtained by applying the MEAN operation to \( x^{(1)} \) as seen in Equation (5.27).

\[
y^{(1)}(i) = MEAN(x^{(1)}) = \frac{1}{2} [x^{(1)}(i) + x^{(1)}(i-1)], \quad i = 1, \ldots, n
\]  

(5.27)

Suppose the sampling time is normalized as 1. From Equation (5.25) we have

\[
\frac{dx^{(1)}}{dt} = x^{(1)}(i) - x^{(1)}(i-1) = x^{(0)}(i)
\]  

(5.28)

And by approximating \( x^{(1)} \) with \( \frac{1}{2}[x^{(1)}(i)+x^{(1)}(i-1)] \), Equation (5.26) can be rewritten as,

\[
x^{(0)}(i) + a \cdot y^{(1)}(i) = b
\]  

(5.29)

The parameters \( a \) and \( b \) can be obtained by using the Least Square Error Method (LSEM) in Equation (5.30)

\[
\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Z_n
\]  

(5.30)

where

\[
B = \begin{bmatrix} -y^{(1)}(2) & 1 \\ -y^{(1)}(3) & 1 \\ \vdots & \vdots \\ -y^{(1)}(n) & 1 \end{bmatrix}
\]  

(5.31)
and

\[
Z_n = \begin{bmatrix}
x^{(0)}(2) \\
x^{(0)}(3) \\
\vdots \\
x^{(0)}(n)
\end{bmatrix}
\]

(5.32)

The solution of equation (5.26) is an exponential function with the initial condition \(x^{(1)}(0) = x^{(0)}(1)\). The predicted value can be obtained as

\[
\hat{x}^{(1)}(n+1) = (x^{(0)}(1) - \frac{b}{a}) \cdot e^{-an} + \frac{b}{a}
\]

(5.33)

Applying the inverse AGO to \(\hat{x}^{(1)}(n+1)\), we can have the predicted value for \(\hat{x}^{(0)}(n+1)\) as \(\hat{x}^{(0)}(n+1) = \hat{x}^{(1)}(n+1) - \hat{x}^{(1)}(n)\). Usually the number of used data in a grey model is rather small. Therefore, the grey model is often used as a local prediction scheme. The grey model prediction can be viewed as a curve fitting approach and is employed in this work.

5.1.3 Genetic algorithm

Genetic algorithm (GA) is a global search methods inspired by a biological metaphor, which comprises the natural evolution mechanisms working on populations of solutions. This method based on the concept “survival of the fittest” is capable of finding the optimal solution in a wide range of optimization problems [48]-[50]. GA has become a powerful and widely used tool for nonlinear optimization purposes.

GA randomly generates a population of chromosomes at the beginning, and each chromosome represents a potential solution. Based on the genetic operators, which are selection, crossover and mutation, GA creates a new population of solutions with better
fitness. After some iterations, GA could find the optimal or near optimal solution [51], [52]. The pseudo code of the GA is illustrated in Fig.5-2.

```
Choose initial population of chromosomes;
Evaluate the fitness of each chromosome;
While the maximum number of iterations is not achieved and
the optimal solution is not attained
   Do {
      Select the chromosomes with best fitness as parents;
      Use crossover/mutation to product offspring;
      Evaluate the fitness of the offspring;
      Replace the chromosomes with worse fitness if the
      offspring has a better fitness;
   }
End
```

Figure 5-2 Pseudo code for genetic algorithm

In this section, GA is used as a comparing optimization tool to find the optimal set point to maximize the thermal comfort. The initial chromosomes are generated in the comfort zone \([T_{\text{min}}, T_{\text{max}}]\), and equation (4.1) is used as the fitness function. The comparison of the performances for PSO and GA is illustrated in the case studies.

5.1.4 Fuzzy logic controller

To calculate the required power for maintaining the indoor thermal comfort, a fuzzy controller is developed for this subsystem. The input of this fuzzy controller includes the error \(\text{error}_T\) and the change of errors \(\text{cerror}_T\). The change of errors \(\text{cerror}_T\) represents the difference between the previous and present errors. The membership functions of the inputs and output of the fuzzy controller are shown in Fig. 5-3. The membership functions of the inputs and outputs include the following values: Negative
Figure 5-3 The membership functions of local temperature controller

Table 5.1 Fuzzy control rules for local temperature controller

<table>
<thead>
<tr>
<th>Required Power</th>
<th>error$_{\text{T}}$</th>
<th>NL</th>
<th>NM</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
<th>PM</th>
<th>PL</th>
</tr>
</thead>
<tbody>
<tr>
<td>error$_{\text{T}}$</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NS</td>
<td>PS</td>
<td>PL</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>NM</td>
<td>NL</td>
<td>NM</td>
<td>NS</td>
<td>PS</td>
<td>PM</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>NS</td>
<td>NL</td>
<td>NM</td>
<td>NS</td>
<td>PS</td>
<td>PM</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>ZE</td>
<td>NL</td>
<td>NM</td>
<td>NS</td>
<td>PS</td>
<td>PM</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>PS</td>
<td>NL</td>
<td>NL</td>
<td>NM</td>
<td>NS</td>
<td>PS</td>
<td>PM</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>PM</td>
<td>NL</td>
<td>NL</td>
<td>NM</td>
<td>HM</td>
<td>ZE</td>
<td>PM</td>
<td>PL</td>
</tr>
<tr>
<td></td>
<td>PL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NS</td>
<td>PS</td>
<td>PL</td>
</tr>
</tbody>
</table>
Large (NL), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM) and Positive Large (PL). The rules of the fuzzy controller are shown in Table 5.1.

5.1.5 Case studies and simulation results

Two sets of data of the daily average temperatures are collected from [53] regarding the area around Toledo, OH in the US. The first data set is a winter daily average temperatures from Jan 1\textsuperscript{st} to January 15\textsuperscript{th} in 2011; the second data set is a summer data set from August 1\textsuperscript{th} to August 15\textsuperscript{th} in 2010. By applying a grey predictor we can forecast the average temperature of the next day by analyzing the former three day’s realistic data. The temperature in the first three days is used for prediction and the temperature for Day 4 through Day 15 is forecasted. Tables 5.2 and 5.3 show the comparison between the predicted temperature and the realistic temperature.

Table 5.2 The predicted temperature and the realistic temperature in winter

<table>
<thead>
<tr>
<th>Date</th>
<th>Real temperature</th>
<th>Predicted temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day 1</td>
<td>5.4</td>
<td></td>
</tr>
<tr>
<td>Day 2</td>
<td>-6.3</td>
<td></td>
</tr>
<tr>
<td>Day 3</td>
<td>-2.9</td>
<td></td>
</tr>
<tr>
<td>Day 4</td>
<td>-0.9</td>
<td>1.4</td>
</tr>
<tr>
<td>Day 5</td>
<td>-5.6</td>
<td>-8.1</td>
</tr>
<tr>
<td>Day 6</td>
<td>-3.4</td>
<td>-0.5</td>
</tr>
<tr>
<td>Day 7</td>
<td>-6.7</td>
<td>-8.9</td>
</tr>
<tr>
<td>Day 8</td>
<td>-8.5</td>
<td>-9.9</td>
</tr>
<tr>
<td>Day 9</td>
<td>-8.9</td>
<td>-9.2</td>
</tr>
<tr>
<td>Day 10</td>
<td>-4.4</td>
<td>1.8</td>
</tr>
<tr>
<td>Day 11</td>
<td>-4.6</td>
<td>-4.7</td>
</tr>
<tr>
<td>Day 12</td>
<td>-5.1</td>
<td>-5.5</td>
</tr>
<tr>
<td>Day 13</td>
<td>-7.1</td>
<td>-8.6</td>
</tr>
<tr>
<td>Day 14</td>
<td>-6.3</td>
<td>-5.4</td>
</tr>
<tr>
<td>Day 15</td>
<td>-2.8</td>
<td>1.9</td>
</tr>
</tbody>
</table>
Table 5.3 The predicted temperature and the realistic temperature in summer

<table>
<thead>
<tr>
<th>Date</th>
<th>Real temperature</th>
<th>Predicted temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day 1</td>
<td>24.2</td>
<td></td>
</tr>
<tr>
<td>Day 2</td>
<td>23.5</td>
<td></td>
</tr>
<tr>
<td>Day 3</td>
<td>25.6</td>
<td></td>
</tr>
<tr>
<td>Day 4</td>
<td>25.7</td>
<td>25.8</td>
</tr>
<tr>
<td>Day 5</td>
<td>25.8</td>
<td>25.9</td>
</tr>
<tr>
<td>Day 6</td>
<td>23.4</td>
<td>21.2</td>
</tr>
<tr>
<td>Day 7</td>
<td>23.1</td>
<td>22.8</td>
</tr>
<tr>
<td>Day 8</td>
<td>24.5</td>
<td>25.9</td>
</tr>
<tr>
<td>Day 9</td>
<td>25.7</td>
<td>26.9</td>
</tr>
<tr>
<td>Day 10</td>
<td>26.8</td>
<td>27.9</td>
</tr>
<tr>
<td>Day 11</td>
<td>25.2</td>
<td>23.6</td>
</tr>
<tr>
<td>Day 12</td>
<td>24.6</td>
<td>24.0</td>
</tr>
<tr>
<td>Day 13</td>
<td>28.1</td>
<td>32.0</td>
</tr>
<tr>
<td>Day 14</td>
<td>26.3</td>
<td>24.6</td>
</tr>
<tr>
<td>Day 15</td>
<td>26.7</td>
<td>27.1</td>
</tr>
</tbody>
</table>

Based on the two data sets, two case studies are conducted in this section by utilizing the FACT model to determine the comfort temperature zones. According to Equations (5.12) and (5.13) all of the fuzzy members should be defined. Based on Equations (5.10) and (5.11), we set the fuzzy member as:

\[
\bar{\alpha}_1 = (l_{\alpha 1}, m_{\alpha 1}, r_{\alpha 1}) = (16.6, 18.6, 20.6) \\
\bar{\beta}_1 = (l_{\beta 1}, m_{\beta 1}, r_{\beta 1}) = (0.13, 0.16, 0.19) \\
\bar{\alpha}_2 = (l_{\alpha 2}, m_{\alpha 2}, r_{\alpha 2}) = (18.4, 20.4, 22.4) \\
\bar{\beta}_2 = (l_{\beta 2}, m_{\beta 2}, r_{\beta 2}) = (0.03, 0.06, 0.09) \\
\tilde{T}_{o,ref} = (l_{o}, m_{o}, r_{o}) = (T_{o,ref} - 2, T_{o,ref}, T_{o,ref} + 2)(^\circ C)
\]
For $T_{\alpha, \text{ref}}$, we use equation (5.6) to calculate the reference temperature using the information from the grey predictor. Considering that the reference temperature is related to the temperature of the past three days, only 12 days’ (Day 4 – Day 15) reference temperatures can be obtained out of the 15 days of outdoor temperature information. The customer acceptability degree is defined as $\alpha = 0.8$. For comparison, the customer-centered (CC) mode is simulated, and the user defined temperature comfort zones in both winter and summer periods are set as $[T_{\text{min}}, T_{\text{max}}] = [20, 24](^\circ C)$ [54].

In the first case the predicted daily average temperature in winter is used. The FACT model is applied to calculate the comfort zone $[T_{\text{min}}, T_{\text{max}}]$ and the set point is tuned by both PSO and GA. Figs. 5-4 and 5-5 illustrate the comfort zone and the set point with the FACT model and the CC model. The comfort zone after applying the FACT model is lower than the CC model. The set point is achieved by using both PSO and GA, respectively. This demonstrates that the PSO has a better performance than the GA in finding the optimal set points.

The second case uses the summer set data to control the building and to observe the effect of the FACT model during hotter weather. Figs. 5-6 and 5-7 are the comfort zones and set points with FACT model and CC model in this case. The different set points obtained from different optimization methods illustrate the comparison of the PSO and the GA. It can be observed that PSO can always achieve the optimized set point in the comfort zone and GA can only find the near-optimum set point sometimes.

All the simulation results above show the different performances of the PSO and GA in finding the set point. Both PSO and GA have the same population size of 10 and the maximum number of iterations 1000. Table 5.4 indicates the average simulation time.
of different cases. The PSO is much faster converging to the optimal solution than the GA. It can be conclude that the PSO has better performance for find the optimal set point to keep the high level of comfort with less time, so it is more adequate to our problem.

Figure 5-4 Comfort zone and set points with FACT model in winter

Figure 5-5 Comfort zone and set points with CC model in winter
Figure 5-6 Comfort zone and set points with FACT model in summer

Figure 5-7 Comfort zone and set points with CC model in summer
Table 5.4 Average convergence time of PSO and GA

<table>
<thead>
<tr>
<th>Cases</th>
<th>PSO</th>
<th>GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>FACT model in winter</td>
<td>0.0300s</td>
<td>0.1202s</td>
</tr>
<tr>
<td>CC model in winter</td>
<td>0.0300s</td>
<td>0.1518s</td>
</tr>
<tr>
<td>FACT model in summer</td>
<td>0.0133s</td>
<td>0.1602s</td>
</tr>
<tr>
<td>CC model in summer</td>
<td>0.0125s</td>
<td>0.1102s</td>
</tr>
</tbody>
</table>

We adopt the PSO as the optimization method to tune the set point. Figs. 5-8 and 5-9 show the energy saving advantage of the FACT model comparing the CC model in both winter and summer. The power consumption for the local temperature controller-agent is obviously reduced under the effect of FACT model. The FACT model not only provides a more rational comfort zone systematically to enhance customers comfort level, but also reduces the power consumption of the building. These advantages achieve the requirements of the control system for smart buildings.

