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Building Temperature Control with Intelligent Methods

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BUILDING TEMPERATURE CONTROL WITH INTELLIGENT METHODS

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Abstract

Temperature control is important for both human comfort and the need in industry. In the thesis, two good intelligent control methods are compared to find their advantages and disadvantages. Matlab is used as the tool to make models and process calculations. The building model is one simple room in Akwesasne in New York State and the target is to keep the temperature indoor around 22℃ from 12/29/2013 to 12/31/2013. Heat pump is used to provide or absorb heat. All data in the experiments is from JRibal Environmental eXchange network and PJM. The first method is fuzzy neural network (FNN). With the control from fuzzy logic and the learning process in neural network, the temperature is kept around 22℃. Another method is model predictive control (MPC) with genetic algorithm (GA). And the temperature is also controlled around 22℃ by predicting the temperature and solar radiation. In addition, the cost is saved by using genetic algorithm with an energy storage system added in the building model. In summary, FNN is easy to build but the result is not very accurate; while the result of MPC is more accurate but the model is hard to develop. And GA is a good optimization method.

Acknowledgements

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Chapter 1: Introduction

The air-conditioning systems now are usually used in the buildings. They are designed to make a good atmospheric environment for people to live or to produce a special environment for some special industrial places. So there are two categories for the different applications, one is for comfort living and the other one is for industrial. The control items in the air-conditioning include temperature, air quality and humidity in one room.

The indoor environment is very important for the health and also can affect the efficiency of production. People usually spend a lot of time in the buildings, so the air-conditioning system is designed to keep a comfortable environment for human beings. Many researchers have donated much time on the comfortable environment indoors and they find temperature and humidity are the major factors to human comfort. So the temperature and relative humidity are the most important parameters in the air-conditioning system. Many of the systems indoors focus on the temperature and relative humidity control within some range. For temperature, it is from 23℃ to 25℃ in summer and 20℃ to 24℃ in winter. For relative humidity, it is usually need to be above 45%.

The indoor environment also affects the performance for industrial places. Some industrial places require accurate temperature and relative humidity. For example, in greenhouse, some crops can just germinate and grow under accurate temperature and humidity. Not only for industrial but also for some scientific experiments, the air-conditioning system for different special environment is needed.

There are more and more requirements for air-conditioning systems, so the energy consumed in buildings for industry and commerce increases quickly. It constitutes about 50% of the world energy consumption [1]. And 50% to 60% of the consumed energy is for air-conditioning and mechanical ventilation (ACMV) systems [2].

Because the resources are not sustainable and the price is increasing, it is important to improve the efficiency in order to reduce the cost.

1.1 Background

In 1970s, energy crisis happened. Due to it, it is urgent to make variable air volume (VAV) components. Many devices such as fans and terminals are produced such as the variable speed drive (VSD) components. Then the direct digital control (DDC) technique is developed in some applications.

If the air volume of supply is constant, the system is constant air volume (CAV) system. For some cooling systems with CAV technology, they need modify the supply air temperature to provide the different cooling volume. For example, the fans need be at high speed with cool air in order to cover the peak load in summer.

But the load may not be at the peak load for most time; therefore in the consumption a lot of energy is wasted for the CAV system. While for VAV system, the airflow rate is changed in the room in order to meet the different requirements. The signal about comfort level is sent from indoor, and then the VAV system can supply proper air flow. The temperature for supply from the system is constant, indoor temperature and humidity can be controlled by changing the rate of supply air flow. Thus different amount of air flow can be used in different time with changing load, and it can save some amount of air. Much of energy is saved at the part-load time using the VAV system.

For temperature, it needs to be controlled in many places. And it can be affected by many activities form industry and commerce. So the system should be strict in some places. For example, the semiconductors with high quality can just be produced in the room, in which the temperature is controlled strictly.

In the large-scale room, central chilled water systems are now usually used. The cool water goes through the air-handling unit (AHU) and absorbs the heat of air, and then the air indoor will become cool after the process in the system.

Heat pump is a device which can provide heat from a source to another place. And now it replaces some original air-conditioners to control temperature in residential and commercial places. Heat pump is designed to provide heat from cold source or absorb heat when it is hotter outside. The heat pump needs some power from external power to finish the work. It is now a common device in the HVAC system.

In general, the method for controlling the temperature and relative humidity is to cool the air to the good relative humidity at first, and then heat the air to the temperature required in the room. But this way wastes much energy, and in the system, the rate of cool water flow and supply air flow are important. So the controller is added in the system to control the rate of cool water flow and supply air flow. The controller can affect the air-conditioning directly, and the target of the controller is to change the capacity of cool water and the rate of supply air flow to meet the different demand of load in room.

PID controllers are now widely used in the air-conditioning system. They are good and reliable in many HVAC applications [3]. However, the parameters of model in the PID control system are not changed; it does not accord with the real condition. Then the well-tuned PID controlled is developed with different parameter [4].

In the recent years, for the modern control, some adaptive and self-tuning controls have been applied [5-6]. The self-tuning controllers have replaced the old PID controllers with single-input single-output (SISO) in many places. However, although the performance of the self-tuning system is better than the old system, the system is not for real time.

In order to handle the task of real time, some artificial intelligence (AI) methods are introduced such as fuzzy logic, artificial neural networks (ANNs). The AI concept is from 1950s, and the common definition of AI is “intelligence is the ability to perceive, understand and learn about new situations” [7]. In the modern projects, fuzzy logic and ANNs are applied in the air-conditioning system control.

In the fuzzy logic system, it generates fuzzy results from the imprecise inputs. It can handle the uncertainty of model in thinking of human with membership functions. ANNs are from the biological system, and they are distributed processing systems. There are not assumptions in ANNs’ inputs or outputs. The networks can learn from the relationship between the inputs and outputs, and the model can be linear or non-linear.

Therefore, it is easy to build the model.

Model predictive control (MPC) is another modern method which can be used in air-conditioning system. Since 1908s MPC has been used in the process in industries. The idea of MPC is to us a dynamic model of process to predict the future actions. And the target of the actions is to minimize the error subject to the restrictions; on the other hand, it is to optimize the cost function built in MPC with restrictions. This characteristic about prediction is the ability which PID controllers do not have. With this feature, MPC may be a better control method for temperature control. The challenge is to build a good dynamic model for temperature.

Genetic Algorithm (GA) is the adaptive heuristic search algorithm according to the natural selection and genetics. It is the intelligent method of a random search for the optimization problems. GA is a good method to solve any optimization problems. It is can be the tool in MPC to solve the problem of minimizing the cost function. GA can use the processes of reproduction to achieve optimized results by using crossover and mutation. This is good for MPC to improve the cost result.

1.2 Objectives

The objective is to control the indoor temperature in the room. The method of controlling is to change the temperature of supply air flow and at the same time maintain the rate of flow. The efficiency is improved by the usage of good control methods such as fuzzy logic, ANNs and MPC, because the methods can save the energy and keep the comfort condition simultaneously.

The advantage of fuzzy logic is that it can build the controller without the model, so in this thesis, it is easy to apply in the air-conditioning system. Then a self-tuning fuzzy logic is designed. A neural network is added in the system controller. The controller puts the advantages of fuzzy logic and ANNs together. In the method, the neural network is to build the structure for the fuzzy controller.

Another method which is used in the thesis is MPC. It has to build the mathematical model for the heat transfer in the room. And the method needs the temperature outside data from forecast. Then an economic MPC using GA is designed after adding the local margin price of electricity signal in the control method to save more cost.

The air-conditioning system in the thesis is the heat pump system in one room. The heat pump is used to supply different temperature to the room. And there is one fan working with constant air flow rate in the system.

1.3 Outline of Thesis

There are nine chapters in the thesis. In Chapter 1, the background of temperature control is introduced. The objective and outline of the thesis are also in this chapter. In Chapter 2, the previous literatures about temperature and air-conditioning are reviewed. And a simple overview of fuzzy logic, neural networks, MPC and GA is also provided in the chapter. Chapter 3 gives the information about heat pump. Different types of heat pumps are talked. The heating mode and cooling model are also introduced. Chapter 4 talks about the model of the air-conditioning system. The relationship between inputs and outputs are given. Chapter 5 shows the design of fuzzy logic controller for temperature control. And the result from Matlab is provided. In Chapter 6, the design of fuzzy neural network control is introduced, and also the results from Matlab are provided. In Chapter 7, it shows the design of MPC controller in the air-conditioning system and the relative results. The improved method of MPC——economic MPC (EMPC) is introduced in chapter 8. In the chapter, GA is used as the tool in MPC for temperature. The summary of fuzzy logic with neural network control method and MPC with GA is shown in Chapter 9. This chapter talks about the advantages and disadvantages of different methods.

Chapter 2: Literature Review

2.1 Temperature

Temperature is the most important comfort parameter in industry and commerce. This variable compared with others such as humidity, human activities, air velocity, and the corrosion of metals and the generation of static electricity, the rate of crystallization, the production of circuit boards is the main control item in the room [8].

The indoor desirable temperature is different for different places. According to the West Midlands Public Health Observatory (UK) in [9], usually 21℃ (70℉) is the best indoor temperature for living, while 18℃ (64 ℉) is good for sleeping. Experts provide the idea that when people go to sleep; the set point of body goes down. And if the indoor temperature is too cold or hot, people's bodies can't get to the set point easily. The little drop of temperature causes sleep. So people need to sleep in the room with a little lower indoor temperature.

And University of Uppsala made a study on the air quality in primary schools, and it states that feeling of high room temperature was related to a poor climate of cooperation. [10] So in order to get a good air quality, the indoor temperature should be under 22℃ (71.6℉).

When in the working places, the required indoor temperature is also different. The temperature can affect the work performance in offices. Many studies made in call centers and laboratory in 2006 [11]. Fig 2-1 shows that in these working offices; work performance is at the high level when the temperature is about 71℉, and decreased as the indoor temperature above or below 71℉.

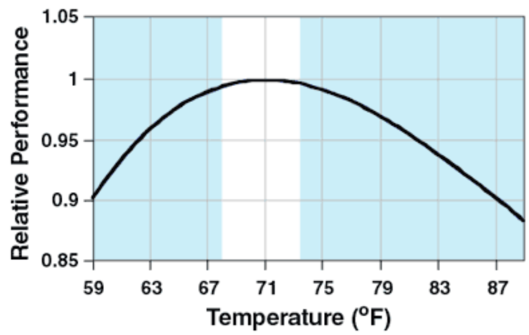

Fig. 2-1 Relationship between office work performance and indoor temperature [11]

And in different time, the comfortable temperature is also different. The studies and standards in [12] show that in summer the indoor temperature should be higher than in winter [13-14]. An interview survey with a sample of 3094 people in Finland shows that the people have a false idea of comfortable temperature. Among the respondents, 41% think that indoor temperature should be lower in summer than in winter. And 22% think the indoor temperature should be 19℃ or below in summer. 15% of respondents have good and correct idea [15]. The result from the false idea is that more unnecessary energy is consumed.

2.2 Control of Air-Conditioning Systems

The control concept comes up to analysis and deal with the different systems in which there are many variables should be kept within limits. The most important thing of control is to design a good controller which can take actions to handle different situations. In the 1930s, the first good controller came up, and it is PID controller. It is successful and used widely in many industries and commerce places. And now, though there are a lot of other digital controllers, the PID controller keeps important [16]. The reason is the PID controllers are very simple and easy to use in any process. In general, the system of air-conditioning is complex because there are many variables and disturbances such as radiation, wind and human activities in the model. It is hard to make a very accurate model for air-conditioning. Then in order to solve the problem, the technique of parameter tuning in PID controller is developed.

Many researchers have made contribution on the model building to meet the required nonlinear model. They used approximate linear models for the air-conditioning system. They made some assumptions and set the range around the operating point. When the gains of PID can change during the operations, the PID controllers provide good performance.

But though the parameters of PID controllers can tune and achieve the good performance around the required operating point, the performance would degrade quickly to instability if there is a big difference between operating point and the designed point. The reason is the air-conditioning system model has high nonlinearity [17].

In the room, the HVAC system is the multi-input multi-output (MIMO) system in which the control system needs loops with many SISO systems in each loop. [16] made a PID controller for HVAC systems. He assumed that there are many SISO systems in the work. Then a controller with feedback came up [18]. This controller got better results than a SISO controller. But the disadvantage is the order of the controller is high and it can't be linearized at some certain points. In 2001, Carlos and Miguel made one controller for each variable in the control system for temperature and relative humidity, and then develop an accurate controller with a decoupling technique. However the design is too complex and many parameters can't be determined easily. Another disadvantage is that the system can't be used in other systems.

With the shortcoming of classical control methods, Self-tuning control is designed. It can meet the dynamics environment quickly and is becoming more significant for many industrial places. But it still has a very complex model with many parameters, and it requires some knowledge of other systems. It is hard to build in order to get accurate model. The inaccuracy in the model degrades the performance of the controllers [19].

Now the researchers focus on the control systems without model because it is hard to build the complex model. Artificial intelligence comes up such as Fuzzy logic and ANNs. There are also adaptive dynamic programming and stochastic programming developed.