Figure 5-8 Power consumption for local temperature controller-agent with FACT model and CC model in winter
According to our current results, the FACT model can provide high-level of comfort temperature in any outdoor situation and significantly save energy in order to maximize the customer benefit. It can be concluded that the FACT model is a suitable method for smart building as it enhances the intelligence and optimizes the entire building system.

5.1.6 Conclusion

This section applied the FACT model with grey predictor to the local temperature controller-agent of the integrated smart building and micro-grid systems. From the simulation results, the appropriateness of this model is demonstrated and discussed. The
customers systematically attain a more reasonable comfort temperature with less power consumption when using the FACT model.

5.2 Local air quality controller-agent

In this section, the occupancy-based intelligent control for the local air-quality controller-agent is illustrated in detail [55]. The simulation results are provided for validating the proposed control strategy.

5.2.1 Background introduction

Although a number of factors could affect the indoor air quality, including microbial contaminants, particulate pollutants and concentrations of various gases, CO₂ concentration is considered to be the major impact factor of indoor air quality [56]. In this study, indoor CO₂ concentration level is used as an indicator of indoor air quality. The indoor CO₂ concentration level is primarily influenced by both the indoor CO₂ generation level and the outdoor air quality. Human beings are considered as the primary CO₂ generation source, while the outdoor air quality impacts the indoor air quality through the air change rate. It has been proved that high level CO₂ concentration will degrade the productivity of occupants and affect human health [56]-[58]. Thus, maintaining CO₂ level in a certain comfort range becomes a major goal of the indoor air-quality control system. Besides the natural ventilation, mechanical ventilation system is used as a primary method to decrease the CO₂ concentration level in order to improve the indoor air-quality of energy-efficient buildings. The performance of a ventilation system has a significant impact not only on the indoor air quality but also on the energy consumption. The overall
control objective is to achieve the highest comfort level to with the minimum power consumption by keeping the indoor CO\textsubscript{2} concentrations as close as possible to the set point [59]. In our research an intelligent control system is proposed to maintain the high indoor air quality while minimizing the power consumed by ventilation.

To save energy, demand-controlled ventilation (DCV) is utilized to prevent the energy waste on ventilating empty building [60]. Over past decade, much work has confirmed the effectiveness of DCV in energy saving. Sensor-based demand controlled ventilation (SBDCV) is discussed in [60], and the primary approaches are CO\textsubscript{2} sensor-based DCV and occupancy sensor-based DCV. The CO\textsubscript{2} concentration of indoor air can be directly measured by the CO\textsubscript{2} sensors. Different experiments in different buildings have been conducted, such as schools, office buildings and family houses. It has been proved the CO\textsubscript{2}-SBDCV can save around 10\% to 35\% energy as compared to the normal fixed ventilation control [61]-[63]. The limitations include the accuracy of the CO\textsubscript{2} sensor and the needs for maintenance. According to [64], the accuracy of CO\textsubscript{2} sensor is determined by multiple factors such as sensor type, sensor location and sensor age. Based on the laboratory studies, it was found that very often CO\textsubscript{2}-SBDCV failed to achieve the anticipated energy savings because of the poor sensor accuracy [64]. After the installation, the CO\textsubscript{2} sensor needs continuous recalibration and maintenance to keep the measurement errors less than 75 ppm [64], [65]. However, it is usually difficult to follow the rules to calibrate the sensors in time for most buildings [60]. Besides the CO\textsubscript{2}- SBDCV, occupancy sensor-based DCV is another strategy to achieve both satisfactory indoor air quality and high energy efficiency. Compared to CO\textsubscript{2} sensors, occupancy sensors of high accuracy are able to directly determine the exact number of people in the
building. For the sake of cost-effectiveness, Sommerville and Craig [66] have suggested the radio frequency identification (RFID) technology since the number of people in the building can be accurately tracked by a RFID tag attached on the personal identification card [65], [66]. Although occupancy sensors still need some maintenance, occupancy sensor-based DCV becomes the most popular method of determining the ventilation rate because of its high accuracy. The occupancy-based DCV continuously adjusts the overall ventilation rate based on the actual number of occupants in the building and the minimum ventilation rate per person recommended by the current ventilation standard. In [67], it was found that energy consumption can be reduced by 51% after deploying the occupancy sensor-based DCV in a Norwegian primary school. It was also reported in [68] that energy savings can be achieved using occupancy-based DCV while maintaining the desired indoor comfort. Another advantage of the occupancy-based DCV is due to the predictable occupancy patterns in some buildings such as classrooms and sports fields. In [59] and [69], dynamic ventilation controllers have been developed based on the predicted building schedules and their effectiveness has been verified by the simulation results. The limitation for occupancy sensor-based DCV lies in the variation and uncertainty of the minimum ventilation rate per person in different situations.

In this research, based on the occupancy-based DCV an intelligent control scheme with particle swarm optimization for ventilation system is proposed. This control system adapts the CO₂ predictive model to reduce its dependency on physical CO₂ sensors for avoiding the inaccurate measurements and uses the minimum ventilation rate per person as a constraint. The simulation results validate an improved performance achieved by the proposed intelligent control system. It is capable of finding the optimal ventilation rate
for keeping the indoor CO\textsubscript{2} concentration as close as possible to the set point with the lower energy consumption. This work provides a promising approach to designing more effective ventilation systems for increasing building energy efficiency by embedding a certain degree of intelligence into the control systems.

### 5.2.2 CO\textsubscript{2} predictive model

In this research a predictive model is used to forecast the indoor CO\textsubscript{2} concentration, which is mainly related to the human CO\textsubscript{2} generation, outdoor air quality and air flow rate [70], [71]. Fig. 5-10 represents a building with both natural ventilation and mechanical ventilation systems. Natural ventilation is implemented by opening the window, and air fans are used to control the mechanical ventilation rate by adjusting the speed. Outdoor air can be drawn into a mixing box by an outdoor air fan and damper, and it is mixed up with the partial return air. The supply air fan is utilized to pull the mixed air through the supply duct into the building as the supply air. The air goes to return air inlets after passing through the building. The return air has two ways out: some of it is exhausted to outdoor directly, while the rest is sent back to the mixing box and mixed up with the outdoor air [72].

Some reasonable assumptions should be made for this research. At first, the indoor air CO\textsubscript{2} is supposed to be fully mixed all the time. Secondly, the volumetric ventilation rate in and out of the facility, which includes both mechanical ventilation and natural ventilation, is assumed to be balanced. The equation referred from [65] which governs the generation of CO\textsubscript{2} in a constant volume of facility is written as follows equation (5.39).
Figure 5-10 The building ventilation systems

\[
V \frac{dC(t)}{dt} = q(C(t) - C_{\text{out}}(t)) + RN(t)
\]  

(5.39)

where

- \( V \) is the volume of the building in m\(^3\);
- \( q \) is the overall ventilation rate in m\(^3\)/s;
- \( C(t) \) is the indoor CO\(_2\) concentration in ppm at time \( t \);
- \( C_{\text{out}}(t) \) is the outdoor CO\(_2\) concentration in ppm at time \( t \);
- \( R \) is the CO\(_2\) generation rate per person in L/s;
- \( N(t) \) is the number of persons in the building at time \( t \).

Assume the initial time is \( t_0 \), the CO\(_2\) concentration at time \( t \) is [44]:
\[ C(t) = (C_{out}(t) + RN(t)/q) - (C_{out}(t_0) + RN(t)/q - C(t_0))e^{-q(t-t_0)/V} \] (5.40)

The difference of CO\(_2\) concentrations between the indoor air and the outdoor environment is defined as:

\[ \Delta C(t) = C(t) - C_{out}(t) \] (5.41)
\[ \Delta C(t_0) = C(t_0) - C_{out}(t_0) \] (5.42)

Thus, (5.40) can be rewritten as follows:

\[ \Delta C(t) = \frac{RN(t)}{q}(1 - e^{-q(t-t_0)/V}) + \Delta C(t_0)e^{-q(t-t_0)/V} \] (5.43)

The CO\(_2\) generation rate per person, \( R \), is related to the activity of a person. According to the ASHRAE standard (62-2001) [73], Table 5.5 illustrates the relationship between the CO\(_2\) generation rate per person and the corresponding activity level.

<table>
<thead>
<tr>
<th>Activity Level</th>
<th>L/s</th>
<th>Metabolic Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seated, office</td>
<td>0.0052</td>
<td>1</td>
</tr>
<tr>
<td>Light machine</td>
<td>0.0083</td>
<td>2</td>
</tr>
<tr>
<td>Heavy work</td>
<td>0.017</td>
<td>4</td>
</tr>
</tbody>
</table>

The accuracy of this CO\(_2\) predictive model has been proved in [70] and this model has been well received by other researchers as a highly accurate model to calculate the indoor CO\(_2\) concentration level. The deployment of the CO\(_2\) predictive model will reduce the dependency on indoor sensory measurements in the control system design by estimating the indoor CO\(_2\) concentration based on the occupancy pattern of a building. Different optimal ventilation rates for different time periods \( t \) should be derived to maintain the comfortable air quality with low energy consumption.
5.2.3 Control methods for ventilation system

The control target of a ventilation system is to keep the CO$_2$ concentration just below a desired value through adjusting the ventilation rate. Besides the proposed intelligent control system, two traditional control strategies are introduced for comparison. Those two traditional control strategies are in terms of ON/OFF control and fixed ventilation control. Then the proposed intelligent control is illustrated in detail.

5.2.3.1 ON/OFF control

A ventilation system can be simply controlled by an ON/OFF scheduling model. When the ON/OFF control strategy is applied to the ventilation system, the fan will only be operated in the ON or OFF mode. Suppose the mechanical ventilation system runs at the full speed in the ON mode, and the speed in the OFF mode is zero. The overall ventilation rate $q$ can be expressed as follows:

$$q = q_{nat} + \sum_{i=1}^{num} s_i \times q_{mech}$$  (5.44)

where

$q_{nat}$ is the natural ventilation rate;

$q_{mech}$ is the mechanical ventilation rate;

$num$ is the number of the mechanical ventilation systems in the building;

$s_i$ is the status of the $ith$ mechanical ventilation system, which is equal to 1 if the mechanical ventilation system is ON and will be 0 if the mechanical ventilation system is OFF.

Considering the indoor pollutants, the requirement for the minimum ventilation rate should be met. The indoor air pollutants are mainly generated by two sources. One
source is the occupants and their activities, and another is the non-occupant-related pollutants. The CO₂ has been evaluated as an imperfect but reasonable surrogate gas for the concentration of occupant-related contaminants [59], [60], [74]. Thus, it is assumed that the occupant-related pollutants can be maintained at the acceptable level if the CO₂ concentration is controlled close to the set point. However, non-occupant-related contaminants may be highly different in different buildings. Also, there is no generalized relationship between the CO₂ concentration and non-occupant-related pollutants. Thus, it is difficult to directly use them as constraints in developing the proposed control system.

Here two parameters are involved in this research, which are occupant minimum ventilation rate \( q_p \) and area minimum ventilation rate \( q_a \). \( q_p \) is applied to dilute CO₂ concentration and the occupant-related pollutants, while \( q_a \) is employed to reduce the impact of the non-occupant-related pollutants.

\[
q_p = q_{mp} \times N \tag{5.45}
\]

\[
q_a = q_{ma} \times S_a \tag{5.46}
\]

where \( q_{mp} \) is the minimum ventilation rate per person, \( q_{ma} \) is the minimum ventilation rate per area, \( S_a \) is the floor area of the building. \( q_{mp} \) and \( q_{ma} \) are referred from the ASHRAE standard (62-2001) [73] in this dissertation.

Thus, the following constrains should be considered for the ON/OFF control system to ensure the acceptable indoor air quality:

\[
q \geq q_a + q_p \tag{5.47}
\]
5.2.3.2 Fixed ventilation control

The fixed ventilation rate control is commonly used because of its simplicity. Considering the energy efficiency and DCV, the control strategy for fixed ventilation control is illustrated as follows [64]:

\[
q_{\text{fix}} = \begin{cases} 
q_a & \text{if no occupants} \\
q_{mp} \times N_{\text{max}} + q_a & \text{otherwise}
\end{cases}
\] (5.48)

where \( q_{\text{fix}} \) is the overall ventilation rate for fixed ventilation control, and \( N_{\text{max}} \) is the designed maximum occupancy of the building.

5.2.3.3 Occupancy-based intelligent control

The limitation of the ON/OFF control is that the overall ventilation rate cannot vary continuously, which has only two operation modes. Thus, the ventilation system using ON/OFF control can be considered as a discrete ventilation system. Based on equation (5.44), it is difficult to find an optimal ventilation rate to maintain the indoor CO\(_2\) concentration just below the set point. To provide a high level of air quality comfort, the ON/OFF control system always chooses a higher ventilation rate at the cost of consuming more energy. The limitation for the fixed ventilation control is that the ventilation rate cannot adapt autonomously with changes of the indoor environment. Thus, there is no guarantee to achieve the control goal all the time for using the fixed ventilation rate control. To eliminate the aforementioned limitations, an occupancy-based intelligent control with the CO\(_2\) predictive model is proposed.