2.3 Fuzzy Logic Control

The fuzzy logic control is already used in some industrial places widely with the fuzzy set theory by Zadeh [20]. Then it is used in the steam engine control by Mamdani & Assilan in 1974. In 1980s, the fuzzy washing machines came up in Japan and in 1990s the first adaptive fuzzy logic was developed. This control method needs the experience of operators in the controller. The inputs and outputs should be numerical in a table using

IF-THEN statements. For example, make a table to control the temperature using a fan: if temperature is low then stop fan; if temperature is normal then keep fan; if temperature if high then speed up fan. These IF-THEN states need the fuzzy logic model and the human experience knowledge.

2.3.1 Fuzzy System

The general fuzzy system is shown in Fig. 2-2. There are crisp inputs, fuzzifier, fuzzy inference system, defuzzifier, and outputs. In fuzzy inference system, there are fuzzy sets with knowledge from human experience.

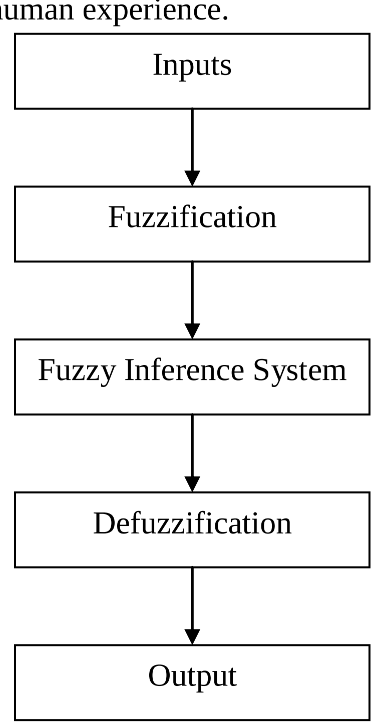

Fig. 2-2 Structure of Fuzzy System

Fuzzifier

In fuzzifier, each input is compared to a set of linguistic variables in fuzzy sets to determine the membership.

Fuzzy Inference System

In the fuzzy inference system, there is a database of fuzzy rules and membership functions from human experience. In every fuzzy rule, there is an antecedent statement and the relative fuzzy consequence using membership function. And the fuzzy logic form is

IF (ANTECEDENT) THEN (CONSEQUENCE)

Defuzzifier

In the defuzzifier, every rule has a reaction as consequence which is a fuzzy set or linguistic variable.

Defuzzification builds a fuzzy set, in which there is an output for each input using the rule in the fuzzy inference system with the degree of membership for antecedent.

At last, it converts the fuzzy output to a control single of the physical device.

Fuzzy Logic Control Design

In order to design a control with fuzzy logic, there are three things to care:

- The first is to decide appropriate linguistic quantities for inputs and outputs.
- Next is to define a membership function for each linguistic quantity.
- The last thing is to define the inference rules.

To understand fuzzy logic control better, in the next section, the concepts of fuzzy IF-THEN rule and fuzzy inference system are introduced.

2.3.2 Fuzzy If-Then Rule

The IF-THEN rules comprise fuzzy logic sets with different conditions.

For a single fuzzy IF-THEN rule, the form is:

If x is A then y is B

Where "x is A" is the antecedent or premise and "y is B" is the consequence or conclusion decided by the fuzzy sets.

An example may be shown below:

If temperature is low then fan stops

Where "low" can be expressed as a number between 0 and 1, and "stop" is represented as a fuzzy result from the fuzzy sets. The word "is" means "=". To rewrite the example

If temperature = low then fan = stops

Where "temperature" and "fan" are the linguistic variables in the IF-THEN rules and the input is "low", while the output is "stops" from the fuzzy set by the membership functions. Then the fuzzy result will be defuzzified later.

2.3.3 Fuzzy Inference System

In Fig. 2-3, the fuzzy inference system is decided by the knowledge from human experience. And the knowledge base from human experience contains a set of fuzzy if-then rules and the membership functions of fuzzy sets used in the fuzzy rules.

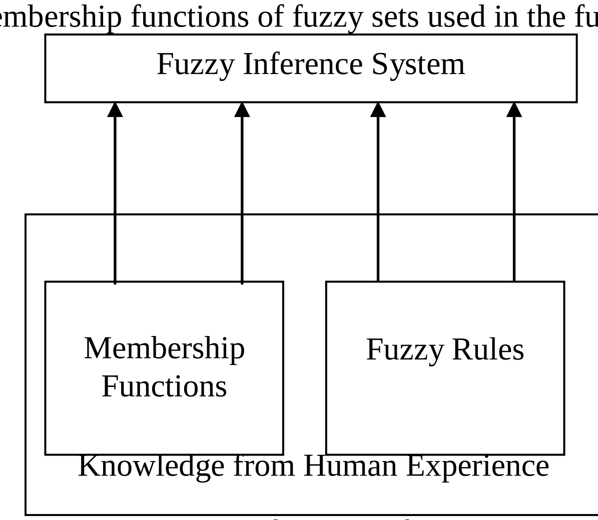

Fig. 2-3 Structure of Fuzzy Inference System

There are some different fuzzy inference systems below.

• Mamdani fuzzy inference system:

The final fuzzy output is gotten using the “max-min” operation in the inference system (every output of the system is equal to the minimum between the firing strength and the output of the membership function of each rule). To get the crisp outputs from the fuzzy outputs, the centroid of area, bisector of area and mean of maximum are used in the system.

• Takagi-Sugeno fuzzy inference system:

In the system, the final outputs are the weighted average values of the outputs of fuzzy rule. If the results of rules are crisp value, the final outputs are also the weighted average values of each rule’s crisp outputs.

There are some features affecting the performance of the fuzzy logic controllers (FLCs) shown below [21].

• Scaling factors for input and output variables.

• Membership functions of fuzzy sets.

• Setting of fuzzy rules.

2.3.4 Applications

In 1991, [22] made a controller combined with a PID controller and a FLC. For the PID controller, the fuzzy sets are for the error of control, integral error and the derivative error. The results from simulations were better than the original PID control because there was no damped oscillations and responded quickly

The FLC was used in the control of system to control the air in [23-24]. In the system, there are the triangular membership functions for error and error rate and the devices controlled in the system were fan, humidifier and reheat coil. Compared with the old tuned and detuned PID control in the computer simulations, the FLC was better in terms of response time and offset. The FLC has been used in the air handling systems to control temperature and relative humidity in [25-26]. But all the experiments were in the computer and the practical models are different with the mathematical models built in the computer, so there would be a big deviation which is not accepted. To improve the FLCs, there should be more practical experiments with complex models.

2.4 Artificial Neural Networks

Artificial neural network (ANN) is the model according to the behavior of biological neurons. In 1958, Frank Rosenblatt designed the first model of perceptron. There are three layers in Rosenblatt's model:

- In the first layer, a "retina" is used to distribute inputs to the next layer.
- In the second layer, the "association units" are used to take inputs with weights and make the threshold step function to the output layer.
- In the last layer, all data is taken together.

The model is good, but the model can't be trained because of the step function. So in 1969, Marvin Minsky and Seynore Papert pointed out the weaknesses of the perceptrons with a critical analysis. Then some other types of neural networks are designed such as probabilistic neural networks, general regression neural networks, functional link networks, Kohonen networks and recurrent networks.

In the thesis, the artificial neural network (ANN) can be the tool added in the fuzzy logic control to the air-conditioning system. The network can be used as the mapping between the inputs and outputs by examples. Many interconnections among neural units are used to improve the performance. The model in the ANN is unique because it has the special architecture and algorithm. The different management of the neural connections leads the different architecture and the activation function specifies the type of neural units. There are two modes for the neural network: the first one is the processing mode and the other one is the training mode. In the processing mode, the algorithm is used to get the outputs by neural units for any inputs; while in the training algorithm, the algorithm is applied to modify the weights for all training patterns by the neural network in [27].

In general, artificial neural network is the multilayer perceptron network. However, there some other types of neural network.

There are four main common types of neural networks with different architectures shown below:

The first one is layered feed-forward neural network which is used widely such as the multi-layer perceptrons. In the network, the all neurons in one layer get inputs from the previous layer.

The next one is recurrent neural network in which the inputs are from previous outputs and external sources.

The third one is laterally connected neural network. There are feedback inputs and a lateral layer in which the neurons are laterally connected to nerghbors.

The last one is the hybrid network in which there are two or more characteristics above together.

The training algorithm is important in ANN. It can be supervised learning and unsupervised learning. For the supervised learning, the neural networks are trained to get the results as close as possible to the examples which are set as input-output pairs. While for the unsupervised learning, the examples are only the inputs and the network is used to classify the examples which have the similar features.

2.4.1 Multi-Layer Perceptron

The multi-layer perceptron (MLP) is used widely now. In 1957, Kolmogorov showed that a three-layer perceptron can be used to get the results approximating to any nonlinear function in [28]. So the MLP may be the tool to replace any function to get better results. There are many interconnections of neurons in the MLP and the structure is shown in Fig. 2-4. As in the figure, there are input layer (on the left), hidden layer (in the middle) and output layer (on the right).

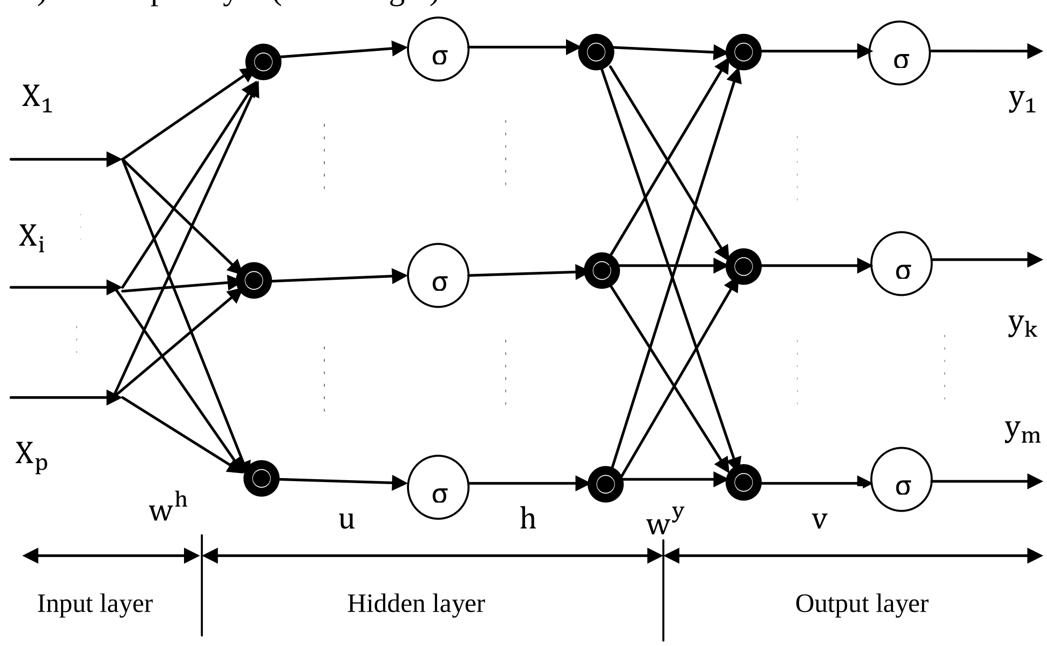

Fig. 2-4 Structure of perceptron network

Input layer: Some variable values ($x_1 \ldots x_p$) are the inputs in the input layer. The input layer distributes the inputs to the each neuron in the hidden layer. The inputs are multiplied by a weight and then added together to the neuron in the next layer.

Hidden layer: In the hidden layer, the weighted sum is going to a transfer function, σ, and then the outputs from the transfer functions are distributed to the next layer. The outputs will be multiplied by a weight and then added together to the neuron in the output layer.

Output layer: The last layer is the output layer. The weighted sum from the output of hidden layer is then going to the transfer function, σ. At last the output, y, from the transfer function is the output of the neural network.

In the three layers, every neuron in each layer is connected to neurons in the layer before and the next layer. But the neuron is not connected to any one in the same layer. During the training process, the neuron is adjusted in the connection.