The CO\(_2\) predictive model (5.43) shows the dynamic nature of relationship between the indoor CO\(_2\) concentration and the ventilation rate, and an optimal ventilation control system should be designed based on the indoor CO\(_2\) concentration. Moreover, the
ventilation system is driven by the energy. Power consumption of a ventilation system is related to the ventilation rate [75]. The higher ventilation rate needs to consume more energy. Thus, the high ventilation rate can lower the CO$_2$ level below the desired value but it costs more energy. Here an optimal intelligent control system is proposed, which is able to adjust the ventilation rate and provide suitable amounts of outdoor air to maintain the indoor CO$_2$ concentration below or at the desired value.

The occupancy pattern of a building for different days is different and the variation of occupancy pattern will impact the indoor CO$_2$ concentration. The optimal ventilation rates which take both air quality and energy consumption into account can always be found by the proposed intelligent control strategy for different occupancy patterns. The occupancy patterns for some buildings such as classrooms and sports fields are somehow predicable. For instance, the occupancy patterns in these buildings can be predicted based on the specific schedules. If occupancy prediction with the reasonable accuracy for a building is not possible, physical occupancy sensors can be installed to accurately monitor the building occupancy in different time periods. For our proposed control system, the building occupancy pattern can be obtained from either prediction or accurate measurement. In simulations, the CO$_2$ prediction model can always be used to forecast the indoor CO$_2$ concentration based on the specific occupancy pattern.

The proposed intelligent control is applied to the continuous ventilation system whose ventilation rate can be changed continuously. The goal of the intelligent control system is to achieve the balance of the air quality comfort and power consumption. For this purpose, the optimal ventilation rate $q_{int}$ should be found to maintain the indoor CO$_2$
concentration in the comfort zone with minimum energy. The control strategy is improved as follows:

\[
q = \begin{cases} 
q_a & \text{if no occupants} \\
q_{\text{int}} & \text{otherwise}
\end{cases} \quad (5.49)
\]

Based on the non-linear relationship between indoor CO\(_2\) concentration and ventilation rate shown in (5.43), PSO is selected to find the optimal ventilation rate \(q_{\text{int}}\) in time \(t\) according to the occupancy, outdoor air quality and volume of the building. In the encoding scheme, each particle only has one dimension, which indicates the ventilation rate \(q\). The air quality comfort function defined in (5.50) is used as the objective function of PSO. The optimization goal is to maximize the objective function. Moreover, considering the industry standards for the minimum ventilation rate in the building environment such as ASHRAE 62, the constraint for the intelligent ventilation rate is added as follows:

\[
\max comfort_{\text{air}} = \begin{cases} 
1 - \left(\frac{C - C_{\text{set}}}{C_{\text{set}}}\right)^2 & C > C_{\text{set}} \\
1 & C \leq C_{\text{set}}
\end{cases} \quad (5.50)
\]

\[
s.t. \quad q_{\text{int}} \geq q_a + q_p \quad (5.51)
\]

where \(C\) is the indoor CO\(_2\) concentration which can be obtained from (5.41) and (5.43), and the \(C_{\text{set}}\) is the set value which may be defined by customers and inputted through GUI. To enhance the flexibility of the control system, the customer is provided with the opportunity to specify a comfort zone instead of a single-value set point. Because of the non-linear comfort function (5.50), PSO is used for searching the optimal set point in the comfort zone as well. The advantage for energy savings after defining the comfort zone will be validated by simulation study.
6.2.4 Fuzzy Logic Controller

A fuzzy logic controller is designed to determine the required power of mechanical ventilation system according to the ventilation rate. The input of the fuzzy controller is the ventilation rate. The output is the required power to be consumed in the mechanical ventilation system which helps maintain high indoor air quality [75]. The membership functions of the input and output of the fuzzy controller are shown in Fig. 5-11. The membership functions of the inputs and outputs include the following values:

Figure 5-11 The membership function for the local air quality controller
Low (L), Medium Low (ML), Slight Low (SL), Slight High (SH), Medium High (MH) and High (H); Start Running (SR), Low Speed (LS), Medium Low Speed (MLS), Medium High Speed (MHS), Full Running (FR). The rules of the fuzzy ventilation controller are shown in Table 5.6.

Table 5.6 Fuzzy control rules for the local air quality controller

<table>
<thead>
<tr>
<th>Ventilation rate</th>
<th>L</th>
<th>ML</th>
<th>SL</th>
<th>SH</th>
<th>MH</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required power</td>
<td>SR</td>
<td>LS</td>
<td>MLS</td>
<td>MHS</td>
<td>HS</td>
<td>FR</td>
</tr>
</tbody>
</table>

5.2.5 Case studies and simulation results

The purpose of the case study is to illustrate the advantage of the proposed intelligent control system as compared with the ON/OFF and the fixed ventilation controls. A large lecture room is chosen as the test system and the simulation is carried out on a 24-hour time scale. The initial parameters for the case study are listed in Table 5.7. The simulation step for the ventilation system is set as 15 minutes, which indicates \( \Delta t = 15 \text{min} = 900 \text{s} \). For the fixed ventilation control, the ventilation rate can be calculated as \( q_a = 0.24 \text{ m}^3/\text{s} \) when the lecture room is empty and \( q_{fix} = 0.99 \text{ m}^3/\text{s} \) when it is scheduled for class according to Table 5.7 and (5.48).

To deploy the \( \text{CO}_2 \) predictive model to estimate the indoor air quality in one day, the varying outdoor \( \text{CO}_2 \) concentration and the occupancy pattern of the room in 24 hours should be known. Fig.5-12 depicts the varying outdoor \( \text{CO}_2 \) concentrations in different time periods of a day. The occupancy pattern for the lecture room can be predicted by investigating the class schedule. The scheduled occupancy pattern for the lecture room is shown in Fig. 5-13.
Table 5.7 Parameters Description

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Variable Description</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V$</td>
<td>Building volume</td>
<td>1000</td>
<td>m$^3$</td>
</tr>
<tr>
<td>$S$</td>
<td>Building floor area</td>
<td>400</td>
<td>m$^2$</td>
</tr>
<tr>
<td>$q_{ma}$</td>
<td>Minimum ventilation rate per area</td>
<td>0.0006</td>
<td>m$^3$/s</td>
</tr>
<tr>
<td>$q_{mp}$</td>
<td>Minimum ventilation rate per person</td>
<td>0.0075</td>
<td>m$^3$/s</td>
</tr>
<tr>
<td>$q_{nat}$</td>
<td>Nature ventilation rate</td>
<td>0</td>
<td>m$^3$/s</td>
</tr>
<tr>
<td>$q_{mech}$</td>
<td>Mechanical ventilation rate</td>
<td>0.833</td>
<td>m$^3$/s</td>
</tr>
<tr>
<td>$C(t=0)$</td>
<td>Initial indoor CO$_2$ concentration</td>
<td>500</td>
<td>ppm</td>
</tr>
<tr>
<td>$C_{set}$</td>
<td>Specified value of the comfortable CO$_2$</td>
<td>800</td>
<td>ppm</td>
</tr>
<tr>
<td>$R$</td>
<td>CO$_2$ generation rate per person</td>
<td>0.005</td>
<td>L/s</td>
</tr>
<tr>
<td>$Num$</td>
<td>Number of available mechanical ventilation system</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>$N_{max}$</td>
<td>Maximum occupancy of the building</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5-12 The outdoor CO$_2$ concentration
The ventilation rate for intelligent ventilation control is obtained using PSO. Figs 5-14 and 5-15 are the comparison using different control strategies. Because the control goal of the ventilation system is to maintain the CO\textsubscript{2} concentration just below or at the set point, it can be observed from Fig. 5-14 that intelligent control leads to a better performance in achieving the control goal. The ON/OFF control can always keep the CO\textsubscript{2} concentration much lower than the set point, while the fixed ventilation control fails to maintain the acceptable air quality in some periods with large amount of occupants. Considering the comfort level defined in (5.50), it can be concluded the maximum comfort level can be always obtained by the intelligent and the ON/OFF controls because there are no periods where the CO\textsubscript{2} concentration exceeds the set point. Moreover, the energy-efficiency for intelligent control is verified by Fig. 5-15. Table 5.8 shows the calculated results of the required power. Compared to the ON/OFF and the fixed
ventilation controls, the required power of the proposed intelligent control is significantly reduced. The reductions are 53% and 12% comparing to the ON/OFF and the fixed ventilation controls, respectively. From the simulation results obtained, the developed local air-quality controller-agent exhibits a good performance in reducing energy consumption while maintaining the occupants’ comfort level.

Table 5.8 The required energy for different control methods

<table>
<thead>
<tr>
<th>Control Methods</th>
<th>Required Energy (kWh/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ON/OFF</td>
<td>68.17</td>
</tr>
<tr>
<td>Fixed Ventilation</td>
<td>35.91</td>
</tr>
<tr>
<td>Intelligent</td>
<td>31.72</td>
</tr>
</tbody>
</table>

Due to its simplicity and efficiency, the proposed intelligent control strategy has great potentials for practical applications by implementing it as a microprocessor based controller. This controller can be embedded in the existing ventilation system without installing any analog CO\textsubscript{2} sensors. For well-scheduled spaces such as classrooms and conference rooms, the installation cost of occupancy sensors can be saved.

Figure 5-14 The CO2 concentration using different control methods
5.2.6 Conclusion

In this study, CO$_2$ predictive model is used to forecast the indoor air quality. In addition, an intelligent control system with embedded PSO is developed for the local air quality controller-agent to maintain the high air quality with improved energy efficiency. According to the simulation results, the proposed intelligent control system exhibits a good performance in reducing energy consumption while maintaining the occupants’ comfort level.

5.3 Local illumination controller-agent

5.3.1 Background introduction

Illumination level is used to indicate the visual comfort which is a key point to assess the indoor comfort level. Artificial lighting systems are served as the primary...
resource to provide high level of visual comfort in most of buildings, so the power consumption of light systems contributes a significant part to the total building electricity usage. According to [76], more than 30% electricity consumption is consumed by the electrical lighting system in residential and commercial buildings in the U.S.

Daylight harvesting is the most widely investigated and received approach to reduce the energy consumed by artificial lighting system. Considerable work has been conducted on daylight harvesting by different researchers: Dounis et al. reported the use of fuzzy logic to control the indoor illumination level [77], while [78] discussed the similar design of using fuzzy logic for daylight illuminance control. In [79], a self-adaptive control strategy had been developed to manage the shading devices as well as the artificial lighting system to meet customers’ desire. Field test had been conducted for the window blinds on daylight-linked dimming and automatic on/off lighting control system in [80], the results show great potential on energy saving. Although developing proper control system to utilize daylight has been proved to enhance the energy efficacy and to reduce the energy usage, few work has designed the lighting control with the consideration of power consumption.

In our work, an occupancy-based intelligent control has been proposed. The venetian blind system and the artificial lighting system can serve as actuators to control the indoor illumination level. Fuzzy logic controller is used for obtaining the required power of the artificial lighting system considering the uncertainties and variations from different manufactures. Different from other researches’ work, the power consumption and the high level of visual comfort are taken into consideration during the design. The control goal is to minimize the power consumption and to keep the indoor illumination
level inside the acceptable range. Because of the complexity and nonlinearity of the mathematical model, PSO is applied to obtain the optimal set point which can reduce the energy usage without compromising the customer visual comfort.

5.3.2 Intelligent control model

The task of the local illumination controller-agent is to manage the venetian blind system and the artificial lighting system, maintaining the indoor illumination level at the desired value with the minimum energy consumption. Daylight is known as the greatest natural factor for influencing the indoor illumination control while limiting the energy usage. The local illumination controller-agent utilizing the daylight-linked model is shown as follows [79]:

\[ E_{set} = E_{out} \times DF \times RI(\alpha) + E_{light} \]  

where:

- \( E_{set} \) is the target indoor illumination level;
- \( E_{out} \) is the external daylight illumination, measured via the photo-sensors.
- \( DF \) is the daylight factor, which is the ratio of internal illumination level to the external daylight level. Usually, it can be set as the average daylight factor which is 1%-2% [81].
- \( E_{out} \times DF \) is termed as the indoor daylight illumination. In consideration of the useful daylight illumination theory which claims only the illumination level falling into the useful range can be effective either as the sole source or in conjunction with the artificial lighting, the daylight may contribute to the indoor visual comfort when the indoor daylight illumination is larger than 100 lux [82].
$RI(\alpha)$ is the blind transmission factor. According to the transmittance of blind materials, it can be assumed this factor relates linearly to the blind position between values 1 (blind completely open) and 0.1 (blind completely closed).

$E_{Alight}$ is the illumination level provided by the artificial lighting system.

Other than the traditional control strategy with fixed set point of the indoor illumination level, here we propose an intelligent control strategy for the local illumination controller-agent [83]. Considering the energy-consuming devices including the venetian blind system and the artificial lighting system, the total power consumption $P$ can be defined as follows:

$$P = P_{blind} + P_{Alight} \quad (5.53)$$

where:

$P_{blind}$ is the power demand for the venetian blind system. For simplification, some assumptions are made: the power demand for the blind system is 1 watt when it is moving; if there are no movements, the power demand is zero.

$P_{Alight}$ is the power demand for the artificial lighting. It is difficult to be determined since there may be significant differences for different manufactures. Considering the uncertainty, fuzzy controller is used here to represent the dynamic relationship between the required power $P_{Alight}$ and the illumination level $E_{Alight}$ provided by the artificial lighting system [84].

The control goal of the local illumination controller-agent is to minimize the energy consumption while maintaining the visual comfort. Due to the highly nonlinear and dynamic relationship between $P_{Alight}$ and $E_{Alight}$, PSO is chosen to derive the optimal
illumination set point \( (E_{\text{opset}}) \). The objective function is \( P \), and the optimization goal is to minimize \( P \):

\[
\min P \tag{5.54}
\]

subject to:

\[
E_{\min} \leq E_{\text{opset}} \leq E_{\max} \tag{5.55}
\]

The comfort range \([E_{\min}, E_{\max}]\) can be defined by customers. Since occupancy pattern has a profound influence on energy savings, it should be taken into account in the control strategy design. Equation (5.56) illustrates the different control strategies for the occupied periods and unoccupied periods. Generally speaking, in the occupied hours, the control system activates the optimizer to tune the set point in order to obtain the acceptable indoor visual comfort with minimized energy. Otherwise, the control system turns off all the artificial lights and keeps the blind position to save energy if there are no occupants in the building.

\[
E_{\text{set}}(t) = \begin{cases} 
E_{\text{opset}}(t) & t \in \text{occupied periods} \\
E_{\text{out}}(t) \times DF \times RI(\alpha)(t - \Delta t) & \text{otherwise}
\end{cases} \tag{5.56}
\]

### 5.3.3 Fuzzy Logic Controller

In the local illumination agent, illumination level is utilized as measured parameters to indicate visual comfort, which is measured in lux. The input of the local fuzzy illumination controller is the error between the outside illumination level and the indoor set point. The output is the required power to be consumed by the lighting system. The membership functions of the inputs and outputs include the following values: Very Low (VL), Low (L), Slight Low (SL), Medium (M), Slight High (SH), High (H), Very High (VH) and Maximum (MAX); Start (ST), Small (SM), Slight Small (SSM), Slight
Large (SLG), Large (LG), Very Large (VLG) and All ON (ALL). The membership functions are shown as following figure, while rules of the local illumination controller are shown in Table 5.9.

Table 5.9 Fuzzy control rules for the local illumination controller

<table>
<thead>
<tr>
<th>Artificial lighting</th>
<th>VL</th>
<th>SL</th>
<th>L</th>
<th>M</th>
<th>SH</th>
<th>H</th>
<th>VH</th>
<th>MAX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required power</td>
<td>ST</td>
<td>SM</td>
<td>SSM</td>
<td>M</td>
<td>SLG</td>
<td>LG</td>
<td>VLG</td>
<td>ALL</td>
</tr>
</tbody>
</table>

Figure 5-16 The membership function of the local illumination controller
5.3.4 Case studies and simulation results

The same large lecture room with the same occupancy pattern as section 5.2.5 is chosen as the test field. The simulation is carried out on a 24-hour time scale and the step \( \Delta t \) is 15 minutes. All the results are obtained based on the simulation studies and initial parameters for case studies are listed below:

1) Daylight factor \( DF=0.02 \);
2) Lower limit for visual comfort \( E_{\text{min}}=700 \text{ lux} \);
3) Upper limit for visual comfort \( E_{\text{max}}=900 \text{ lux} \).

To illustrate the energy saving potential for the local illumination controller-agent, the traditional fixed set point control is simulated for comparison and the fixed set point is set as 800 ppm. Fig. 5-17 shows different indoor illumination levels obtained by different control strategies based on the same indoor daylight illumination. Fig. 5-18 illustrates power demands for both control strategies.

![Figure 5-17](image)

Figure 5-17 The indoor illumination level for different illumination controls
Figure 5-18 Required power for different illumination controls

It can be seen that both control strategies can maintain the indoor illumination in the comfort range for providing a high level of visual comfort to students in the class hours. The optimal set point intelligent control requires 26.42kWh/day compared with 38.50kWh/day consumed in the fixed set point control. Thus, about 31% energy can be saved by using the proposed local illumination controller-agent.

5.3.5 Conclusion

This section is presented the design of the local illumination controller-agent. From the simulation result, it can be observed the indoor illumination level keeps in the comfortable range using both of the fixed set point control method and the proposed intelligent control system during the occupied hours. However, the energy usages have
significant difference, and the energy saving can be as high as 30% by applying the proposed control strategy.
Chapter 6

Load agent

In this chapter, the description of load agent is presented in details. A GUI based platform is designed as well to provide more flexibility to customers to be involved in the control process. A case study has been conducted to illustrate the effectiveness of the proposed load agent.

6.1 Introduction and GUI design

The load agent controls all the equipment which has no direct connection with the three main comfort factors (temperature, air quality and illumination level). Considering the different functionalities of buildings and the variety of equipment, customers should be given the flexibility to manage the controllable loads according to their own preferences. To fulfill this need, some load profiles are built and a GUI is designed for customers to configure corresponding parameters. Through the GUI-based platform, customers can define the load characteristics as shown in Fig. 6-1. as well as the load priorities.

In order to determine the amount and the proper order of shed loads, the detailed information about loads is required. The basic information for a specific load is its power
consumption, operation periods in a day, and the priority among all the loads. The priority indicates the ranking of the loads by their importance. Loads in Priority 1 have the highest importance, which means that when the power supply is in a shortage, loads in Priority 1 will be shed at last. Detailed information about loads can be collected from users. Therefore, a GUI is built for users to define their own loads. As shown in Fig. 6-1, users can manage building loads by adding/deleting items to/from the load list. Basic properties of a load including load name, operation time, and priority can be configured through the panel [23].

![Figure 6-1 GUI for configuring interruptible loads](image)

6.2 Case study and simulation results

In this case study, five 4.5-kilowatt solar panels and four 5-kilowatt wind turbines are used [32][33]. The batteries with total storable energy of 35kWh and a minimum
storage threshold of 5kWh are selected for distributed energy storage. Fig. 6-2 illustrates the total energy production from all the renewable resources. Table 6.1 shows the interruptible loads selected in this case study [34]. Customers determine the amount, the operation periods, and the priority of each selected load. It is assumed no plug-in loads existing in this case study. Fig. 6-3 illustrates the total energy demand of the building in a day.

Figure 6-2 Energy production of the renewable resources

Table 6.1 Interruptible Load Profiles

<table>
<thead>
<tr>
<th>Load</th>
<th>Power</th>
<th>Number</th>
<th>Operation Periods</th>
<th>Priority</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fountain Pump</td>
<td>1200W</td>
<td>1</td>
<td>8:00-22:00</td>
<td>4</td>
</tr>
<tr>
<td>Electronic Billboard</td>
<td>500W</td>
<td>12</td>
<td>0:00-3:00, 8:00-24:00</td>
<td>1</td>
</tr>
<tr>
<td>Decoration Bulb</td>
<td>300W</td>
<td>10</td>
<td>0:00-24:00</td>
<td>2</td>
</tr>
<tr>
<td>Swimming Pool Pump</td>
<td>1800W</td>
<td>1</td>
<td>10:00-20:00</td>
<td>3</td>
</tr>
</tbody>
</table>
Assume some unacceptable disturbances such as poor power quality and voltage distortion occur in the grid interconnection or the utility grid, the building will operate in the islanded mode. Here the islanded operation mode without optimization will be first examined and then the effect of the S-PSO will be demonstrated. The overall customer comfort is expected to be improved after S-PSO is applied, but there is still a possibility that optimization itself is not adequate to maintain the highest comfort level in all time periods. Thus, if desired, load agent can be activated to improve the overall customer comfort by shedding some interruptible loads. Fig. 6-4 illustrates the energy consumption of each interruptible load based on Table 6.1 in the normal condition, while Fig. 6-5 illustrates the power consumption of each interruptible load when load shedding is applied to improve the overall comfort level. The drops mean those loads are shed, which switch the devices off in the implementation.
Figure 6-4 Energy consumption of each interruptible load in the normal condition

Figure 6-5 Energy consumption of each interruptible load with load shedding
Figs. 6-6 to 6-8 show the changes of the overall customer comfort in the islanded mode using different operating strategies. Fig. 6-6 depicts the overall customer comfort in islanded mode without optimization. Fig. 6-7 shows the overall customer comfort in islanded mode after S-PSO is applied to tune the set points but load agent is not activated. It can be observed that overall comfort level is somehow improved with optimization. If desired, load shedding can be used to further improve the overall comfort level. The S-PSO is applied to find the optimal set points, while the load agent is activated to shed load for enhancing the customer comfort level. Fig. 6-8 shows the overall customer comfort in islanded mode with both optimization and load shedding. It can be seen that the overall comfort level is maximized using the optimizer coupled with the load agent.

Figure 6-6 Overall customer comfort in islanded mode without optimization

Figure 6-7 Overall customer comfort in islanded mode with optimization
Figure 6-8 Overall customer comfort in islanded mode with optimization and load shedding
Chapter 7

Switch agent with negotiation agent

In this chapter, the switch agent and the negotiation agent are introduced and discussed. Two types of negotiation agents are developed to facilitating bi-directional energy trading between smart building and utility grid, which are in terms of the adaptive attitude bidding strategy (AABS) based negotiation agent and the particle swarm optimization-adaptive attitude bidding strategy (PSO-AABS) based negotiation agent. The feasibility of the proposed negotiation agents is evaluated by the simulation results.

7.1 Switch agent

Integrated building and micro-grid system has two operation modes: grid-connected mode and islanded mode. The switch agent works with the central-coordinator agent to determine the switch status for connecting/disconnecting the micro-grid to/from the utility grid. Fig. 7-1 shows the procedure for selecting the specific operation mode in different scenarios. If there is any disturbance in the utility grid or the negotiation is failed to make a deal, the micro-grid will be islanded from the main grid. The switch in these scenarios will be open and corresponding optimization or mitigation schemes will be adopted to maximize the overall comfort level using the available renewable energy.
resource. Otherwise, the micro-grid is connected to the utility grid. However, the building will always consume the available renewable energy first. If there is any surplus energy from the renewable resources, the batteries will be charged only if the negotiation is failed. Also if there is insufficient renewable energy from the micro-grid and the negotiation has successfully achieved the mutual agreement, utility power will be purchased to fulfill the total load demands of the building.
7.2 Negotiation agent

Negotiation agent is embedded in the switch agent as Fig. 3-2 shown. Bridging the utility grid and the smart building system, the intelligent negotiation agent is intended to facilitate both sides to reach a rational deal efficiently [85].

7.2.1 Background introduction

The electricity industry is moving toward an open and competitive market to replace the regular monopolies in the energy market [86], [87]. Besides electric utilities, the participation of independent power producers (IPPs) in the electrical market makes the price of electricity unregulated and variable. Buyers and sellers are allowed to negotiate so as to reach rational deals to maximize payoffs of both sides [86]-[89]. The process of negotiation involves at least two parties communicating with one another to obtain a mutually acceptable agreement by multiple rounds of proposal and counter-proposal [89]. Usually the negotiation has a deadline, which means a number of rounds are always set for a negotiation process. In each round, one party proposes its offer to see if it is acceptable to others. If not, another party will submit a counter-offer. The negotiation will end only if the agreement is reached or the transaction is expired. In order to successfully reach an agreement, negotiating parties should be willing to compromise to reduce the differences between their mutual expectations in the transaction [89]-[91].

In this chapter, a negotiation process is considered in the electricity market involving the utility grid and the smart building. As a cutting-edge building management technology, smart buildings utilize modern information and communication technologies
to manage energy consumption and the indoor environment in an automatic fashion. In order to make the smart building environmentally friendly, the renewable energy sources are used as the primary power supply and the utility grid is utilized as the secondary energy supply [92]. When the renewable production is insufficient, the building needs to purchase energy from the utility grid. On the other hand, when the renewable resources produce more energy than the building demands, the building may sell the redundant energy back to the utility grid. In this process, the building and utility grid are two parties in the negotiation, and they may switch roles as a buyer or a seller under different conditions [93]. In case both parties reach an agreement in the energy trading, a successful transaction is achieved, which means a certain amount of electrical power will be exchanged at the price that both parties have agreed upon in the negotiation.

Over the past decade, significant efforts have been devoted to designing various negotiation agents [94]-[103]. For instance, zero intelligence (ZI) agent was proposed by Gode and Sunder [100], which randomly generates the bid/ask price without intelligence for maximizing the profit. Gjerstad and Dickhaut presented a new agent termed GD agent in [101] for maximizing the profit based on the belief-based strategy, and the belief of acceptable bid/ask is calculated using the historical data. However, these agents have no or little adaptability. Cliff and Bruten developed the zero-intelligence plus (ZIP) agent, which has some degree of adaptability so that it is capable of wisely increasing/decreasing the profit margin based on the recent market information [102]. Inspired by prior work while accounting for the characteristics of smart buildings, this study proposes two novel negotiation agents for smart building applications.
A negotiation agent based on adaptive attitude bidding strategy (AABS) is proposed in this chapter. A comprehensive set of factors for the integrated smart building and utility grid system is taken into account in developing the negotiation model. The AABS based negotiation agent turns out to be able to dynamically adjust its behavior in response to varying attitudes in the negotiation process. In addition, an improved particle swarm optimization-adaptive attitude bidding strategy (PSO-AABS) based negotiation agent is developed for adaptively adjusting the trader’s decisions according to the opponent’s behaviors. It turns out to be capable of making rational deals in bi-directional energy trading by maximizing the trader’s payoffs with reduced negotiation time. The feasibility of the proposed negotiation agents is evaluated by the simulation results.