2.4.2 Neuron

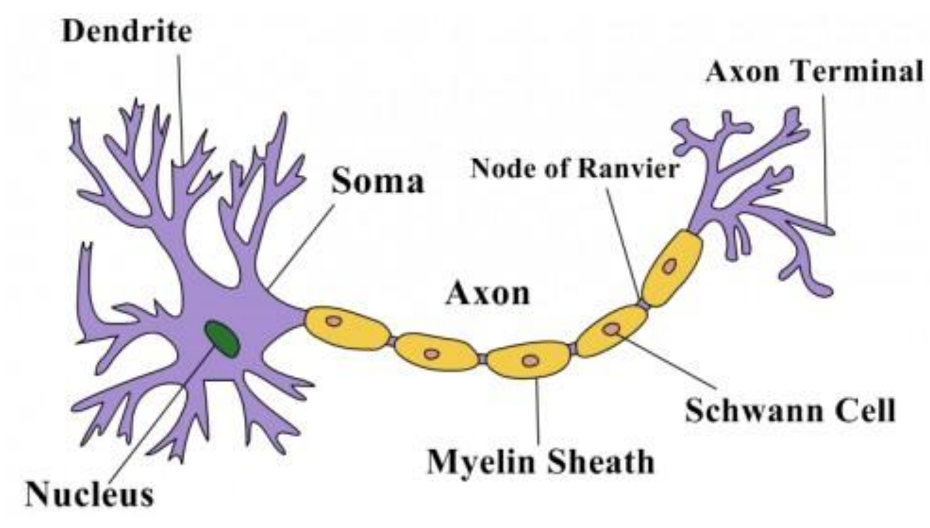

Fig. 2-5 Structure of a neuron [29]

Fig. 2-5 shows the structure of a neuron. The neuron is the basis of nervous system. The most important difference between neurons and other cells in the body of human is that the neurons are used to transmit information in the body. The main structures are dendrites and axon. The functions of them are shown below:

Dendrites: Receive messages from other neurons

Axon: carry messages destined for other cells

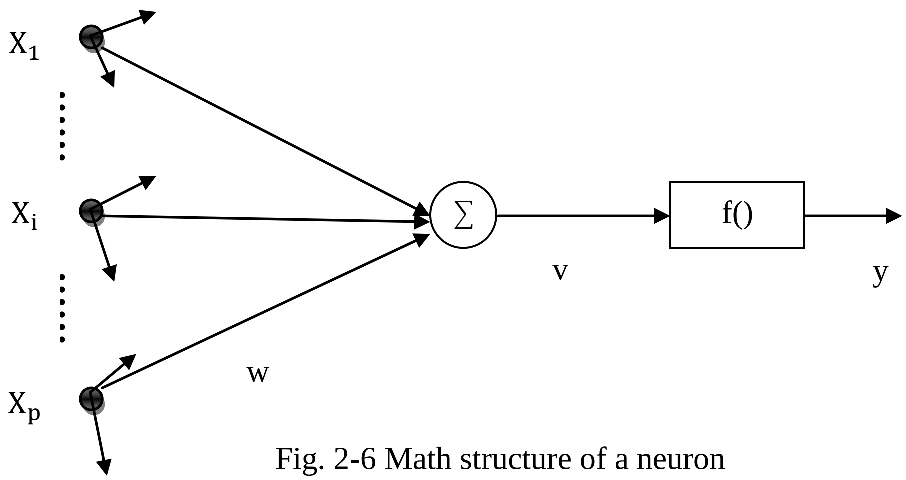

Fig. 2-6 Math structure of a neuron

Fig. 2-6 shows the math structure of a single neuron. The function of the neuron is shown below.

$$v = \sum w_i x_i \tag{2-1}$$

$$y = f(v) \tag{2-2}$$

Where y is the output of the neuron

x_i, i=0,…,n are the input

w_i, i=0,…,n are the weights multiplying the input to the neuron,

F() is the activation function

Typically, x is used as the bias input and it usually be set as constant 1. Then the bias input is adjusted by multiplying w when it is going through the weight value.

The common activation functions used in the neural network are shown below.

Threshold function:

$$f(v) = \begin{cases} 1, & v \geq 0 \\ 0, & v < 0 \end{cases} \tag{2-3}$$

Sigmoid function:

$$\text{(Unipolar) } f(v) = \frac{1}{1+e^{-v}} \tag{2-4}$$

$$\text{(Bipolar) } f(v) = \frac{1-e^{-v}}{1+e^{-v}} \tag{2-5}$$

2.4.3 Training Multilayer Perceptron Networks

Training multilayer perceptron networks is important because it can trend the outputs of neural networks close to the desired results as possible. The method of training is to modify the weights in the networks.

There are some important issues shown below when the MLP is designed and trained:

- The first one is to select the hidden layers
- The second is to decide the neurons
- The third is to find the globally optimal solution
- The next one is e to converge to an optimal solution
- The last one is to test the network

And these issues are introduced separately below:

- Selecting the number of hidden layers

In general, one hidden layer is enough. The two hidden layers are used when the data of model is like a saw tooth wave pattern. There is no lecture showing where to use two or more layers. In addition, more layers mean the risk of converging to the local minima.

- Deciding neurons in layers

The number of neurons is important in the perceptron network. If there is not adequate number of neurons in the hidden layer, the complex model can't be built and the result is bad.

If there are too many neurons in the network, it is not good either. The processing time may be too long. In addition, the network may over fit the data. If the network over fit the model data, it can't handle the disturbance or noise. The result would be bad to some new data.

- Finding a globally optimal solution

There are maybe many weights in the neural network, so the weights may be hard to find the best values to the optimal solution. If the networks are linear, it is easy to find the weight. If the networks are nonlinear, it is very complex to find the good weights.

- Converging to the Optimal Solution

To converge to the optimal solution, a set of random weights are used. And the conjugate gradient algorithm is used to get the better weights.

- Test the network

Test the network is the most important issue. For the values achieved from any method, the testing muse be used to validate.

With the issues above, the common cycle used to refine the weight values is shown below:

Step 1: tentative weights are used in the network with the inputs

Step 2: get the error between the desired results and the actual value

Step 3: get the average error for the all inputs

Step 4: send the error back through the network and get the gradient of change in error with the changes in weights

Step 5: modify the weights in order to reduce the error

This training method is called backward propagation because the error is sent back. The method is important and used widely. In 1986 the back propagation training method was designed by Rumelhart and McClelland. It is the first practical method for neural networks. At first, reducing the gradient is the most important step to modify the weights. But the result is not good enough because the error is used more widely with better result.

For the method to reduce the gradient, it usually takes long time to converge to the optimal solution. And if there is a wrong value, it may not converge. Though the method of reducing the gradient to achieve optimal weights is used now in some places, it is no longer best method.

2.4.4 Learning Algorithm

In the multi-layer perceptron (MLP), the training pairs including inputs and relative outputs are needed in the training process, so the MLP is the supervised training network. There are weights which can change to reduce the difference to the final desired outputs in the neural network. There is an error is in the network. Before the error goes to the acceptable level, many training pairs are required to reduce the error.

Learning algorithm is important in the ANN and now many algorithms are created. The back-propagation (BP) algorithm is used widely.

The following notations are introduced below for the BP algorithm.

$y_j^l(p)$	the output of the jth node in layer l for the pth training example
$net_j^l(p)$	the net input to the jth node in layer l for the pth training example
$w_{ji}^l(p)$	the weight between the ith node in the previous layer and the jth node in layer l for the pth training example
$d_j(p)$	The desired response of the jth output node for the pth training example
$\delta_j^l(p)$	The local gradient for jth node in layer l for the pth training example
N_l	Number of nodes in layer l
l	The number of layers
p	The number of training examples

The nodes in the first layer provide the inputs to the next layer. The output of a node in layer l, for l≥2, is given by

$$y_j^l(p) = f(net_j^l(p)) \tag{2-6}$$

Where

$$net_j^l(p) = \sum_{i=0}^{N_{l-1}} w_{ji}^l(p)\, y_j^{l-1}(p) \tag{2-7}$$

For the special cases

$y_j^l(p)$ is the ith component of the input vector to the network

$y_j^{l-1}(p) = 1$, and $w_{j0}^l(p)$ is the bias weight

The gradient search is used in BP to find the network weights which can minimize the objective function. The objective function is usually the average squared error function:

$$J_{av} = \frac{1}{P}\sum_{P=1}^{P} J(P) \tag{2-8}$$

Where J(P) is the total squared error at the last layer for the pth example:

$$J(P) = \frac{1}{2}\sum_{j=1}^{N_L}(d_j(p) - y_j^L(p))^2 \tag{2-9}$$

Where N_L is the number of nodes in the last layer.

The weights of the network are determined iteratively depending on:

$$w_{ji}^l(p+1) = w_{ji}^l(p) + \Delta w_{ji}^l(p) \tag{2-10}$$

$$\Delta w_{ji}^l(p) = -\eta \frac{\partial J(p)}{\partial w_{ji}^l(p)} \tag{2-11}$$

Where η is the learning rate, and it is positive. To implement this algorithm, an expression for the partial derivative of J(p) with respect to each weight in the network is developed. For an arbitrary weight in layer l, this can be computed using the chain rule:

$$\frac{\partial J(p)}{\partial w_{ji}^l(p)} = \frac{\partial J(p)}{\partial y_j^l(p)} \frac{\partial y_j^l(p)}{\partial w_{ji}^l(p)} \tag{2-12}$$

$$\frac{\partial y_j^l(p)}{\partial w_{ji}^l(p)} = \frac{\partial}{\partial w_{ji}^l(p)}\left[f\left(net_j^l(p)\right)\right] = f'\left(net_j^1(p)\right) y_i^{l-1}(p) \tag{2-13}$$

The local gradient $\delta_j^l(p)$ is defined by

$$\delta_j^l(p) = \frac{\partial J(p)}{\partial net_j^l(p)} \tag{2-14}$$

If layer l is the output layer, l=L

$$\delta_j^L(p) = (d_j(p) - y_j^L(p))f'\left(net_j^L(p)\right) \tag{2-15}$$

If layer l is a hidden layer,

$$\delta_j^l(p) = f'\left(net_j^l(p)\right)\sum_k \delta_k^{l+1}(p)w_{kj}^{l+1}(p) \tag{2-16}$$

Where the kth neuron in the l+1 layer is connected to the jth neuron. At last, the correction $\Delta w_{ji}^l(p)$ is:

$$\Delta w_{ji}^l(p) = \eta\delta_j^l(p)y_i^{l-1}(p) \tag{2-17}$$

This equation includes the BP learning algorithm. At first, the weights are set to some random values. And the learning rate is changed with many methods. In the training process, the computing is repeated to get the gradient and proper weights in order to reduce the error to the required level. The MLP can be used as the approximator or classifier.

2.4.5 Applications

In 1994, [30] build a system to control the energy in a central plant. In the system, he used the BP feedforward ANN with two hidden layers, in which each layer has 10 neurons. It is proven that ANN can be used to build the model for energy. And [31] set the delay time for a HVAC plant by using an ANN. Then they built another ANN with four layers, in which, the two hidden layers were built by the delta rule BP. The delay time is determined well and ANN is proven to be a good method to tolerate different levels of input measurement noise.

Now there are more and more methods about ANNs used in the HVAC control. In 1990, [32] built a control system for the heating and cooling by using an ANN. And [33] used the general regression neural network (GRNN) to control the heating coil and valves. Some ones also trained the ANNs to be compensators in order to improve the feedback control. [34] built an ANN based predictive controller to replace the old PID controller. And then [35] built another adaptive ANN to predict the future situation for the plants. In the network, he used the BP algorithm. Compared with the well-tuned PID controller, the ANN based predictive controller is good enough but the learning rate needs to be chosen properly.

And in 1995 a combined controller for a MISO system with ANN for air controlling was developed [36]. There was a comparison among ANN, well-tuned PID and fuzzy logic. The result was that the response rate of ANN is slower than the fuzzy logic, and the state accuracy of ANN is little worse than the well-tuned PID. But ANN has its own advantages such as it doesn't need tuning as in the PID or the knowledge as in the fuzzy logic

2.5 Model Predictive Control (MPC)

Model predictive control (MPC) or called receding horizon control (RHC) is an optimal control method in order to minimize the energy or cost. The objective function is set for both present and predicted parameters and used to predict the future outputs.

In MPC, a finite horizon optimal control problem is solved at sampling time using the current state as the initial condition in order to develop the current action for controlling the plant. Then the control action is used in the system. The method uses prediction and this is the difference from other control methods.

2.5.1 Characteristics of MPC

MPC has been used for years recently. Many systems use the method instead of old control methods to handle multivariable control with constrains now. Moreover, it can be used for off-line control problem.

There are some characteristics for MPC shown below.

First one is that MPC can handle the problems with constraints on controls or operation condition. In practical systems, the constraints usually cone up such as safety limits like pressure and temperature, cost limits and some special limits. And these limits applied in the system are used to get safe operation and reduce cost. For this reason, MPC is applied as a tool for researchers especially in some industries where many control system problems and implement problems come up.

Next characteristic of MPC is that it can solve the control problems with difficult off-line computation. Some systems with unconstrained nonlinear models require dynamics of process, and MPC can be used to solve the problem to develop systems with special structures.

A comprehensive discussion of MPC, and the advantages and demerits of the control can be seen in [37].

MPC is important to solve the problems with a finite horizon. And it can be first to use on-line technique for the current condition of process to solve the optimization problems, while other methods can just provide all conditions for control to decide the actions.

The results from on-line technique are used to solve the problems, in which the initial state is the current state of one mathematical problem. In order to decide the solution of feedback, it requires Hamilton-Jacobi-Bellman (Dynamic Programming) differential or difference equation. Because of this, MPC is different from some other control methods in implementation.

2.5.2 Linear MPC

For the linear models, MPC is a good method for feedback. Now the technique of MPC is mature. People can understand the feasibility of on-line control and the stability of systems with linear models.

All the implementations of MPC base on the system models. It is easy to switch among state space, transfer matrix and convolution type models in [37]. Moreover, now the MPC is usually formulated in the state space in many literatures. Here a linear discrete time model in the state space is used to introduce the MPC system.

$$\mathbf{x}(\mathbf{k}+\mathbf{1}) = \mathbf{A}\mathbf{x}(\mathbf{k}) + \mathbf{B}\mathbf{u}(\mathbf{k}), \mathbf{x}(\mathbf{0}) = \mathbf{x_0} \tag{2-18}$$

Where $\mathrm{x}(\mathrm{k})$ is the vector of state at sampling time k, and $\mathrm{u}(\mathrm{k})$ is the vector for operations variables by the controller.