### 7.2.2 AABS based negotiation agent

One of major issues in the deregulated electricity market is the trading pricing. This work discusses the mechanism of buying and selling power between two traders based on a negotiation model. The bidding strategy of the negotiation model is time-dependent and behavior-dependent. The changes of price are influenced by the remaining time and the next period price is determined based on the previous ones.

In this study the AABS is developed and evaluated, and it can be deployed in the integrated smart building and utility grid system. The negotiation agent adopting adaptive attitude bidding strategy explores various attitudes in bid determination. Practically, the negotiation agent should be computationally efficient. The proposed negotiation model is designed based on the hypothesis of bounded rather than perfect rationality.
Attitude is a complex mental state involving beliefs, feelings, values and dispositions for acting in a certain way. The term “eagerness” is used to indicate the attitude of the agent’s interest to negotiate and reach a deal [90], [104], [105]. Dumas et al. [106] defined eagerness as “the minimum probability of obtaining the goods by the deadline”. The value of eagerness represents the level of interest and drives the negotiation behaviors. A large value of eagerness indicates that the agent is motivated to make this transaction successfully by the deadline at any price, if the reservation price permits. On the contrary, the low eagerness value indicates the agent is willing to risk missing the deadline (and losing the deal) in exchange for the chance of a better price.

In the real market, eagerness is affected by multiple factors such as the historical record. For instance, human traders will feel eager to close a deal if they have not traded their goods for a long time; otherwise, they will be interested to find a better price for gaining more profits rather than eagerly reaching a deal if they have completed many successful transactions recently. Different from other researchers’ work [105], [106], where eagerness is set as a fixed value at the beginning of experiments and is maintained constant all the time, the proposed AABS based negotiation is to mimic the feeling of eagerness and the behavior of traders. Similar to the human trader, the eagerness of the negotiation agent will be adjusted according to real-time situations. In the integrated smart building and utility grid system, some dynamic factors such as comfort level and battery state-of-charge (SOC) condition have great effects on the negotiation outcome. A mathematical function to represent and calculate the eagerness is proposed in this work.
7.2.2.1 Eagerness for utility grid

The utility grid can play the role of either seller or buyer. Decision-making is mainly dependent on previous transaction history. Eagerness $EA_L$ for the utility grid can be determined by the following function:

$$Tr = \begin{cases} 
0 & \text{for successful transaction} \\
1 & \text{for unsuccessful transaction} 
\end{cases}$$

(7.1)

$$H(k) = Tr(k-1) + (n-1)/n \times Tr(k-2) + \cdots + 1/n \times Tr(k-n)$$

(7.2)

$$EA_L = \begin{cases} 
e_p \text{min} & \text{if } H = H_{\text{min}} \\
H \times Adj_{grid} & \text{if } H \in [H_{\text{min}}, H_{\text{max}}] \\
e_p \text{max} & \text{if } H = H_{\text{max}} 
\end{cases}$$

(7.3)

where:

$Tr$ represents the status of a transaction. If the transaction is successful, which means the agreement is achieved by negotiation deadline, $Tr$ is set as 0. Otherwise, if the transaction is failed, $Tr$ equals 1.

$H$ is the historical record of previous transactions. $n$ is the number of previous transactions which may impact the current one based on the specific requirement. Different transactions have different weights in the historical record, with the most recent transaction playing the most important role. In another word, the most recent transaction will have the most significant influence on the current negotiation behavior. In the simulation studies $n$ is set as 3, which means three most recent transactions are kept in record and used in deciding the current eagerness. The weights are 1, 2/3 and 1/3, respectively. After calculation, it is found that $H_{\text{min}}=0$ and $H_{\text{max}}=2$.

$k$ is the current transaction. $k-1$, $k-2$ and $k-n$ represent the first, second, $n$-th prior transaction, respectively.
$EA_L$ is the attitude for the utility grid, which falls into the range $[e_{p\text{min}}, e_{p\text{max}}]$. $Adj_{grid}$ is the adjustment factor to convert historical values to eagerness values.

Based on the attitude function, $H$ will decrease if there are many successful recent transactions, diminishing the eagerness. A low eagerness value means that the buyer/seller is willing to hold out for greater profit rather than quickly giving ground to close the deal in the current transaction. The trader believes that they have left lots of profit to the opponent in the last several transactions so that they should increase the ask price or decrease the bid price for more profit back from the opponent. On the other hand, a high eagerness value indicates the buyer/seller is eager to make this deal, so they may be willing to make more concessions in the transaction.

7.2.2.2 Eagerness for the smart building

The eagerness function will be different when the smart building plays different roles. When the smart building serves as buyer, the current comfort level will be the primary factor impacting the bidding strategy of the next transaction since one goal of the smart building is to provide a high-level comfort to the customers. Moreover, the building is capable of deciding if a load should be served or not at different prices [107]. Interruptible load demands (ILDs) can be shed when the building system needs to curtail some loads. Considering the reliability of the building system and the life-cycle of the equipment, frequent use of demand curtailment should be avoided. Thus, a fixed number of ILDs for a day should be specified. When renewable energy is insufficient and an agreement cannot be attained by the negotiation deadline, the negotiation agent will declare the need for an ILD. The load agent we have proposed will be activated to shed
the interruptible loads. Consequently, the number of remaining allowable ILDs becomes a major factor in determining the eagerness function of the negotiation model. The negotiation agent has some freedom to choose not to satisfy all the demands if there are large amounts of ILDs remaining [107]. However, energy supplied to the comfort-related actuators such as auxiliary heating/cooling system, electrical lighting system and mechanical ventilating system cannot be sufficiently guaranteed to be able to maintain the maximum comfort level. Thus, the current comfort level will influence the eagerness of the next transaction. If the comfort level drops below a certain threshold, the customer will become more eager to close the next deal so that the comfort level can be brought back to the desired level with sufficient energy supply.

\[
EAL = \sigma \times \begin{cases} 
  e_{p_{\text{min}}} & \text{if } N < 0.2 \times N_{\text{max}} \\
  N \times \text{Adj}_{\text{building}} & \text{if } N \in [0.2 \times N_{\text{max}}, N_{\text{max}} - 1] \\
  e_{p_{\text{max}}} & \text{if } N = N_{\text{max}}
\end{cases}
\]

(7.4)

\[
\sigma = \begin{cases} 
  L_1 & \text{if } \text{comfort} < Ce \\
  1 & \text{if } \text{comfort} \geq Ce
\end{cases}
\]

(7.5)

where:

- \(N_{\text{max}}\) is the maximum number of ILDs for a day specified by the customer;
- \(N\) is the number of the used allowable ILDs;
- \(e_{p_{\text{min}}}\) and \(e_{p_{\text{max}}}\) are the minimum limit and maximum limit, respectively;
- \(\text{Adj}_{\text{building}}\) is the adjustment factor to convert the number of remaining ILDs to the eagerness values;
- \(\sigma\) is the comfort impact factor; \(Ce\) is a tolerable comfort level which can be defined by the customers, fell in \([0.8, 1]\). When the current comfort level is greater than \(Ce\), which indicates that the customers are satisfied with the current environment, \(\sigma\) will
be 1. Otherwise, $\sigma$ will be set as a large positive number $L_1 (L_1 > 1)$. This is because the comfort level is a major control goal in smart buildings. If the comfort drops below the customer’s acceptable level, the building will become eager to buy energy from the utility grid in the next transaction to improve the comfort level.

The smart building only serves as the seller when there is surplus renewable energy after supplying all demands. This suggests that the comfort level will be maintained at the highest value because of the sufficient energy supply. Thus, comfort level is no longer a primary factor in impacting the eagerness function when the smart building acts as the seller. Besides the previous history, the SOC will be a primary factor under this situation. Normally, considering the life span of the batteries, the maximum and minimum SOC ($SOC_{\text{min}}$ and $SOC_{\text{max}}$) should be appropriately specified. The SOC is defined as the ratio of the energy storage and the capacity of the battery. The formulae for the eagerness function are described as follows:

\[
\beta = \begin{cases} 
S & \text{if } SOC_{\text{min}} \leq SOC < SOC_{\text{max}} / 3 \\
1 & \text{if } SOC_{\text{max}} / 3 \leq SOC < 2 \times SOC_{\text{max}} / 3 \\
L_2 & \text{if } 2 \times SOC_{\text{max}} / 3 \leq SOC \leq SOC_{\text{max}}
\end{cases} \quad (7.6)
\]

\[
E_{\text{AL}} = \beta \times \begin{cases} 
e_{\text{p min}} & \text{if } H = H_{\text{min}} \\
H \times Adj_{\text{building}} & \text{if } H \in [H_{\text{min}}, H_{\text{max}}] \\
e_{\text{p max}} & \text{if } H = H_{\text{max}}
\end{cases} \quad (7.7)
\]

where $S, L_2$ are two positive numbers, and $0 < S < 1$ and $L_2 > 1$; the other parameters are defined as before; $\beta$ is the factor reflecting the impact of batteries.

It can be observed that the seller is less eager to trade the redundant energy when the SOC is small, because the energy can be stored in the batteries; on the other hand, the smart building will become more eager to sell the energy back to the utility because of the large value of SOC (limited storage capacity remaining).
7.2.2.3 Adaptive attitude bidding strategy

For practical negotiations, time pressure is one of the most important factors for concession. The agent is willing to concede quickly to close a deal when the negotiation deadline is approaching. Moreover, the attitude of the agent has a significant influence on the quickness of conceding during the negotiation. The agent with a large eagerness value will concede quickly to reach a deal, while the agent with low eagerness will not easily concede since it is willing to wait for more profits instead of making the deal quickly. Therefore, a time pressure function $T$ with agent attitudes $EA$ is used as follows [90], [108], [109]:

$$T(t) = 1 - \left(\frac{\min(t, t_{\text{max}})}{t_{\text{max}}}\right)^{1/EA}$$

(7.8)

where $T(t)$ denotes the time pressure given the time $t$ represented by the number of negotiation rounds; $t_{\text{max}}$ indicates the deadline for an negotiation, and it is expressed as the maximum number of negotiation rounds allowed. If $EA>1$, the agent will be eager to make a deal so it will concede quickly. If $0<EA<1$, which means the agent wants more profit so it may not give ground easily during negotiation. Note in the AABS model, $EA$ is equal to $EA_L$.

In order to clearly describe the bidding strategy, the basic notions are listed as follows:

$OA$ is the outstanding ask, which is the lowest ask in the current market;

$OB$ is the outstanding bid, which is the highest bid in the current market;

$Phl$ is the high limit, which is the highest acceptable price in the market, which can be obtained from the historical data;
Pll is the low limit, which is the lowest acceptable price in the market, which can be obtained from the historic data;

Csl is the reservation price of the seller calculated from the utility function;

D is the reservation price of the buyer calculated from the utility function;

Pb is the basic price, which gives a starting profit to the trader to start from;

Pt is the target price, which gives a target profit to the trader to move towards;

γ is a small positive number to adjust the size of the negotiation step.

1) Bidding strategy for the seller

At the beginning of a transaction, the seller and buyer have only their own utility functions (reservation prices) and the acceptable price ranges but no market information. In the first round of the transaction, the seller will submit its original ask price. Considering the different load demands and potential network congestion conditions for different time periods, all the hours are classified into on-peak hours and off-peak hours. At the on-peak hour period, the seller is willing to submit a higher ask price; otherwise, the seller will submit a lower ask. The original ask price can be computed as follows:

On-Peak hour:  \[ OA = C_{sl} + \lambda_1 \times (Pll - C_{sl}); \lambda_1 \in rand[0.85, 1] \]  \hspace{1cm} (7.9)

Off-Peak hour:  \[ OA = C_{sl} + \lambda_2 \times (Pll - C_{sl}); \lambda_2 \in rand[0.5, 0.85] \]  \hspace{1cm} (7.10)

The seller needs to compute their basic price Pb and target price Pt. According to the reservation price, the basic price will give the seller some profit instinctively. The current bid price from the buyer serves as the target price and the equations are described as follows:

\[ Pb = C_{sl} \times \lambda_2; \lambda_2 \in rand[1, 1.5] \]  \hspace{1cm} (7.11)
The basic price and the target price are the start profit and the destination for the seller, respectively. The seller calculates the ask price according to the time pressure and the eagerness value to maximize its profit. The size of the step derived from [98] is calculated as follows:

\[
\text{Step} = \begin{cases} 
(P_t - P_b) * \gamma * T, & \text{if } P_t > P_b \\
\max(P_t, C_{sl}) - P_b) * \gamma * (1 - T), & \text{if } P_t < P_b 
\end{cases}
\]  
(7.13)

The ask price for the next round can be obtained from the following equation:

\[
OA_{\text{next}} = P_b + \text{Step}
\]  
(7.14)

2) Bidding strategy for the buyer

Similar to the bidding strategy for the seller, the buyer submits its original bid price according to its reservation price and the price range. The equations (7.15) and (7.16) illustrate the original prices for on-peak hour and off-peak hour, respectively.