The typical optimization problem for MPC is introduced below:

$$\mathrm{J}_{(\mathrm{p,m})}(\mathrm{x}(\mathrm{k})) \tag{2-19}$$

Subject to

$$\mathrm{u}(\mathrm{k}) \in \mathrm{U} \tag{2-20}$$

$$\mathrm{x}(\mathrm{k}) \in \mathrm{X} \tag{2-21}$$

Where U is the constraints for the operations and X is the constraints for state. And $\mathrm{J}_{(\mathrm{p,m})}(\mathrm{x}(\mathrm{k}))$ is the objective function in the optimization.

All control operations are based on the prediction, so the prediction horizon m is longer than the control horizon p. The process for MPC is to use the first control u(k) in the control horizon to achieve x(k+1), and then u(k) is not useful and x(k+1) is applied to update the optimization problem at the new initial condition. Next u(k+1) is computed to achieve x(k+2) and then get new state and new optimization problem.

This process above is repeated in the control scheme, and at each time, only the control for the first time is used to get the new initial condition. Next the cost ahead one time step is changed. And then repeat the action.

These are shown in Fig. 2-7. That is why MPC is also called receding horizon control (RHC) or moving horizon control (MHC).

At each time step, there are some new operations to compensate the disturbances and inaccuracy in the system which can lead the different results from the predictions. Fig. 2-7 shows the picture of MPC.

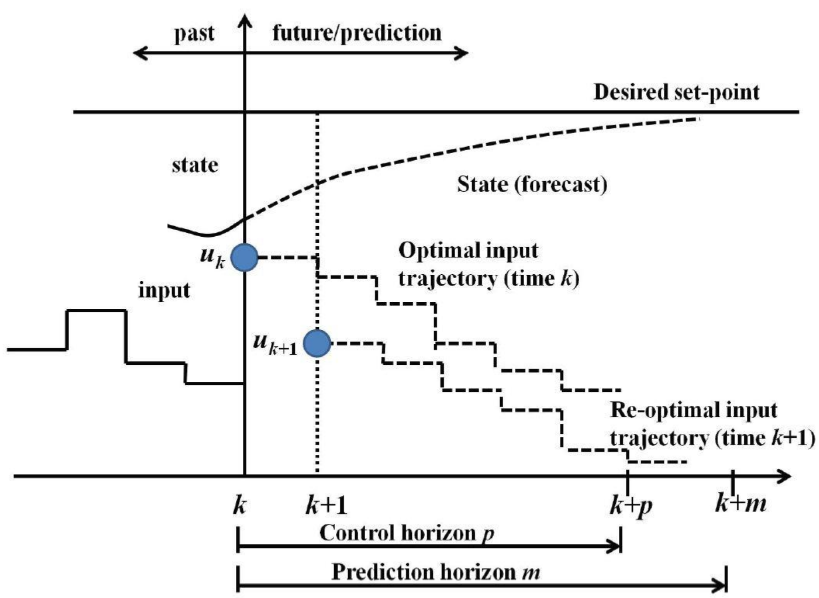

Fig. 2-7 Description of MPC [37]

Feasibility

The constraints sometimes may lead the infeasibility for the optimization problem. For example, at some special time step, the optimization problem becomes infeasible sue to the disturbance. And the algorithm for the open-loop may lead the closed-loop system infeasible.

Closed loop stability

In some cases with finite or infinite constrains, it is not easy to make sure when the closed loop system is stable. Many researchers now focus on the problem with linear MPC. There are two methods developed to get the stability. The first one is depending on the original problems and in the other one, a constraint is added in [38-39]. When the constraint is added, the standard of the state would be reduced on time and stability in the system. If there is no constraint, the problem of stability is complex.

Open-loop performance objective VS closed loop performance

In MPC, only the first control action is used in the system and other control actions are not applied. So the actual control actions maybe different from the calculated control actions at a special time step. Therefore, the minimization objective with finite horizon is connected with the value of objective function after the control operations are moved.

2.5.3 Nonlinear MPC

Linear MPC has been used for long time, so the linear technique is mature. Then many researchers are working on nonlinear MPC. In 1970s, many linear MPC were applied in the industries and in 1990s, there was an increasing attention for nonlinear model predictive control (NMPC).

In practical, many systems are nonlinear rather than linear. And modern systems need better and tighter operation performance. Moreover, there are more constraints and disturbances for environment and safety which are added in the system. In these systems, linear system can't handle the dynamic control while the nonlinear system can be used to deal with the problem. This increases the attention to NMPC.

Difficulties of NMPC

There are some difficulties of NMPC. The problems about feasibility and mismatch between open loop performance objective and actual closed loop performance are not solved in NMPC. Another difficulty is that there are no redeeming features in nonlinear programs when the problem is solved on line. So it can't make sure to get convergence to a total optimum. In the quadratic system, the global optimality is not needed because of the monotonicity property of the value function when the cost decreases very small. Though the local minimum does not influence the stability, the performance is becoming bad.

Closed-loop stability

The important problem is if the NMPC with a finite horizon can cause the stability in the closed loop system. [40-42] are reviewed for some NMPC methods. For the following sections, it is assumed that the prediction horizon is set equal to the control horizon (p=m).

Infinite horizon NMPC

The problem with a finite prediction and control horizon is that the predicted and actual closed loop operations are different. The method to get stability is to use an indinite horizon cost in [43-44], which means $p \rightarrow \infty$. As in [45], in general cases, the feasibility at one time means the feasibility at next time. In [46] Bellman's Principle of Optimality made the idea that the input and state of optimization problems for the NMPC at one instance are the same as the input and state for the nonlinear system. The remaining parts of the trajectories after one sampling instance are the optimal solution at the next sampling instance. This means the stability for closed loop system.

Finite horizon NMPC

The possibilities are proposed for the closed loop stability for NMPC with a finite horizon. Like the linear system, the value function is used as a Lyapunov function. At every time step, the global optimal operation is needed to get the stability. For finite horizon, the feasibility at one time means the feasibility for all future time. But it is different from the linear system that the problem with an infinite horizon can't be solved numerically.

To get the stability for closed loop systems, many methods can change the setup for NMPC. Usually proper equality or inequality constraints are added in the objective function. The constraints are not form the physical restrictions or desired performance requirements. But they have the ability to lead the stability for the closed loop system. Therefore the constraints are called stability constraints.

Terminal equality constraint

In [47-48], the simple method to get the stability with a finite prediction horizon is to add a zero terminal equality constraint at the end of the prediction horizon for the optimization problems. Because the feasibility at one time means the feasibility for all future time and decreases in the value function, the method can result in the stability for the closed loop system, if there is a solution at the special time step.

For the form, the method of MPC for time-varying, constrained, nonlinear, discrete-time systems was made by [43]. In the lecture, the analysis of stability of MPC is made and the value function is shown using the infinite horizon method. There are also properties of stability for MPC using the terminal quality constraint.

For the advantage of the zero terminal constraint, it is easy to use in the application and the concept is simple. While for the disadvantage of the terminal constraint, the system should get the origin in the finite time and this causes the problems about feasibility for short prediction or control horizon. [49] shows that the optimization problem with terminal constraints is easy to solve with principle, while it is hard to solve the problem with equality constraints. It can just be finished asymptotically. Moreover, although there is a solution of feasibility, maybe there is no convergence to the solution. In addition, the operation from the terminal constraint is not good to the system, because the artificial operation may lead to the bad behavior. At last, though the small number of variables or the short control horizon reduce the complexity of the MPC problem, the short horizon makes a big difference between the open-loop performance objective and the actual closed loop performance.

2.5.4 Steps for Common MPC Problems

- Step 1: Prediction for relative data such temperature and wind
- Step 2: Modeling for the control system using system data
- Step 3: Formulate optimization problem. Build MPC formulation with constraints and cost formulation
- Step 4: Solve optimization problem and send best solution to the step 2
- Step 5: Apply the result to the system

There is the flowchart below introducing the steps for MPC.

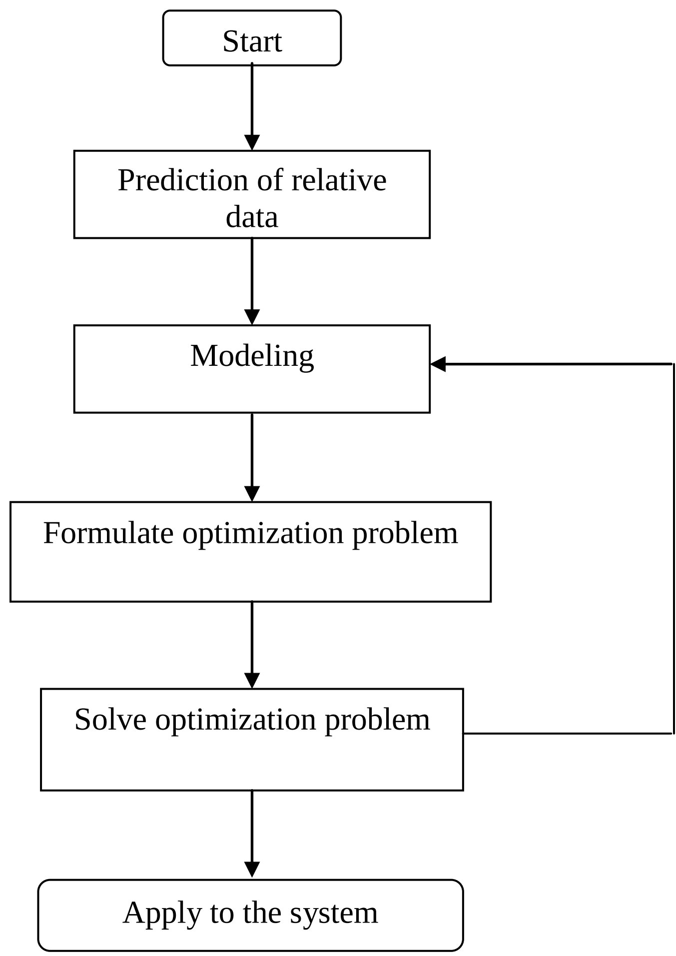

Fig. 2-8 Flowchart of common MPC

2.5.5 Conclusion

MPC is a good method for models with linear models and constraints which has been proven in the control systems. For nonlinear models, there are more computation and challenges because of the practical systems. The stability of nonlinear MPC and the challenges are reviewed in the previous sections. Although a lot of challenges come up in the nonlinear MPC, it is important for practical implications.

Fig. 2-9 shows the role of MPC in the operational hierarchy in practice.

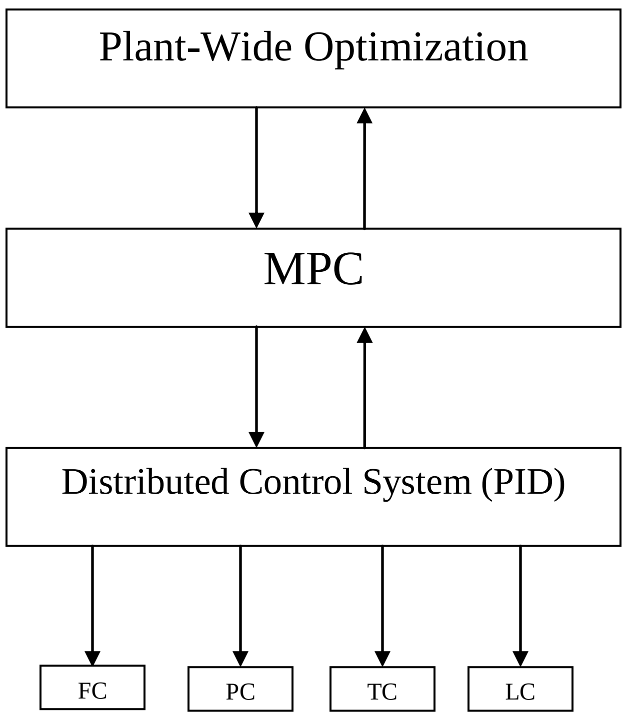

Fig. 2-9 Role of MPC in the operational hierarchy

- The first hierarchy is used to determine the plant-wide the optimal operating condition for the day.
- In the second hierarchy, make the good adjustments for local units.
- In the final hierarchy, take each local unit to the optimal condition fast but smoothly without violating constraints

2.5.6 Applications

MPC is used at shell Oil first and at other refineries in late 1970s. Most of applications are advanced control systems in process industries. There are more than 4600 worldwide installations and “in-house” installations as in a survey in 1999. And major of the applications (about 67%) are in refining and petrochemicals. Many vendors are now specializing in the MPC technology. The early players were DMCC, Setpoint, Profimatics, for now the players are Aspen Technology, Honeywell, Invensys, ABB. The models used in the systems are predominantly empirical models developed through plant testing. The MPC technology is not only used for multivariable control but for most economic operation within constraint boundaries.

2.6 Genetic Algorithm

Genetic Algorithm (GA) was built from some genetic processes in natural. Because the complex life can evolve in relative short time, GA is used to solve the optimization problems. In early 1970’s, John Holland invented the first Genetic Algorithm.

GA is the adaptive heuristic search algorithm according to the natural selection and genetics. It is the intelligent method of a random search for the optimization problems. In the method, GA directs the search to the place in which there is better result by using the historical information. GA is designed to simulate the natural processes in evolution to find the fittest region in the search space because in nature, the fittest individuals are found due to the competition among individuals.