On-peak hour: \( OB = D - \lambda_3 \times (D - Pl) \); \( \lambda_3 \in \text{rand}[0.5,0.85] \)  
(7.15)

Off-peak hour: \( OB = D - \lambda_3 \times (D - Pl) \); \( \lambda_3 \in \text{rand}[0.85,1] \)  
(7.16)

The basic price, the target price and the size of step are described as follows [98]:

\[
P_b = D * \lambda_4, \lambda_4 \in \text{rand}[0.5,1]
\]  
(7.17)

\[
P_t = OA_{\text{current}}
\]  
(7.18)

\[
\text{Step} = \begin{cases} 
(P_t - P_b) * \gamma * T, & \text{if } P_t \leq P_b \\
\min(P_t, D) - P_b) * \gamma * (1 - T), & \text{if } P_t > P_b 
\end{cases}
\]  
(7.19)

So the bid price for the next round can be calculated by (7.20):

\[
OB_{\text{next}} = P_b + \text{Step}
\]  
(7.20)
7.2.3 PSO-AABS based negotiation agent

The major limitation of the AABS based negotiation agent is that it depends on the assumptions for the negotiation environment, making it difficult to generalize. To eliminate the aforementioned limitation, a PSO-AABS based negotiation agent is developed. It is well known that the traders tend to maximize their own payoffs while ensuring the agreement can be achieved. The PSO-AABS based negotiation agent is adopted to approach this tendency. It has the advantage of seldom relying on detailed assumptions or specific negotiation environments so that it can be generalized to deal with a variety of negotiation situations. In addition, heuristic optimization may lead to faster convergence for complex problems by saving negotiation time and resources.

Normally, traders only know their own preferences (utility function) but lack complete knowledge of their opponent’s preferences. Thus, based on the AABS negotiation model for integrated smart building and utility grid system, the improved PSO-AABS intelligent negotiation agent is designed here, which can gradually learn the opponent’s preference based on incomplete and uncertain information such as movements and concessions in the negotiation process. Moreover, the proposed PSO-AABS negotiation agent is able to adjust its behaviors by changing eagerness in order to adapt to the changes of the opponent.

The eagerness function $EAL$ formulated in Section 7.2.2 is regarded as long-term attitude and remains constant during a transaction. The learning process of the agent is primarily reflected by a new factor termed short-term attitude $EAS$, which is affected by the opponent’s behaviors. The value of short-term attitude may change in every round of negotiation, so it is a variable for a transaction. For instance, the trader will become less
eager if it observes the opponent is hard to give ground in order to protect its own benefit. The overall function to compute eagerness $EA$ contains two parts: long-term attitude $EA_L$ and short-term attitude $EA_s$. A possible improved mathematical function to compute the overall eagerness is proposed as follows:

$$EA = EA_L \times EA_s$$  \hspace{1cm} (7.21)

### 7.2.3.1 Short-term attitude

Generally speaking, the short-term attitude $EA_s$ is used for the negotiation agent to mimic the opponent’s concession-matching behavior in the transaction and to make its own adjustments. If the opponent gives ground, the negotiation agent becomes cooperative and makes concessions as well. However, if the opponent has not conceded in the last several rounds, the negotiation agent will refuse to make significant concessions as well to protect its own benefit. In this study, a time window to calculate the average concession rate is defined in order to observe the opponent’s behavior. The short-term attitude $EA_s$ for both of the utility grid and smart building can be illustrated as follows:

$$Conc_{avg} = \frac{\sum_{t=2}^{n} (p_{opp}(t) - p_{opp}(t-1))}{n - 1}$$  \hspace{1cm} (7.22)

$$EA_s = \begin{cases} C_s & \text{if } Conc_{avg} < 0.01 \\ 1 & \text{Otherwise} \end{cases}$$  \hspace{1cm} (7.23)

where:

- $p_{opp}$ is the price counter-offered by the opponent;
- $t$ represents the number of negotiation rounds;
$n$ is length of the time window which can be defined by the trader, and here we set $n=6$;

$Conc_{avg}$ is the average concession rate;

$C_s$ is a small positive value, and $C_s = 0.1$ in this study.

Notice the concession rate may decrease naturally when the deadline or the agreement is approaching; thus, the time window is only employed when the deadline is not imminent and the gap between the asking and bidding prices is large enough.

**7.2.3.2 PSO-based bidding strategy**

In practical negotiations, the trader is usually only aware of its own utility function, and it is different to learn the opponent’s utility function directly. Our proposed concession generation mechanism predicts the opponent’s preferences indirectly by examining its previous counteroffers. For the proposed PSO-based negotiation agent, every possible offer is a particle. The global best position of all particles in the search space, according to the objective function, is to form a feasible negotiation solution in a round. Considering both maximizing the benefits and reaching the agreement before the deadline, the following mathematical formula derived from [90] is used as a potential objective function applied to the PSO-based negotiation agent and the optimization goal is to maximize the objective function:

$$\max \quad Obj(p) = (1 - \eta \times T(t)) \times (1 - |p - p_{opp}|/|p_{opp} - p_{lim}|) + \eta \times T(t) \times E(p)$$

$$\text{s.t.} \quad p \in [\min(p_{lim}, p_{re}), \max(p_{lim}, p_{re})]$$
where:

- \( p \) represents a possible offer, which is the electricity price in this study. Generally the limit price is defined as \( p_{\text{lim}} \), which includes the highest and lowest acceptable prices \( (P_{\text{hl}} \text{ and } P_{\text{ll}}) \) in the market.

- \( p_{\text{opp}} \) is the price counter-offered by the opponent.

- \( p_{\text{re}} \) is the reservation price for the trader which can be obtained from its own utility function, it equals \( C_{\text{sl}} \) for the seller and \( D \) for the buyer.

- \( E \) is the valuation function and \( E(p) \in [0,1] \). It is used to adjust the offer \( p \) from the negotiation range which includes the limit \( p_{\text{lim}} \) and the reservation price \( p_{\text{re}} \) into the evaluation range \([0,1]\).

\[ |p - p_{\text{opp}}| \] is the distance between \( p \) and \( p_{\text{opp}} \). Similarly, \[ |p_{\text{opp}} - p_{\text{re}}| \] is the distance between \( p_{\text{opp}} \) and \( p_{\text{re}} \). Because of the unknown reservation price of the opponent, valuation function is impossible to apply. Here we utilize the ratio of the distance difference to evaluate the opponent’s counteroffer.

- \( \eta \) is the trade-off factor which controls the relative importance of optimizing one’s own payoff or reaching a deal by cooperating with the opponent. This can be also expressed as the cooperation degree and \( \eta \in [0,1] \); \( \eta \) of a cooperative agent used in this study is set as 0.5.

### 7.2.4 Case studies and simulation results

Three case studies are discussed in this section. The process of negotiation in a single transaction for the AABS based negotiation agent is illustrated in the first case study, while the factors impacting the eagerness function are examined. Then the validity
of the proposed PSO-AABS based negotiation is examined in the second case study, and the improved effectiveness of the proposed PSO-AABS model is verified through comparing with the AABS based agent. The third case study simulates over a 24-hour period to illustrate the behavior of different negotiation models in a day as well as make a comparison of the fixed attitude bidding strategy (FABS) based negotiation agent, the AABS based negotiation agent and the PSO-AABS based negotiation agent.

All the simulations are implemented using Matlab. Simulation results are presented and discussed in this section.

7.2.4.1 Case study one

For verifying the effectiveness of the proposed AABS based negotiation model in a single transaction, some parameters are pre-defined as follows:

The trade quantity is \( p = 1000 \text{kW} \);

The eagerness limit is \([e_{p_{\text{min}}}, e_{p_{\text{max}}}] = [0.1, 10] \);

The maximum number of ILDs in a day is \( N_{\text{max}} = 6 \);

The highest acceptable price in the market \( Phl = 11.0 \text{(cent/kWh)} \);

The lowest acceptable price in the market \( Pll = 1.0 \text{(cent/kWh)} \);

The utility function of the seller is \( C_{s}(p) = 0.001p + 1 \)[111];

The utility function of the buyer is \( D(p) = 11 - 0.002p \)[111];

The SOC range is \([SOC_{\text{min}}, SOC_{\text{max}}] = [0.1667, 0.9] \);

The constant rate for the step size is \( r = 0.1 \);

The maximum number of negotiation rounds is \( t_{\text{max}} = 100 \).
To examine the impact of the ILDs, the building is assumed to be the buyer and the utility grid is the seller. When the remaining allowable ILDs are dwindling, the building will become more eager to buy energy from the utility grid since it has less freedom to choose loads to shed. To illustrate an eager buyer makes a deal with a careless seller, we set $N=4$ and the previous three transactions are assumed to be successful. To show the negotiation process between an eager seller and a careless buyer, it is assumed that the previous three transaction are failed and $N=0$. The result is illustrated in Fig. 7-2. It can be observed from Fig. 7-2 that the trader with a large value of eagerness will make more concessions to close the deal quickly.

To indicate the influences of comfort level when the building is buyer and the SOC value when the building is the seller, two more tests are conducted. Based on the test of an eager seller with a careless buyer, the first one supposes the previous comfort level had dropped under the tolerable level so the eagerness for the buyer (building) is markedly increased, and the result is shown in Fig. 7-3. By comparison, it can be observed that the comfort level impacts the eagerness since the buyer makes more concessions to close the deal quickly after perceiving the unacceptable comfort level.

The building serves as seller while the utility grid plays the role of buyer in the second test. The SOC value will play the most important role in the negotiation process. Fig. 7-4 illustrates the impacts for different SOC values. Two SOC values are defined, including a very low SOC=0.2 and a high SOC=0.8. It can be observed that the seller is careless when the SOC is small since the redundant energy can be stored in the battery system, so that the seller is not willing to make more concessions and prefers to sell the energy at a high price. When the SOC value is large (i.e., there is a limited capacity left in
the battery system), the seller will be more eager to trade the power and will give ground more easily during the negotiation.

The validity of AABS based negotiation agent has been examined by the simulation results above. The proposed AABS based negotiation agent makes the proper decision of concessions according to dynamic factors of the integrated smart building and power grid system.

Figure 7-2 An eager buyer negotiates with a careless seller and an eager seller negotiates with a careless buyer

Figure 7-3 An eager seller with a comfort-dropped buyer
7.2.4.2 Case study two

The performance of the improved PSO-AABS based negotiation agent is illustrated in this case study. The pre-defined parameters are the same as the first case study. In this study, we assume the utility grid serves as the seller and the smart building is the buyer, and \( N=4 \), \( Comfort=1 \).

In the negotiation process, the smart building can only observe the price offered from the utility grid but no information about the reservation price or eagerness. Fig. 7-5 shows the results of smart building with the AABS based negotiation agent and with the PSO-AABS based negotiation agent, respectively. It can be observed the price for buying energy is reduced from 4.4 cent/kWh to 4.1 cent/kWh, while the number of negotiation rounds is decreased from 30 to 22. It means the smart building can reduce 7% cost for buying the energy from the utility grid while saving 27% in negotiation time after applying the PSO-AABS based agent.
In order to verify the improved learning capability of the PSO-AABS based negotiation agent, the following simulation test is conducted. The utility grid is required not to give ground in a period during the negotiation of a single transaction, and the performances of the AABS with limited learning capability and the PSO-AABS with improved learning capability are presented in Fig. 7-6. It can be observed that the AABS based negotiation agent is not able to adjust its own negotiation movements for adapting to its opponent’s changes, while the PSO-AABS based negotiation agent successfully mimics the opponent’s behavior. During the periods where the utility grid (seller) hardly gives ground, the smart building with the PSO-based negotiation agent makes very little concessions as well in order to protect its own benefit. After simple calculations it can be found that the smart building can save up around 17% of the cost from the energy purchase as well as 9% of the negotiation time.

All the simulation results confirm the viability of the PSO-AABS based negotiation agent with improved learning capability for enabling bi-directional energy trading in a smart grid environment. It turns out to be effective in maximizing the trader’s payoffs as well as saving the negotiation time.

![Figure 7-5 The smart building with the AABS based and PSO-AABS based negotiation agents](image-url)
7.2.4.3 Case study three

In this case study, 400 solar panels and 500 wind turbines are used as the renewable energy supply [32][33], and the simulation is carried out on a 24-hour time scale. The battery system totally contains 30 batteries, and the maximum storage capacity for each battery is 30 kWh. $SOC_{\text{min}} = 17\%$ and $SOC_{\text{max}} = 90\%$. Fig. 7-7 shows the renewable energy supply and the customers’ demands in a sample day.
To examine the effectiveness of the proposed AABS and PSO-AABS based negotiation models, a simple Fixed Attitude Bidding Strategy (FABS) based negotiation model is simulated for comparison. The used bidding strategy is similar with the exception by defining the attitude as a fixed value all the time. As the primary goal of the smart building is to provide a high level of comfort to the customers, the attitudes for the building and the utility grid are defined as eager and neutral, respectively. This ensures that sufficient energy is supplied to the building for maintaining the high comfort level, while the redundant energy can be sold back to the utility grid. The eagerness of the building is specified as $e_p=10$ and the eagerness of the utility grid is $e_p=1$. The frequency of negotiation in a day is every 15 minutes, and the prices after negotiation is shown in Fig. 7-8. Positive price indicates that the building sells energy back to the utility grid while the negative price is the building’s cost for buying energy from the utility grid. The customer’s total cost can be obtained by multiplying the price by the exchanged energy, and in this test the customers’ total cost is 152.6$/day by calculation.