Compared with some old artificial intelligent systems, GA is better and more robust. The GA doesn't break easily because of the slight change of inputs or some noise. Compared with some common methods such as linear programming and heuristic, GA may be better in the large state-space or multi-dimensional system.

GA simulates the fittest survival among individuals over generation in natural to solve an optimization problem. Every generation includes a population of character strings which are similar with the chromosome in people's DNA. The individual is a point and goes through the evolution.

There are some foundations in GA according to the analogy with the genetic structure and behavior of chromosomes.

- The first one is that all individuals have to compete for mates and resources
- The second one is that better individuals have more offspring while for poor individuals the offspring is less
- The next one is that two parents with good genes reproduce better offspring
- The last one is that better generation adapt to the environment better

For GA, in the population as in Fig. 2-10, every individual is a solution to the problem. And every individual is coded with variables or alphabet, usually binary 0 and 1. The individuals are like the chromosomes in genetic process and the components are like the genes, so one solution of the problem includes some variables. There is a number called fitness score which is the abilities of a solution to compete with others. Optimal fitness score means optimal result. The target of GA is to produce better new offspring from parents by selecting information in chromosomes.

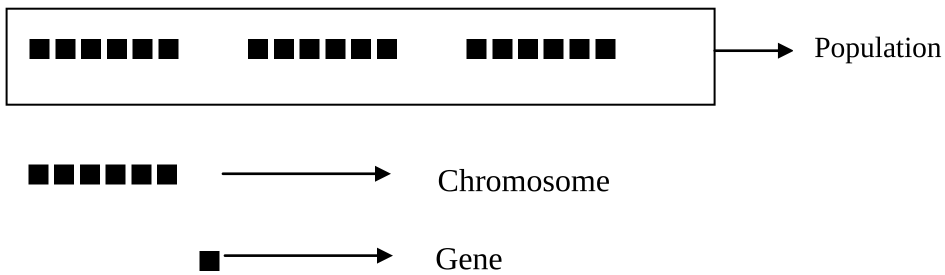

Fig. 2-10 Structure of population

In GA, parents with better fitness are selected to produce offspring using a reproductive plan. So solutions with high fitness have more opportunities and the offspring inherit the good fitness form parents. Because the population should be kept at a specific size, old individual dies and will be replaced by new and better offspring. At last, a new generation is created with better solutions.

In general, the solutions in new generation have more good genes than old solution. And successive generations have good partial solutions than old ones. Therefore, when there is no new offspring form population, the GA has converged to solutions to the problem.

2.6.1 Basic Algorithm for GA

The figure below shows the basic generic algorithm used most.

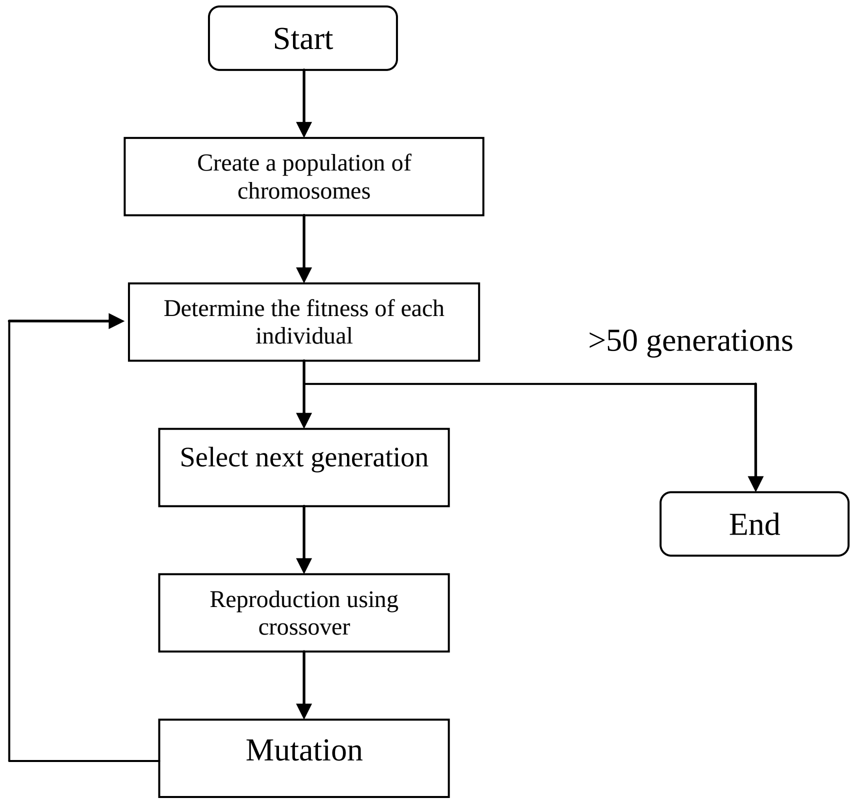

Fig. 2-11 Flow chart of basic generic algorithm

The following sections discuss the need for each of these steps in terms of their relevance to evolutionary processes.

2.6.2 Population

The first population is built with the solutions using random inputs. The type of problem decides the population. For the simple problem, a small population (40 to 100) is sufficient. For some complex problems, larger population (400 or more) is needed. But the large population makes it difficult to find solutions to problems.

2.6.3 Fitness

The fitness of chromosome is different for different problem. When the problem is to get max, if an individual is higher than others with the fitness function, it is fitter. In the cases with some criteria, comparisons among individuals carry out to see if one individual is better than others in the population by taking criteria into consideration. The most dominant are set to the Pareto solutions which are candidate solutions to the problem.

Selection of the Fittest

GA makes some generations in the process. For the evolutionary, fitter individuals are maintained in the next generation. The selection method used in many approaches is the roulette wheel selection process. In nature, fitter solutions have better chances to survive.

Roulette wheel selection

In the selection, the basic step is to select randomly individuals from a generation to make the next generation. And the target of roulette wheel shown in Fig. 2-12 is that the fitter individuals have a better chance to survive then the weaker individuals. This process replicates nature. In nature, this kind of individuals with genetic coding is useful to the future generations.

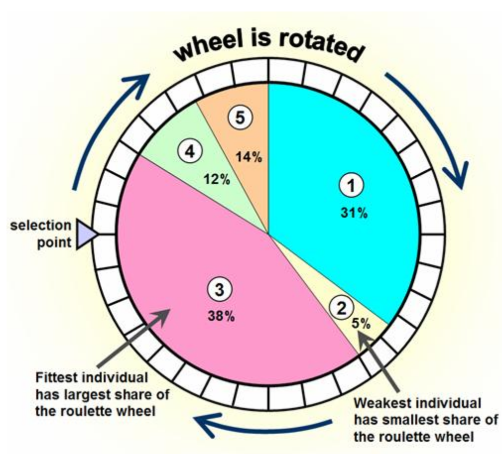

Fig. 2-12 Roulette wheel selection [50]

2.6.4 Crossover

The mating process is used to produce the next generation in nature. The offspring have genetic information from both parents. Compared with parents the offspring may be weaker or better or similar. In nature, if the offspring are weaker, they will die out; while if the offspring are better, they have more chances to survive. GA replicates this process by using the crossover operator.

Nature

The mating process is used to form the next generation. Two parents provide genetic information and the offspring include material from both parents. There are three options according to the fitness of offspring; they may be weaker, similar or better than the parents. In general, if the parents are stronger, the offspring will be fitter. This process allows the offspring to find better fitness values and solutions.

Replicating nature

GA replicates the above process by using the crossover as shown in Fig. 2-13. The target is that the offspring have important genetic information of both parents and at the same time the crossover can introduce changes to improve the fitness. The crossover operator emulates the process by exchanging chromosome patterns between individuals to produce the next generation.

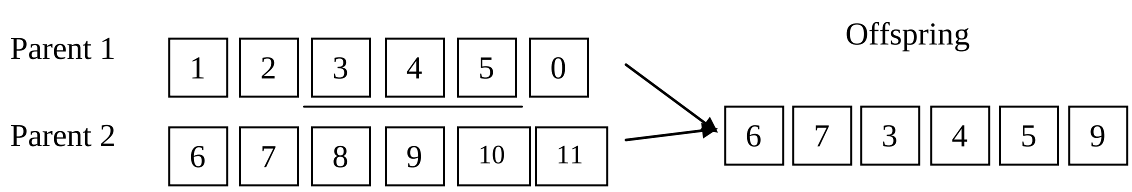

Fig. 2-13 Crossover

2.6.5 Mutation

Mutation leads an unanticipated change in the chromosome pattern in nature process. The process may provide weaker individual or better individual. The change happens spontaneously and there is no reference to others. And the process is rare. If the change is useful to improve the fitness, the individual has more chance to survive. GA replicates the nature process by using the mutation operator. It is very important that the mutation happens very rarely, if not it will cause the problem of disruptive effect to all population.

Mutation operator

In the above steps, the fitness, selection of fittest and mating process are talked. It can be assumed that there are enough solutions by the good distribution of the chromosome. But actually there is no new variation in chromosome patterns because of the above processes and the spread of chromosome with initial random population.

Nature mutation

In nature, the mutation is thought the important force for evolution though the process happens rarely. The mutation changes some part of the chromosome. So it may produce a weaker individual or better individual. In general, mutation is something new. If the change is useful, the individual will have more chance to survive and then form the next generations; otherwise it will die out.

Replicating mutation within a GA

GA replicates the mutation process by using a simple mutation operator shown in Fig. 2-14. The process of mutation is to select a single bit in the chromosome and change it. The most important thing is that mutation happens rarely and the individual changes slightly.

before mutation	1	2	3	4	5	0
after mutation	1	4	2	3	5	0

Fig. 2-14 Mutation

2.6.6 Summary

In the above sections, operations of selection, crossover, and mutation are introduced. At last, GA finds the global optimal result. GA is a fast and robust method because GA has effective manner in search.

GA can produce new solutions with good information from parents, so it can trend to the best result.

For the times of generations, there are no definitive methods to establish. Simple problems may converge on good solutions after only 20 or 30 generations. More complex problems may need more. It is not unusual to run a GA for 400 generations for more complex problems such as job shops.

Chapter 3: Heat Pump System

The heat pump is a good system which can replace the current heating systems. The heat pump is an electrically driven device which is used to transfer heat from one place to another one. Heat pump can be used as the heating unit or the water heater. In general, the heat pump is used as a device for heating/cooling in buildings.

The components in heat pumps are introduced in Table 3-1:

Table 3-1

Components in heat pumps

Components	Function
Compressor	pump used to push refrigerant through the system
Condenser Coil	heat exchanger used to reject heat energy
Evaporator Coil	heat exchanger used to absorb heat energy
Metering Valve	Controls the flow of refrigerant and allows for phase change from a liquid to vapor
Reversing Valve	Control used to switch between heating and cooling mode
Fan	moves air across coils for heat transfer between the air and refrigerant

The coefficient of performance (COP) of a heat pump is the ratio of heating or cooling provided to electrical energy consumed in [51-52]. If the heat pumps have high COPs, the operating costs become low. The COP may exceed 1. For complete systems, COP should take all energy consumption into consideration. COP usually relies on the conditions of operation such as absolute and relative temperature between sink and system in [53].

The equation is:

$$\mathrm{COP} = \frac{\mathrm{Q}}{\mathrm{W}} \tag{3-1}$$

Where

Q= the heat supplied to or removed from the reservoir

W= the work consumed by the heat pump

3.1 Types of Heat Sources

There are three main types of heat pumps. The first one is air-to-air, the second one is air-to-water and the last one is air-to-ground.

In general, heat pumps draw heat from the air (outside or inside air) or from the ground (groundwater or soil) as in [54]. The heat from the ground is usually from solar, but it is different from the direct geothermal heat. The real geothermal heat which is used in the heating system need a circulation pump not the heat pump because the temperature in ground is higher than it in the place that is to be heated. For heat pump, the temperature from sources is usually lower than that in the place to be heated. So for direct geothermal heat, it just needs simple convection.

For other sources used in heat pumps such as water, streams, natural water and domestic waste water, their temperature is often higher than the temperature outside in winter, but it is still lower than that in the place to be heated. Now there are many sources which have been applied as the heat source for buildings as in [55].

3.1.1 Air (ASHP)

Table 3-2

Air source heat pump

Types of air source heat pump	Description
Air–air heat pump	Transfer heat to inside air
Air–water heat pump	Transfer heat to a heating circuit and a tank of domestic hot water

As shown in Table 3-2, there are two kinds of air source heat pumps for the air source heat pumps. Both of them set the air outside as the heat source.

The air-air heat pump gets heat from the air outside and transfer the heat to the air in the place to be heated. And this kind of heat pumps is the most common in buildings now with the low price. It is different from the function of air conditioners because the target of heat pump is to provide heating to the buildings, while for air conditioners they usually transfer heat out of the buildings. The air-air heat pumps also can provide cooling to the buildings, and it just needs the opposite direction in the pumps.

The air-water heat pumps are similar to the air-air heat pumps. The difference is that the air-water heat pumps transfer heat to the heating circuit like floor heating circuit, and they can also transfer heat to the hot water tank in which the water is used in the shower or hot water taps in buildings.

Now it is found that ground-water heat pumps have higher efficiency than air-water heat pumps, so the ground-water is widely used to provide heat to the floor and hot water circuits in buildings.