When the proposed AABS based negotiation agent is applied, the transaction price after negotiation is illustrated in Fig. 7-9. Because loads are seen as the price-sensitive demands and the ILD is applied, some loads have to be shed if the negotiation is failed and comfort level may decrease due to the shortage of power supply. However, the customers’ cost is significantly reduced from 152.6$/day to 8.2$/day after calculation.

The performance of the PSO-AABS based negotiation agent is shown in Fig. 7-10. Comparing Figs. 7-9 and 7-10 regarding the trading price, the overall cost is continuously reduced to -61.2$/day. That means the customer gains profits instead of paying bills after applying the PSO-AABS based negotiation agent.
The comfort levels by using the FABS, AABS and PSO-AABS based negotiation agents are illustrated in Fig. 7-11. It can be observed that the FABS based negotiation model maintains the comfort at the maximum value all the time, while the comfort levels for the AABS based and PSO-AABS based negotiation agents have slightly dropped in some time periods.

Figure 7-8 Electricity price using the FABS based negotiation agent

Figure 7-9 Electricity price using AABS based negotiation model

Figure 7-10 Electricity price using PSO-AABS based negotiation agent
From the above simulation results, it can be seen that the AABS and PSO-AABS based negotiation agents are able to offer tradeoff solutions. Table 7.1 shows several sample solutions using the FABS, AABS, and PSO-AABS based negotiation agents. The negative value of the cost indicates the profit gained from the utility through effective negotiations. After the AABS and PSO-AABS based negotiation agent are applied, the total customers’ cost is reduced although they have to bear the slightly dropped comfort level.

Table 7.1 Selected Solutions

<table>
<thead>
<tr>
<th></th>
<th>FABS</th>
<th>AABS</th>
<th>PSO-AABS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost($/day)</td>
<td>Average</td>
<td>Cost($/day)</td>
<td>Average</td>
</tr>
<tr>
<td></td>
<td>Comfort</td>
<td>Comfort</td>
<td>Comfort</td>
</tr>
<tr>
<td>152.6</td>
<td>1.000</td>
<td>8.2</td>
<td>0.999</td>
</tr>
<tr>
<td>163.2</td>
<td>9.3</td>
<td>-8.4</td>
<td>0.999</td>
</tr>
<tr>
<td>152.0</td>
<td>11.2</td>
<td>-9.5</td>
<td>0.999</td>
</tr>
<tr>
<td>148.0</td>
<td>11.2</td>
<td>-9.5</td>
<td>0.999</td>
</tr>
<tr>
<td>157.3</td>
<td>11.2</td>
<td>-9.5</td>
<td>0.999</td>
</tr>
</tbody>
</table>

Figure 7-11 Overall comfort using PSO-AABS based negotiation agent
7.2.5 Conclusion

In this chapter, two intelligent negotiation agents are proposed and compared for the integrated smart building and utility grid system. The primary objectives of the work are achieved through designing the AABS based negotiation model, improving the AABS based negotiation agent to the PSO-AABS based negotiation agent which has impressive learning capability of mimicking the opponent’s behavior to adjust its own movements, building the detailed mathematical model for bidding strategy and evaluate the resultant performance and providing tradeoff solutions to customers in order to maximize their profits. From the case studies and simulation results, it can be seen that the proposed models are effective in making the reasonable negotiation decision as well as in reducing the customers’ energy cost or increasing the customers' economic profit.
Chapter 8

Integration of PHEV into smart building

In this chapter, PHEV has been integrated into the smart building as the distributed storage system. Two different PHEV-agents named adaptive PHEV-agent and intelligent PHEV-agent have been proposed [112]. Simulation studies has been presented and discussed.

8.1 Introduction of PHEV

The IEEE defines those vehicles, that have at least four kWh of storage, can be recharged from an external energy resource and have the ability to drive 10 miles or more without consuming any gasoline, as the plug-in hybrid electric vehicles (PHEVs) [113]-[117]. The primary advantages of the PHEVs include cutting down the consumption of fossil fuels and reducing the emissions of greenhouse gases [117] [118]. It is reported that fueling a PHEV will cost US $0.10/kWh of electricity while gasoline costs the equivalent of US $0.70 per gallon [120]. These claims lead the PHEVs to the world market, and make them become promising in the transportation sector of the near future.

Besides the economic and environmental benefits, large fleets of PHEVs will also have some impacts on the distribution network. The concept of using PHEVs as a
distributed energy source, which is also known as the vehicle-to-grid (V2G), is to aggregate a number of PHEVs for connecting to the energy provider. The PHEVs have in common the batteries, which can store and release energy in different conditions. The individual PHEV has a very slight impact and it can be represented as a “noise” to the system, but the aggregation of a large number of PHEVs will markedly affect the system behaviors. These impacts are far too essential to be ignored [117] [120] [121].

The smart building with renewable energy resources proposed in this dissertation can be seen as a micro-grid system. A large aggregation of PHEVs controlled by the PHEV-agent is used as both the storage and energy provider. The impacts of the aggregation of PHEVs should be measured and quantified to optimize the power supply reliability in the overall micro-grid system. The primary charging patterns include the uncoordinated charging and coordinated “smart” charging [118]. To maintain the system’s integrity and to minimize the power loss and voltage drop, the coordinated “smart” charging, that charges the PHEVs through effective coordination within a multi-agent system, is chosen in this research.

8.2 The adaptive PHEV-agent

A single PHEV has negligible impact on the power system. However, the impact becomes larger for a small-scale system such as a smart building. An aggregation of PHEVs produces significant and non-neglectable impacts. The PHEV system not only provides a distributed energy resource when it is discharging, but also adds a load when it is charging. In this section an agent termed adaptive PHEV-agent is developed to manage
the aggregation of the PHEVs. Fig. 8-1 depicts the framework of the overall PHEV system.

For the charging scenario, the coordinated “smart” charging is used. The PHEV-agent cooperates with the multi-agent control system of the smart building, to control the charging and discharging pattern of the PHEVs. The renewable energy is used as the primary energy supply to meet the smart building demands. Only if the energy production is higher than the total demands, the PHEV-agent will allow for charging the batteries. When the building is lack of energy, the PHEV system releases the stored energy to supply the building. Overall, the PHEV system serves as a generation/storage device for providing both energy and capacity to the building to enhance the power supply adequacy.

One important characteristic in a practical PHEV system is due to the varying number of the useable PHEVs in different time periods, and this will impact the system behavior through changing the capacity/stored energy. Different functions of buildings
and individual differences of the commuting time are key factors in determining the varying number pattern. In order to conduct a rational simulation test in the future, a set of assumptions regarding the PHEV system is given as follows [117]:

1) The building is an office block and the number of the currently plugged-in vehicles in the parking lot is the useable number of PHEVs.

2) All the PHEVs have the same batteries and the energy losses in the batteries are ignored. All the batteries will maintain a power output at one sixth of their capacity. The charging/discharging time is 6 hours.

3) PHEV owners are independent of any other PHEV owners, and all the PHEVs are plugged-in when they are in parking lot.

4) The capacity of the parking lot is large enough.

The simulation procedure for the adaptive PHEV-agent derived from [117] is described as follows: Assume the system works in the islanded mode. If the capacity of the PHEV system is too small, the redundant energy is lost when renewable energy production \( P_r \) exceeds demands \( P_d \). Likewise, the small capacity of the PHEV system cannot provide enough additional energy when the renewable energy is in a shortage. Thus, the goal of the procedure is to track building load demands. State of charge (SOC), which is defined as the ratio of the energy storage to the capacity of the battery, varies from 0% (the battery is totally discharged) to 100% (the battery is fully charged). Considering the life time of the batteries, the maximum and minimum SOCs \( S_{\text{max}} \) and \( S_{\text{min}} \) need to be appropriately specified. \( C \) is the PHEV battery storage, which normally varies from 1 kWh to 30 kWh. According to the characteristic of batteries, the charge/discharge time is set as 6 hours. The simulation step is \( \Delta t \) and the maximum
simulation time is \( t_{max} \). Thus, the power output can be simulated as \( \pm \frac{C}{6} \), and \( \pm \frac{\Delta t}{360} \) is chosen to simulate the charging/discharging pattern. \( S_k(t) \) represents the SOC value of the \( kth \) PHEV at the time \( t \), while \( N \) is the usable number of the PHEVs. At every time interval \( t \), the PHEVs which have enabled SOC will play the role of load when the produced power is more than demands. The SOC of each PHEV increases with the decreasing power output from the renewable resource. When power production is insufficient as compared to the demand side, the PHEVs work as a generation unit to increase power level. Figs. 8-2 and 8-3 show the pseudocodes of charging and discharging PHEVs. The simulation procedure of the adaptive PHEV-agent is shown in Fig. 8-4.

![Figure 8-2 Pseudo code of charging PHEVs](image1)

![Figure 8-3 Pseudo code of discharging PHEVs](image2)
8.3 The intelligent PHEV-agent

The design of the adaptive PHEV-agent is focused on the building level and aims to enhance the reliability of energy supply by controlling the charging/discharging pattern of PHEVs. The limitation of the adaptive PHEV-agent is its lack of considerations from the perspective of a PHEV customer. The driver usually expects to spend as little money as possible on gasoline in the next trip after unplugging the PHEV from the building system. Using the aforementioned PHEV-agent, one possible consequence is that the stored energy for some PHEVs is far more than needed while other PHEVs cannot be charged with enough energy for the next trip. Considering both economic payoff and environmental friendliness, the requirement on consuming minimum gasoline for the next trip should be met.

An intelligent PHEV control system is developed in this study and the design goal is to improve the building comfort level as well as to minimize the overall cost for gasoline. The overall cost function can be defined as follows:

![Pseudo code of simulation procedure of the adaptive PHEV-agent](image)

Figure 8-4 Pseudo code of simulation procedure of the adaptive PHEV-agent
\[ Cost = \sum_{k=1}^{N} \text{Cost}_k \]  \hspace{1cm} (8.1)

\[ \text{Cost}_k = \begin{cases} 0 & \text{if } d_{\text{electricity}} \geq d_{\text{next}} \\ P_{\text{gas}} \times (d_{\text{next}} - d_{\text{electricity}}) & \text{Otherwise} \end{cases} \]  \hspace{1cm} (8.2)

where \( \text{Cost} \) is the overall cost for gasoline, \( \text{Cost}_k \) is the cost of the \( k \)th PHEV for gasoline; \( P_{\text{gas}} \) is the unit price of gasoline ($/mile); \( d_{\text{electricity}} \) is the maximum gas-free driving distance after unplugging the PHEV, and \( d_{\text{next}} \) is the planned distance of the next trip.

MAS technology is chosen to build the PHEV control system, and the overall configuration is shown in Fig. 8-5. Two layers of agents are involved which are intelligent PHEV-agent and individual PHEV-agent. GUI embedded in each individual PHEV-agent provides some flexibility for each customer to configure a personalized driving pattern. An example GUI is shown in Fig. 8-6. The GUI-based panel allows customers to configure the driving pattern and to observe system performance. In this sample GUI, drivers can choose or define the distances of traveling, and monitor the charging/discharging pattern of their own PHEVs as well as the maximum gas-free driving distance after unplugging.

The individual PHEV-agent is used to obtain the initial SOC value of each PHEV when it is plugged into the building system \((S_k(0))\) and to estimate the desired SOC \((S_{k\text{desired}})\) based on the driving pattern configured through the GUI. The intelligent PHEV-agent coordinates the multi-agent control system of the smart building and all the individual PHEV-agents to determine the charging/discharging pattern of each PHEV. Different from the adaptive PHEV-agent, the intelligent PHEV-agent has one extra step, which is termed “classification”. All the PHEVs are classified into two different classes.
based on the current SOC ($S_k(t)$) and desired SOC ($S_{k\text{desired}}$). If $S_k(t)< S_{k\text{desired}}$, which means the current stored energy is not enough for driving the planned distance for the next trip, this PHEV is classified into Class 1 ($\text{Class}_k(t)=1$). On the other hand, the PHEV with $S_k(t)\geq S_{k\text{desired}}$, which means the stored energy meets or exceeds need, will be in Class 2 ($\text{Class}_k(t)=2$). By this definition, it can be observed the PHEV belonging to Class 1 prefers charging while the PHEV in Class 2 prefers discharging. Pseudocode illustrating the simulation procedure of the intelligent PHEV-agent is shown in Fig. 8-7. Generally speaking, when renewable production is more than demands, PHEVs in Class 1 will charge first to increase the SOC approaching the desired level. If there is still surplus power after charging all PHEVs in Class 1, PHEVs with $\text{Class}_k(t)=2$ will charge. Likewise, PHEVs in Class 1 will only discharge if the power supply is still insufficient to fulfill demands after all PHEVs in Class 2 have been discharged.