In general, air source heat pumps are cheaper and they are easy to install in buildings. So they have been the most widely used in the buildings in history. But there are some limitations in them because of the air outside used as the heat source. When the temperature is too high or low, the efficiency would become low. In common weather, the coefficient of performance (COP) is around 4, when the temperature is below 0 ℃ (32 ℉), the COP is just about 2.5 which is very similar to the art oil or gas heaters as in [56]. And the average COP is usually 2.5-2.8, while in common weather, the COP can be 6 in [57].

Some companies are focusing on improving the COP, and they build better low temperature models for air source heat pumps. These models are better for cold weather because they are not easy to freeze or shut down. However some of them use electrical resistance to prevent freezing, the electricity consumption increases the cost in buildings in cold weather. For some places where there is not much fossil fuel, the heat pumps using electricity can replace the devices to provide heat. And when the price for electricity is lower than the fossil fuel, it is a good way to save money. However fossil-fuel, solar hot water or biomass heat source may still be required.

The performance of heating in low temperature is better for the optimized heat pumps. And the threshold when efficiency starts to drop is lower than common ones.

3.1.2 Ground (GSHP)

Table 3-3

Ground source heat pump

<table>
<tr><td colspan="2">Types of Ground source heat pump (extracts heat from the ground or similar sources)</td><td>Description</td></tr>
<tr><td rowspan="3">Ground–air heat pump (transfers heat to inside air)</td><td>Soil–air heat pump</td><td>Soil as a source of heat</td></tr>
<tr><td>Rock–air heat pump</td><td>Rock as a source of heat</td></tr>
<tr><td>Water–air heat pump</td><td>Body of water as a source of heat, can be groundwater, lake, river etc</td></tr>
<tr><td rowspan="3">Ground–water heat pump (transfers heat to a heating circuit and a tank of domestic hot water)</td><td>Soil–water heat pump</td><td>Ground as a source of heat</td></tr>
<tr><td>Rock–water heat pump</td><td>Rock as a source of heat</td></tr>
<tr><td>Water–water heat pump</td><td>Body of water as a source of heat</td></tr>
</table>

As shown in the Table 3-3, there are total six types of ground source heat pumps. The ground source heat pumps are also called geothermal heat pumps with higher efficiency than the air source heat pumps. The reason is that the source temperature in the ground below a depth of about 30 feet (9 m) is usually constant as in [58]. So the differential of temperature is small. The ground source heat pumps have COP of 3 at first and later the COP would reduce a little. But it is expensive to install the ground source heat pumps because it needs to drill holes to put heat exchanger pipes or to dig trenches for horizontal to put pipes in order to carry the heat exchange fluid.

Among the ground source heat pumps, ground water heat pumps usually have higher efficiency than ground soil heat pumps. The problem of ground soil heat pumps is that the heat exchangers would accumulate cold if nearby ground water does not flow or there is not enough conductivity for the soil and the system is simply undersized for the load as in [59].

One method to solve the problem is to use ground water to cool the floors of the building on hot days, thereby transferring heat from the dwelling into the ground loop. There are also some other methods such as to build a big solar panel and under the roof put plastic pipes as in [60]. The best method to save money is to use the big air-to-water heat exchanger on the roof.

3.1.3 Other Types of Heat Pumps

There are some other types of heat pumps such as exhaust air heat pumps, water source heat pumps and hybrid heat pumps.

The exhaust air heat pumps get heat from the exhaust air and transfer it to buildings. There is some information about them in Table 3-4.

Table 3-4

Other types of heat pump

Types of heat pump	Description
Exhaust air-air heat pump	Transfers heat to intake air
Exhaust air-water heat pump	Transfers heat to a heating circuit and a tank of domestic hot water

For the water source heat pumps (WSHP), they use flowing water as the source. There are single-pass type and recirculation type for the WSHP. The single-pass heat pumps use a body of water or a stream as the water source. And for the recirculation heat pumps, there are cooling and heating operations. When cooling in buildings, the heat is transferred to the cooling tower or the chiller. While heating, the heat is from the combustion in the central boilers.

Another type of heat pumps is Hybrid heat pump (HHP) which is also called twin source heat pump. It can select different working modes at different conditions. When the temperature is around 4℃-8℃ (40℉-50℉), the air is used as the heat source. When it is colder for the air, the ground source heat pumps mode is used. It can store heat in summer by running ground source water through the air exchanger or through the building heater-exchanger, even when the heat pump itself is not running. The advantages of the hybrid heat pumps are that they can improve the efficiency by about 4 percent for one degree when the temperature of ground source increases and they can save cost for the heating and cooling.

3.2 Heating/Cooling Operation Modes

There are two operation modes for heat pumps which are heating mode and cooling mode. They use the same system with opposite direction to provide heating/cooling services.

3.2.1 Heating Mode

As shown in Fig. 3-1, item 1 is the compressor, item 2 is the reversing valve, item 3 is the fan, item 4 is the condenser, item 5 is the liquid refrigerant, item 6 is the metering valve and item 7 is the evaporator.

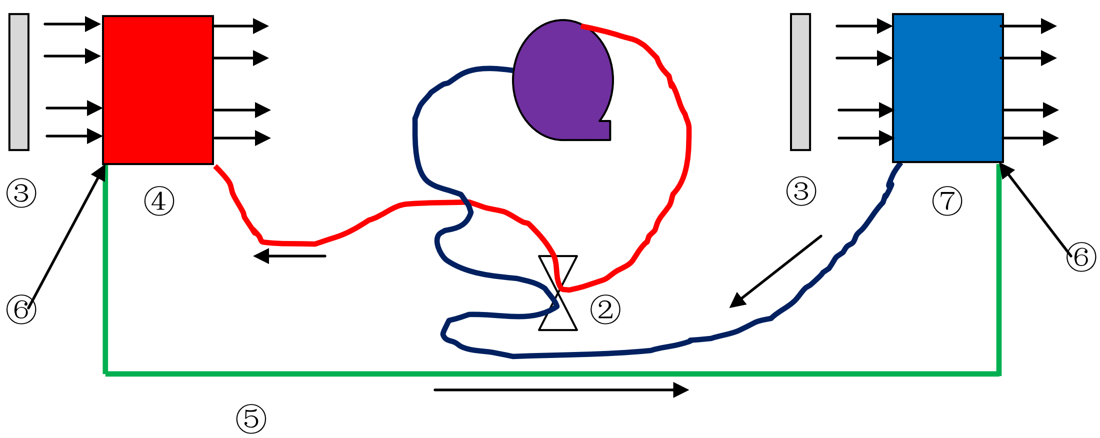

Fig. 3-1 Heating mode

In the system, the liquid refrigerant is used to transfer heat. In the heating mode, the vapor refrigerant with high temperature is pumped to the condenser coil by the compressor and the fan blows the cold air in building over the condenser to receive heat from the vapor refrigerant. The heated indoor air is flowed into the room. When the heat is transfer into the room, the refrigerant would condense to liquid and then go to the evaporator. In the evaporator, the refrigerant is expanding because the pressure drops. When the liquid refrigerant passes through the evaporator, the liquid refrigerant would change to the vapor refrigerant by collecting the heat from outside. Then the vapor refrigerant would go to compressor to finish one cycle. In compressor, the heating cycle is repeated to provide heat into the buildings.

3.2.2 Cooling Mode

Heat pump can also be used in the cooling mode as in Fig. 3-2, the components are the same, but the direction of flow is opposite. This kind of using makes heat pumps have an ability to work at two different modes-heating or cooling with the same components.

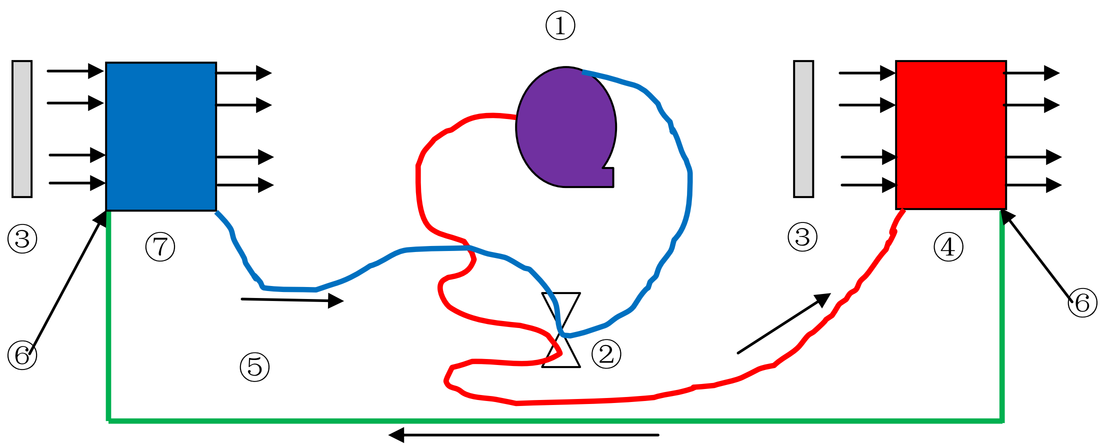

Fig. 3-2 Cooling mode

In cooling mode, the compressor deliver the refrigerant vapor with high pressure to the reversing valve and then to the condenser coil. In the condenser coil, the refrigerant vapor becomes to liquid. And the fan blows the air through the coil to release some heat to outside. In the next step, the liquid refrigerant goes to evaporator coil and is metered by the metering valve. In the coil, the refrigerant absorbs heat from the air blown through the evaporator coil to provide cooling to room. Then the air is delivered into the room to cool the air. And the liquid refrigerant becomes to vapor refrigerant and it is delivered to the compressor to repeat the cooling cycle.

These modes are for air-to-air heat pumps. For the air-to-water heat pumps, the air-to-water units are used to heat water in buildings such as for shower and hot water tap. The heat energy is transferred to a water tank to store. This method has much higher efficiency (three to five times) than common natural gas water heaters.

3.3 Control Methods of Heat Pump

In [61], there are different control methods for load balancing and load shifting in grids. There are also some different control methods for heat pumps, there are three main control methods shown below:

1) Frequency based control

The heat pump follows the grid frequency. Between demand and supply, if the demand is higher, the frequency would fall; while the supply is higher, the frequency would increase. The heat pumps can change the working time for compressor for a short time for the difference of the frequency with common condition. The advantage of this type of control is that the controller is cheap compared to other control methods because there is no additional necessary communication between the utility and the heat pump. But it is hard to respond autonomously.

2) Price based control

The price from utility is changing, and the heat pump controller can make an operation schedule for units. So the working time for heat pump can shift to the time when the price is low. This control method requires a good communication between utilities and residence. This method can save money. But the drawback of this control method is that it is relatively complex.

3) Direct control

With the equipments for communication required for the price based control, utility can direct send control signals to the heat pump to increase or reduce the demand. The direct control is realized by using the method. And the heat pump just need receive signal and send information to the utility. The drawback of direct control is that there should be a large amount of problems for the coordination among heat pumps to solve by utility.

3.4 Selecting a Heat Pump

When selecting an air-source heat pump, it is better to consider the following three characteristics carefully and they are the energy efficiency rating, sizing, and the system's components.

3.4.1 Energy Efficiency Rating

The energy efficiency is rated by how many British thermal units (Btu) of heat it transfers for one watt-hour of electricity. There is a label called EnergyGuide Label in the United States which shows the heating/cooling efficiency performance rating. It is an important characteristic when consumers select a heat pump.

There is another factor called heating seasonal performance factor (HSPF) which is also important when consumers buy heat pumps. The factor also gives how many Btu produced with one watt-hour used. Good heat pumps have an HSPF of about 9.

The above factor is for heating, and for cooling, there is a factor called seasonal energy efficiency ratio (SEER) which rates the efficiency. High efficiency can save energy but investment is high.

The next useful label is Energy Star label which is supported by the U.S Department of Energy (DOE) and the U.S. Environmental Protection Agency (EPA). Now many heat pumps have good performance, the label is the most credible factor when consumers want to buy one new heat pump.

3.4.2 Sizing

The good sizing is another important characteristic when consumers select a new heat pump. Big size doesn’t mean good for consumers. The problem is that the heat pump often starts and stops so that the efficiency is low. A proper heat pump provides better performance for heating and cooling.

In order to select proper size of heat pumps, it needs complex calculations, so it is better to consult with an experienced contractor. The experience of contractor is important. The good contractors know sizing methods very well accepted by the heat pump industry. Don't consult the contractors who just simply guess the size of the heat pump. They usually use the Rule-of-thumb sizing techniques which are generally inaccurate, and it often results in higher investment and energy costs for one year.

3.4.3 System Components

To improve the comfort level and the economy of the heat pumps, the system components are significant. The design, materials and the space required for installment are the factors influencing the selecting of heat pumps. There should be enough space designed for the ducts and fans when the builder designs the building. But in fact, the space is often not enough. The heat pumps systems have to be squeezed in the small space. However it influences the performance of heating and cooling because of the lack of airflow and constricted ducts. And the proper indoor coil is needed to remove the moisture in summer.

Chapter 4: Modeling

In the section, a model is built for comfort level. As in the Fig. 4-1, it is a single story wood-built house. The floor and walls are lightweight sandwich constructions based on a Masonite beam insulated with mineral wool. And there is a heat pump which is connected with a battery in the room.

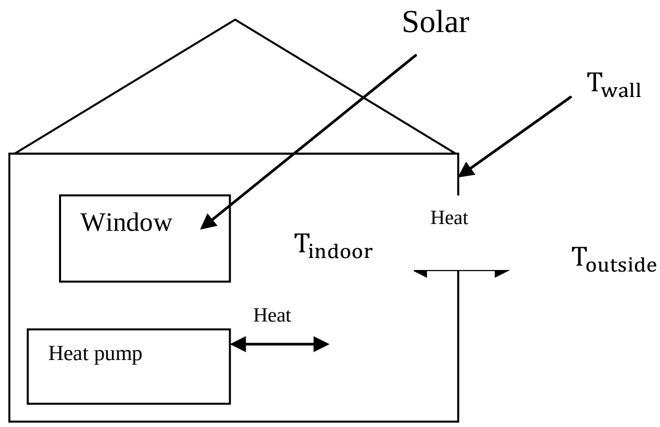

Fig. 4-1 Model of room

In order to get a simply model, there are some assumptions: no wind influence for heat; no influence from the people activities in the room. So the heat balance in room is shown below:

$$Q_{hp} - Q_{indoor-wall} + Q_{solar-indoor} = C_{building}T_{bc} \quad (4\text{-}1)$$

Where

Q_{hp}= supply heat from heat pump

$Q_{indoor-wall}$= heat transfer between indoor and wall

$Q_{solar-indoor}$= heat transferred to indoor from solar radiation

$C_{building}$= thermal capacity indoor

T_{bc}= temperature change of indoor

And for the heat from heat pump and the heat from solar to indoor, the equations are shown below:

$$Q_{hp}=COP*W \tag{4-2}$$

$$Q_{solar-indoor} = \beta P_s \tag{4-3}$$

Where

W= power supplied by the heat pump

β = Fraction of incident solar radiation from window on air indoor

P_s= Power of solar radiation

There is another model for the wall which is also important. Fig 4-2 shown below introduces the heat balance in the wall.

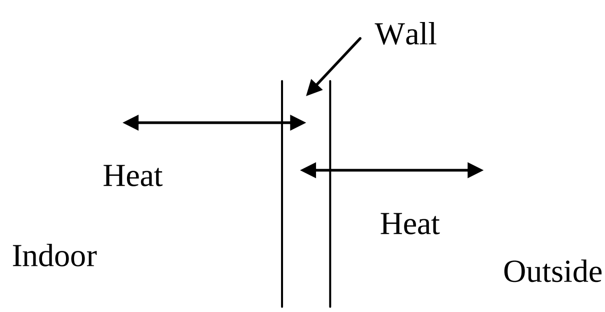

Fig. 4-2 Model of wall

The heat balance in the wall is shown below:

$$Q_{indoor-wall} + Q_{solar-wall} - Q_{wall-outside} = C_{wall} T_{wc} \tag{4-4}$$

Where

$Q_{solar-wall}$= heat transferred to the wall from solar radiation

$Q_{wall-outside}$= heat transfer between outside and wall

C_{wall}= thermal capacity in the wall

T_{wc}= temperature change of wall

And for the heat from solar to the wall

$$Q_{solar-wall} = \gamma P_s \quad (4\text{-}5)$$

Where

γ= Fraction of incident solar radiation from widow on wall

The heat equation is shown below:

$$Q_{indoor-wall} = UA_{indoor-wall} * (T_{indoor} - T_{wall}) \quad (4\text{-}6)$$

$$Q_{wall-ouside} = UA_{wall-outside} * (T_{wall} - T_{outside}) \quad (4\text{-}7)$$

Where

T_{indoor}= Indoor temperature

T_{wall}= Wall temperature

$T_{outside}$= Outdoor temperature

And for UA, the equation is:

$$UA_{indoor-wall} = 1/R_{indoor-wall} \quad (4\text{-}8)$$

$$UA_{wall-outside} = 1/R_{wall-outside} \quad (4\text{-}9)$$

Where R is the resistance against heat flow, and it is the reciprocal value of UA which is the product of the heat conductivity and the surface area of the layer between two heat exchanging Medias in [62]. So the final state model in the room can be expressed as:

$$\alpha W - UA_{indoor-wall} * (T_{indoor} - T_{wall}) + \beta P_s = C_{building} T_{bc} \tag{4-10}$$

$$UA_{indoor-wall} * (T_{indoor} - T_{wall}) + \gamma P_s - UA_{wall-outside} * (T_{wall} - T_{outside}) = C_{wall} T_{wc} \tag{4-11}$$

Chapter 5: Fuzzy Logic Control System

In Chapter 4, the model of the building is already introduced. In this Chapter, the fuzzy logic control for the experiment in order to control the indoor temperature is shown. To control the temperature, the temperature of supply air from heat pump is changed in the experiment. In this experiment, the power for fan in heat pump is not considered and only the power for compressor is concerned as the energy consumption for the heat pump.

The target of the system is to control the indoor temperature at the comfort level. The diagram of the common control system is shown in Fig 5-1.

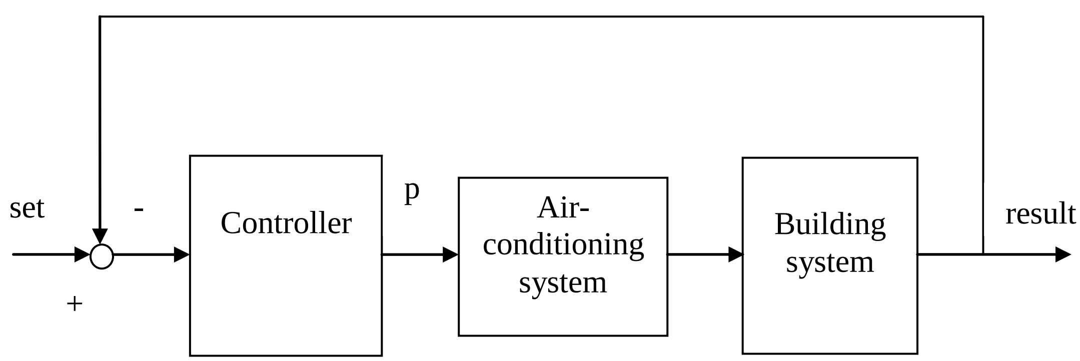

Fig. 5-1 Fuzzy logic control system

The controller is to calculate the supply heat from air with proper amount to the heat pump system in order to keep the comfort level indoor. The signal of heat is then sent to the air-conditioning system. In the next step, the operation of air-conditioning system influences the comfort temperature in the building and the result signal is returned to the first step in the control system.

5.1 Fuzzy Controller Design

The controller for the heat pump is using fuzzy logic to maintain the comfort temperature indoor. The inputs of the system controller are the comfort temperature, actual temperature indoor and the temperature outside. And the output of the system controller is the heat needed of the heat pump to keep the comfort level.

The control strategy used can be expressed by the following linguistic rules:

If room temperature is higher than the comfort point, then increase the power for cooling in heat pump.

If room temperature is lower than the comfort point, then increase the power for heating in heat pump.

If room temperature is at the comfort point, then keep the situation of heat pump.

5.1.1 Structure of the Fuzzy Logic Controller

The method in the system is to use SISO controller as shown in Fig. 5-2.

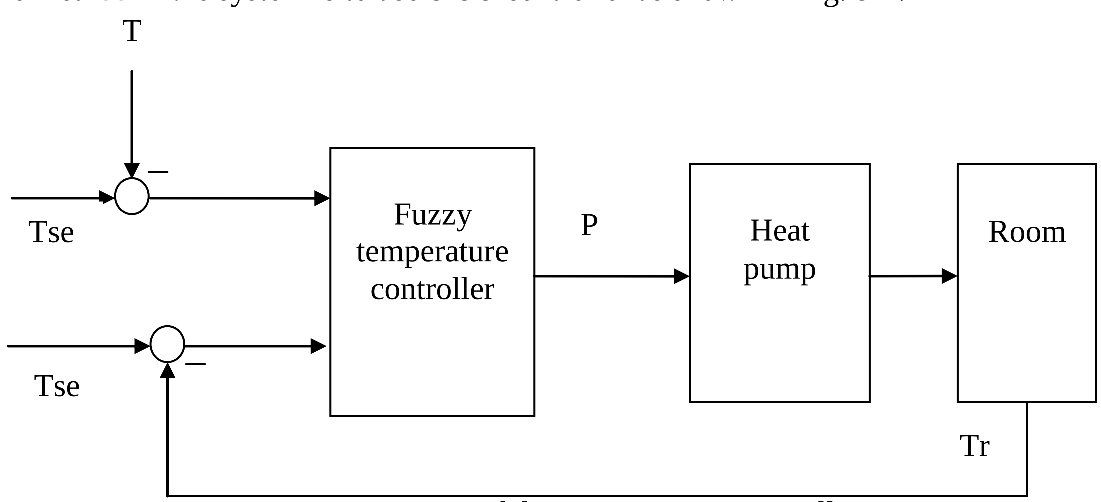

Fig. 5-2 Structure of the Fuzzy Logic Controller

In order to control the temperature indoor, the first step is the fuzzy logic controller reads the actual temperature indoor, temperature outside and the comfort temperature. The temperature difference between the actual temperature indoor and set comfort temperature; and the temperature difference between the set comfort temperature and the temperature outside are calculated as the inputs to the fuzzy temperature controller.

$$e_1 = T_{set} - T_{rk} \tag{5-1}$$

$$e_2 = T_{set} - T_{ak} \tag{5-2}$$

Where T_{rk} is the measured temperature indoor at the kth sampling instant and T_{ak} is the temperature outside at the kth sampling instant

The result power of supply from heat pump is the output of the fuzzy logic temperature controller using fuzzy inference.

$$p = f(e_1, e_2) \tag{5-3}$$

5.1.2 Membership Function

In the fuzzy logic controller, the If-Then rules are finished with fuzzy sets and the sets have their membership functions. In the fuzzy logic controller, there are seven fuzzy sets for inputs. They are negative large (NL), negative medium (NM), negative small (NS), zero (ZO), positive small (PS), positive medium (PM) and positive large (PL).

In the fuzzy sets, the triangular membership functions are used because they have been proven to be successful in many places. Fig. 5-3 and Fig. 5-4 below show the membership functions for temperature difference.

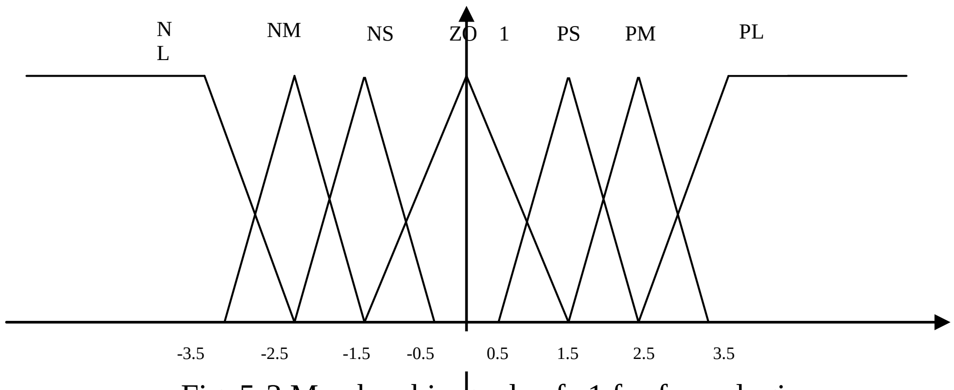

Fig. 5-3 Membership grade of e1 for fuzzy logic

The membership functions for e1 (horizontal axis is for e1)

$$\text{NL: u11} = \begin{cases} 0 & \text{e1} \in [-2.5, \infty] \\ -2.5 - \text{e1} & \text{e1} \in [-3.5, -2.5] \\ 1 & \text{e1} \in [-\infty, -3.5] \end{cases} \tag{5-4}$$

$$\text{NM: u12} = \begin{cases} 1 - |\text{e1} + 2.5| & \text{e1} \in [-3.5, -1.5] \\ 0 & \text{otherwise} \end{cases} \tag{5-5}$$

$$\text{NS: u13} = \begin{cases} 1 - |\text{e1} + 1.5| & \text{e1} \in [-2.5, -0.5] \\ 0 & \text{otherwise} \end{cases} \tag{5-6}$$

$$\text{ZO: u14} = \begin{cases} 1 - \frac{|\text{e1}|}{1.5} & \text{e1} \in [-1.5, 1.5] \\ 0 & \text{otherwise} \end{cases} \tag{5-7}$$

$$\text{PS: u15} = \begin{cases} 1 - |\text{e1} - 1.5| & \text{e1} \in [0.5, 2.5] \\ 0 & \text{otherwise} \end{cases} \tag{5-8}$$

$$\text{PM: u16} = \begin{cases} 1 - |\text{e1} - 2.5| & \text{e1} \in [1.5\ 3.5] \\ 0 & \text{otherwise} \end{cases} \tag{5-9}$$

$$\text{PL: u17} = \begin{cases} 0 & \text{e1} \in [-\infty, 2.5] \\ -2.5 + \text{e1} & \text{e1} \in [2.5, 3.5] \\ 1 & \text{e1} \in [3.5, \infty] \end{cases} \tag{5-10}$$