![Figure 8-5 The configuration of the intelligent PHEV control system](image-url)
Figure 8-6 GUI for individual PHEV-agent

Input Information: $P_r(t)$, $P_d(t)$, $S_k(0)$
$t = 0$

While ($t < t_{max}$)
  Do{
    Classification
    IF $P_r(t) > P_d(t)$
      Charging PHEVs in class 1
      IF $P_r(t) > P_d(t)$
        Charging PHEVs in class 2
      END
    ELSE IF $P_r(t) < P_d(t)$
      Discharging PHEVs in class 2
      IF $P_r(t) < P_d(t)$
        Discharging PHEVs in class 1
      END
    ELSE
      No charging/discharging
    END
    $t = t + \Delta t$
  }

Figure 8-7 Simulation procedure of the intelligent PHEV-agent
8.4 Case studies and simulation results

An office building is chosen for simulation test. Assume 10 staffs in the office building driving the Chevrolet Volt PHEV daily. According to the specifications for Chevrolet Volt as shown in Table 8.1, it is assumed that the battery storage of each PHEV is 16 kWh, the charge and discharge time are 6 hours, and the electricity consumption of driving is 0.4kWh/mile. Considering the lifetime of batteries, we set $S_{\text{min}} = 20\%$ and $S_{\text{max}} = 80\%$.

Table 8.1 Chevrolet Volt Specifications

<table>
<thead>
<tr>
<th>Battery</th>
<th>MPG (miles per gallon)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Lithium Ion</td>
</tr>
<tr>
<td>Energy (kWh)</td>
<td>16 kWh</td>
</tr>
<tr>
<td>Charge Time (Hours)</td>
<td>6 to 6.5</td>
</tr>
<tr>
<td>Range (miles)</td>
<td>40</td>
</tr>
</tbody>
</table>

All PHEVs can be charged and discharged when plugged in the parking lot. Driving patterns for each staff are listed in Table 8.2 and staffs can specify their driving patterns through the GUI embedded in the individual PHEV-agent. Notice here the distance from office to home is regarded as the planned distance for the next trip. Assume all PHEVs have been fully charged at home and the working hours are from 09:00 to 17:00. For simplicity, we assume all staffs should arrive at the office building around 09:00 and leave after 17:00. The simulation is carried out from 09:00 to 17:00 and the simulation step is 15 minutes. Here the renewable supply includes 23 solar panels and 18 wind turbines [32][33]. The renewable power production and total power demands of the office building are illustrated in Fig. 8-8.
Table 8.2 Driving patterns of the staffs

<table>
<thead>
<tr>
<th>PHEVs (kth)</th>
<th>Home to office (miles)</th>
<th>Office to home (miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>13</td>
</tr>
<tr>
<td>4</td>
<td>14</td>
<td>16</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
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</tr>
<tr>
<td>6</td>
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<td>7</td>
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<tr>
<td>8</td>
<td>18</td>
<td>20</td>
</tr>
<tr>
<td>9</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>13</td>
</tr>
</tbody>
</table>

Figure 8-8 Renewable production and power demands of the building
The power supply for the building, with the adaptive PHEV-agent applied, is illustrated as Fig. 8-9. Compared to renewable production, the power supply has clearly been improved after using the PHEVs since it can track the building demands better by storing the surplus power during low demand periods and releasing the stored power during high demand periods. To examine the performance of an individual PHEV, the 4th PHEV is chosen as an example. Fig. 8-10 shows the GUI for the 4th PHEV and the charging/discharging pattern can be monitored. It can be seen the stored energy for 4th PHEV can drive 15 miles without consuming any gasoline after unplugged from the office building. Based on the owner’s driving pattern, the required driving distance for the next trip is 16 miles. It means this PHEV will need to consume gasoline for one mile to reach home. Given the 37 MPG rating of the vehicle, and assuming the fuel cost at
$4.00 /gallon, the fuel cost for the 4th PHEV will be $0.11. Table 8.3 illustrates the maximum gas-free driving distance for each PHEV and the cost of gasoline for arriving at home. The overall cost for gasoline is $3.76 by calculation.

<table>
<thead>
<tr>
<th>PHEVs (kth)</th>
<th>Maximum gas-free driving distance (miles)</th>
<th>Cost of gasoline ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17.33</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>17.33</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>15.67</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>0.11</td>
</tr>
<tr>
<td>5</td>
<td>15.67</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>10.67</td>
<td>0.48</td>
</tr>
<tr>
<td>7</td>
<td>3.67</td>
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<td>1.17</td>
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<td>9</td>
<td>18</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>15.67</td>
<td>0</td>
</tr>
</tbody>
</table>

The performance of the proposed intelligent PHEV control system is presented as follows: Fig. 8-11 shows the power supply after using the intelligent PHEV-agent.
Compared to Fig. 8-9, the supplied power has been improved slightly by tracking the demands more accurately. Fig. 8-12 displays the GUI for the 4th PHEV utilizing the intelligent PHEV control system. Note that the gas-free driving distance becomes sufficient for the customer to arrive at home. Thus, the cost of gasoline for the 4th PHEV is reduced to zero. The information on gas-free distances and costs for all PHEVs is listed in Table 8.4. By calculation, the overall cost of gasoline is reduced from $3.76 to $0.37.

Fig. 8-13 illustrates the overall comfort level after using the PHEV-agent. It can be observed the comfort level remains at the near-maximum levels through either the adaptive PHEV-agent or the intelligent PHEV control system. Combined with the results about the overall cost of gasoline, it can be concluded that the intelligent PHEV control system is able to achieve the goal of simultaneously enhancing the overall comfort level and minimizing the total cost of gasoline.
Figure 8-12 The GUI for 4th PHEV using the intelligent PHEV control system

Table 8.4 The driving distance and the cost using the intelligent PHEV control system

<table>
<thead>
<tr>
<th>PHEVs (kth)</th>
<th>Maximum gas-free driving distance (miles)</th>
<th>Cost of gasoline ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.67</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>15.67</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>16.67</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>5.67</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>15.67</td>
<td>0</td>
</tr>
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<td>7</td>
<td>18.67</td>
<td>0.37</td>
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<tr>
<td>8</td>
<td>21.33</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>9.67</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>14</td>
<td>0</td>
</tr>
</tbody>
</table>
8.5 Conclusion

In this chapter, two PHEV-agents system for integrated PHEV and smart building systems are proposed. The new integrated system is able to wisely manage the charging/discharging patterns for each PHEV for enhancing the overall comfort level of the smart building by utilizing both proposed PHEV-agents. In addition, the intelligent PHEV-agent can maximize the overall smart building comfort while minimizing the overall cost of gasoline. The effectiveness of both PHEV control systems has been validated by simulation results.

Figure 8-13 The comfort level for different controls of the PHEV system
Chapter 9

Concluding remarks and outlook

9.1 Concluding Remarks

The integrated smart building and micro-grid systems have some salient advantages such as environmental friendliness. However, the major challenge is to reduce the energy consumption and to maintain the high level of indoor comfort simultaneously. To meet this challenge, a reliable, responsive, and flexible building control system needs to be developed. This dissertation is focus on designing an intelligent multi-agent control system with heuristic optimization for integrated smart building and micro-grid systems, and it has been shown to be capable of achieving the control goals by coordinating the multiple agents and the optimizer. More detailed summaries of this dissertation are listed as follows:

- The designed framework of the integrated smart building and micro-grid systems have been presented in Chapter 3. Multi-agent based control system for building energy and comfort management has been developed and explored, and artificial intelligent techniques such as PSO have been applied to enhance the system performance.
Two possible comfort index functions embedded into the central coordinator-agent have been proposed in Chapter 4. The customer-centered comfort index offers the flexibility to customers to set their preferences, while the information fusion based comfort index can find the optimal weights through applying PSO. A GUI based platform is designed for customers to input their preferences and observe the system outputs. Detailed mathematical models have been developed and explored, and the effectiveness of proposed models has been demonstrated by case studies and simulation results.

Chapter 5 discusses the detailed design of three local controller-agents. A FACT model with grey predictor has been designed for the local temperature controller-agent, in order to maintain the thermal comfort inside a more rational range with lower power usage. Intelligent occupancy-based control strategy is developed and utilized for the local air-quality controller-agent and the local illumination controller-agent. Simulation models have been built based on developed mathematical models, and the results show the capability of local controller-agents of achieving energy savings without compromising the comfort level.

Load agent is presented in Chapter 6, and a GUI is designed for customers to determine the type and the priority of interruptible loads. It has been approved by simulation results that the load agent can enhance the comfort level through load shedding.

Contribution is made regarding negotiation agent in Chapter 7. Comprehensive set of factors for integrated smart building and utility grid system has been involved in the negotiation agent design, and PSO-AABS negotiation agent has
been developed to enhance the learning capability of the negotiation agent. The proposed agent has been validated to be able to facilitate the energy exchange with more rational price and less negotiation time.

- PHEV has been integrated into the building energy and comfort management system as distributed storage system in Chapter 8. Different PEHV-agents have been developed to fulfill the different requirement. In addition, GUI is designed for inputting the necessary parameters. Simulations are carried out to validate the proposed PHEV-agent.

The proposed multi-agent control system can be integrated with the building energy management system (BEMS) and the required hardware facilities such as sensors, microprocessors, actuators, and communication devices should be installed in the building. Some potential implementation issues are discussed as follows:

- To implement the proposed multi-agent control system in a physical building, a two-level control structure can be utilized to enable the inter-agent communication and collaboration. In the high-level control layer, various system configuration and agent coordination tasks are performed. At the low-level control layer, environmental parameters are measured and controlled directly by corresponding sensors, microprocessors, and actuators. Communication devices can be used in the control network for enabling data exchanges.

- The central coordinator-agent lies in the high-level control layer. It is responsible for overseeing the behaviors of the entire building control system as well as making final decisions for all other agents. This agent can be embedded in the
BEMS as a piece of application software. The building manager or operator is in charge of configuring the required parameters including comfort and economic preferences of customers through the GUI-based BEMS panel for enabling informed decision making. Switch agent and load agent also lie in this layer. They are implemented as software entities in distributed microprocessors and communicate with the central coordinator-agent through the control network during system operations.

- Sensors, actuators and local controller-agents lie in the low-level control (field) level. The devices in this level interact directly with the physical environment. They are responsible for data acquisition, preliminary control manipulation, and actuation operations for controlling the physical environment. Various sensors are distributed and embedded in the building environment to continuously collect the ambient environmental parameters. Sensors for environmental parameter measurement include thermometers, photometers and indoor air quality meters. Different fuzzy control laws can be implemented in the distributed microprocessors of local controller-agents. Under the control of local controller-agents, actuators act on the physical building environment. Field actuators include environmental parameter actuators (e.g., air conditioners, lighting systems, and ventilators), load shedding actuators, and energy flow switch.

- Building Automation and Control network (BACnet) can be utilized as the protocol for facilitating inter-agent communications as well as linking the heterogeneous devices together. This standard protocol is developed specifically
to meet the requirements set forth by ASHRAE for building automation and control.

- In practically implementing the proposed building control system, there are a couple of major issues that engineers should pay attention to. First, the user-defined parameters such as set points, weights, and comfort zones should be able to reflect the true preferences of the occupants in the building. These can be collected in multiple ways such as questionnaires and online surveys. The final parameters can be keyed into the BEMS by the building operator/manager based on the survey results. Second, all the space in the building which shares the same comfort ranges can be seen as a “building zone” which can be controlled by a set of corresponding local controller-agents. If a building has multiple function zones with different comfort ranges, the building should be appropriately divided into different “building zones”. Multiple sets of local controller-agents with distinct parameters can be employed for all these zones.

9.2 Outlook

Building energy consumption is major contributor to the total energy usage. Thus, it is a very important and promising research area to investigate the building energy savings. This study has shown the great potential of utilizing artificial intelligence to improve the energy efficiency and maintain the high level of customer comfort. There are multiple research directions that could be followed up based on this dissertation:

- Integration of the geothermal heat pump system into the smart building system is highly promising for the future development. Different from the current building
energy system which exchanges heat/cooling load with the changing outdoor environment, the geothermal heat pump system exchanges the heating/cooling load with ground. That is because the temperature remains nearly constant (between 50 °F to 60 °F) below the upper 20 feet of earth's surface. It indicates the building energy system could exchange heat with a more constant environment with higher efficiency.

- Quantitative analysis is necessary for the optimization of economic and environmental benefits in system operations. Those benefits include the renewable energy installation and payback assessment, the energy-usage savings assessment, detrimental gas saving assessment, equipment life-cycle assessment, etc.

- Optimal sizing of the micro-grid including PV panels, wind turbines, and battery/PHEV storage could be investigated. Considering the different first costs of various components, different maintenance fees and payback periods, intelligent sizing tool can be developed based on the specific objective functions such as minimizing first costs and minimizing maintenance costs. Multi-objective optimization is a good option to provide trade-off solutions for the sizing problem.

Other potential research topics in this area include the comparison of different intelligent algorithms such as neutral network and ant colony optimization, transfer capacity and congestion conditions of the agent communication, and the cyber security issues of the multi-agent system.
References