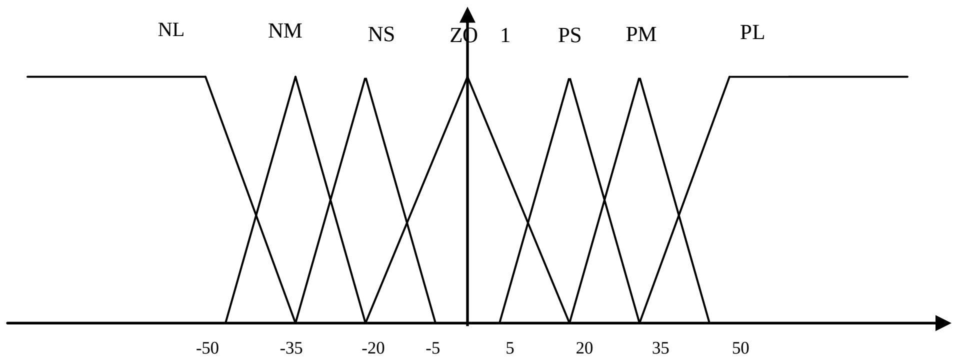

Fig. 5-4 Membership grade of e2 for fuzzy logic

The membership functions for e2 (horizontal axis is for e2)

$$\text{NL: u21} = \begin{cases} 0 & e2 \in [-35, \infty] \\ -\frac{7}{3} - e2/15 & e2 \in [-50, -35] \\ 1 & e2 \in [-\infty, -50] \end{cases} \tag{5-11}$$

$$\text{NM: u22} = \begin{cases} 1 - |e2 + 35|/15 & e2 \in [-50, -20] \\ 0 & \text{otherwise} \end{cases} \tag{5-12}$$

$$\text{NS: u23} = \begin{cases} 1 - |e2 + 20|/15 & e2 \in [-35, -5] \\ 0 & \text{otherwise} \end{cases} \tag{5-13}$$

$$\text{ZO: u24} = \begin{cases} 1 - \frac{|e2|}{20} & e2 \in [-20, 20] \\ 0 & \text{otherwise} \end{cases} \tag{5-14}$$

$$\text{PS: u25} = \begin{cases} 1 - |e2 - 20|/15 & e2 \in [5, 35] \\ 0 & \text{otherwise} \end{cases} \tag{5-15}$$

$$\text{PM: u26} = \begin{cases} 1 - |e2 - 35|/15 & e2 \in [20, 50] \\ 0 & \text{otherwise} \end{cases} \tag{5-16}$$

$$\text{PL: } u27 = \begin{cases} 0 & e2 \in [-\infty, 35] \\ -\frac{7}{3} + e2/15 & e2 \in [35, 50] \\ 1 & e2 \in [50, \infty] \end{cases} \tag{5-17}$$

The membership functions have to cover the input range. The choice of membership functions affects the performance the controller.

If the slopes of triangles are steeper, the sensitivity of the membership function is high. While for the flat slopes, though the sensitivity is not good, the control is smoother and the stability is good.

So the distribution of membership functions needs to consider carefully in their definition. In the place near to zero, the functions with higher resolution are selected. While the functions with lower resolution are selected in the areas far from zero in order to get the stability and sensitivity together.

If the region for the fuzzy sets is so small that sets are not easy to define, the actual input should be translated by using the scaling factors.

$$E_1 = e_1 * K_{e1} \tag{5-18}$$

$$E_2 = e_2 * K_{e2} \tag{5-19}$$

Where

K_{e1} and K_{e2} are the scaling factors for e_1 and e_2.

And the temperature difference is transferred to the fuzzy value with the membership functions.

5.1.3 Fuzzy Inference

The zero-order T-S fuzzy rules are used as below:

If E_1 is A_i and E_2 is B_j, then $P=K_{ij}$

Where A_i and B_j are the fuzzy sets for E_1 and E_2 respectively. The output is K_{ij} which can be found in the fuzzy inference table.

The advantages of this rule are simple calculation and easy tuning as in [63]. Setting the differences of temperature among indoor, set comfort point and outside as the inputs is easy as the common controllers. The consequent K, is the operation in the heat pump. The output signal of the controller is then sent to the heat pump.

The Min inference method and the weighted mean method (WMM) are used in defuzzification step.

Fig 5-5 shows the process of combinations of E_1 and E_2 depending on the rules. Each combination of E_1 and E_2 will provide a crisp value of the control action depending on the table of fuzzy rules.

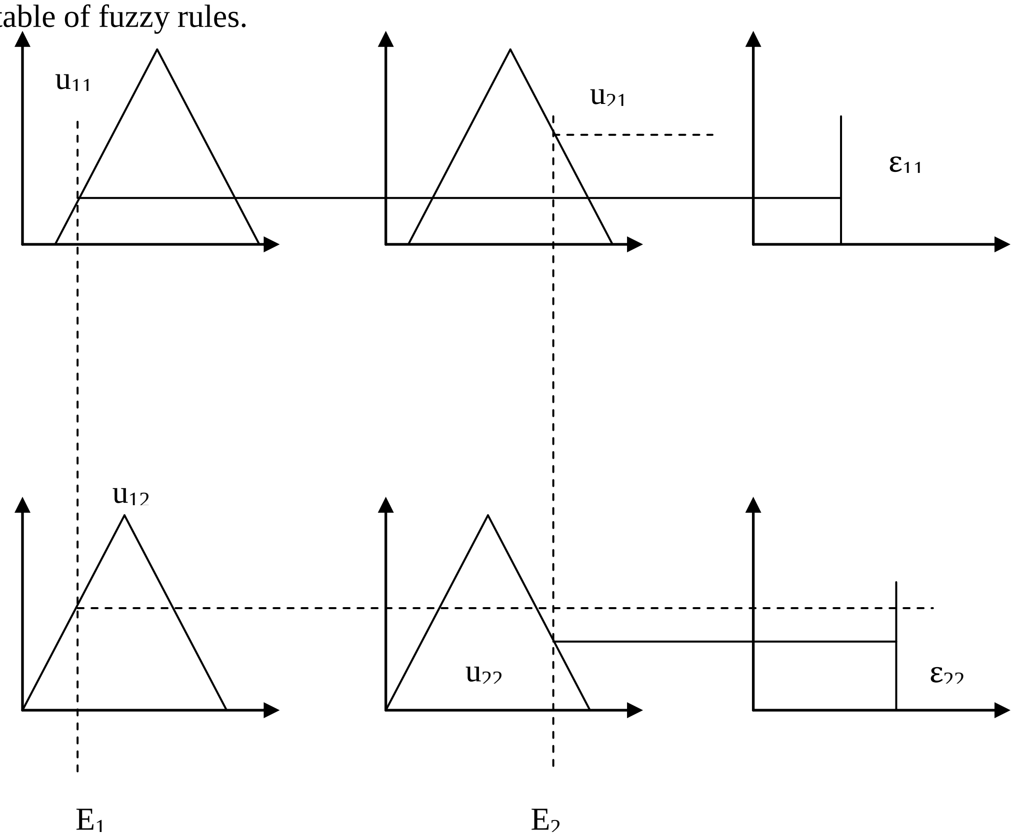

Fig. 5-5 Fuzzy inference diagram

At first, E_1 and E_2 are resolved by the fuzzy linguistic sets. Next in the fuzzification section, E_1 is "A_1" at the degree u_{11} and "A_2" at the degree u_{12}, while E_2 is "B_1" at the degree u_{21} and "B_2" at the degree u_{22}.

Then the Min operation is shown below used to decide the needed degree and in the next step it is used to get weighted mean.

$$\varepsilon_{ij} = \min\left(u(A_i), u(B_j)\right) \tag{5-20}$$

At last, the actual output of FNN is calculated with WMM as shown below:

$$p = \frac{\sum \varepsilon_{ij} K_{ij}}{\sum \varepsilon_{ij}} \tag{5-21}$$

The fuzzy control rules are designed according to various publications as in [63]. These rules can be modified according to the performance of system on the linguistic plane in [64]. The rules include fuzzy sets and operation K listed in the Table 5-1. In the table, there are 7 rows and 7 columns. Each 7 sets are for each of E_1 and E_2. It is seen that the big negative operations are in the upper left places because E_1 and E_2 are negative large, while the big positive operations are in the bottom right places due to E_1 and E_2 are positive large. It is logical relying on the rules. For example, if the temperature is too low, the power in heat pump for heating is large to keep the comfort temperature indoor.

Table 5-1

Fuzzy logic control rules

E2 \ E1	**NL**	**NM**	**NS**	**ZO**	**PS**	**PM**	**PL**
NL	-1700	-1650	-1600	-1550	-1200	-1100	-1000
NM	-1300	-1200	-1100	-1000	-700	-600	-500
NS	-1100	-1000	-900	-500	200	300	400
ZO	-500	-400	-300	0	200	300	400
PS	-400	-300	-200	500	900	1000	1100
PM	500	600	700	1000	1100	1200	1300
PL	1000	1100	1200	1550	1600	1650	1700

In order to introduce the table, an example for the fuzzy rule is shown below.

If the temperature difference between indoor and comfort point is negative large and the temperature error between indoor and outside is also negative large, then increase the power for cooling in the heat pump.

The operation P is calculated with the weighted mean of all control actions according to the fuzzy rules.

The actual output operation, U, is then introduced using the following equation:

$$U = K_u * P \tag{5-22}$$

Where

K_u is the control gain constant and P is the output from the controller. So the operation for next sampling instant is U.

5.2 Experiments Results

In the thesis, the software Matlab is used to simulate the process. The target is to do the temperature control for 12/29/2013-12/31/2013. The location data used is from Akwesasne in New York State. All the environmental data are from JRibal Environmental eXchange network. The temperature outside is shown in Fig. 5-6.

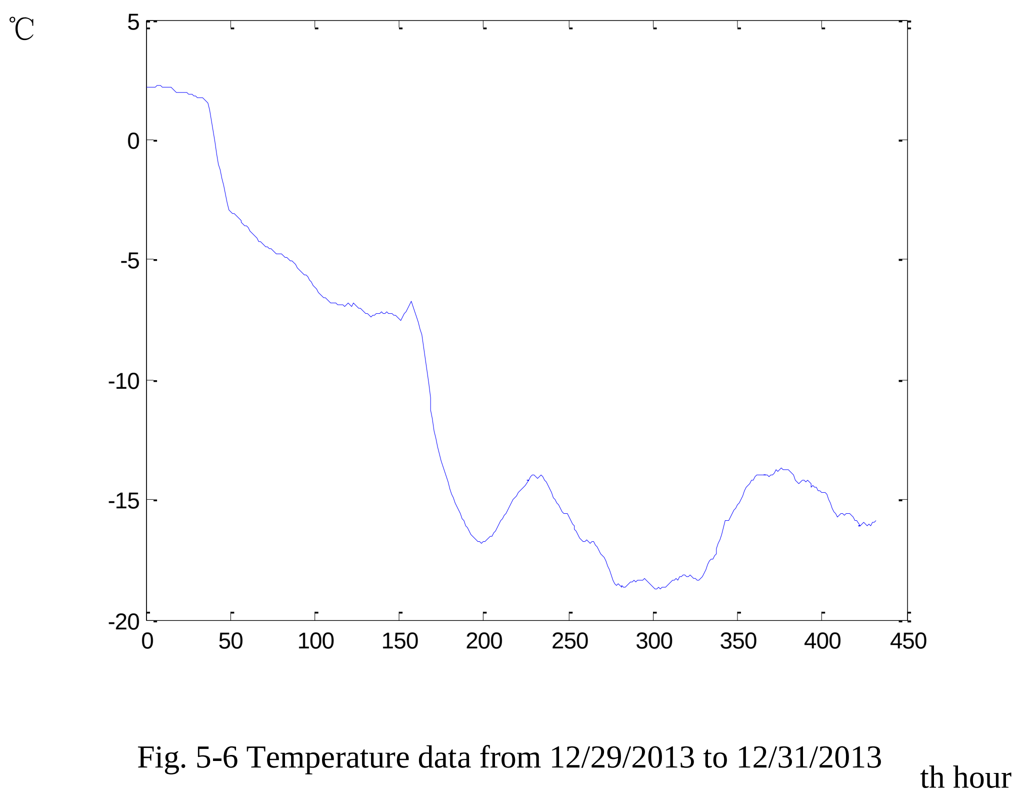

Fig. 5-6 Temperature data from 12/29/2013 to 12/31/2013

And the price signal is the local marginal price from PJM as in Table 5-2.

Table 5-2

Electricity price

12/29	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00
$/Mwh	28.57	27.08	26.39	26.22	25.99	25.86	26.42	26.93	29.32
	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00
$/Mwh	30.71	31.92	31.6	31.33	31.04	30.45	29.95	29.26	32.17
	18:00	19:00	20:00	21:00	22:00	23:00			
$/Mwh	41.59	39.18	38.27	36.76	32.42	31.19			
12/30	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00
$/Mwh	28.92	28.42	27.96	27.99	28.2	28.8	30.97	35.73	39.18
	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00
$/Mwh	39.95	40.01	40.55	40.71	36.84	35.92	34.77	34.88	40.62
	18:00	19:00	20:00	21:00	22:00	23:00			
$/Mwh	61.24	69.87	52.58	50.84	47.26	36.01			
12/31	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00
$/Mwh	34.51	31.25	30.6	30.51	30.51	30.97	32.77	38.27	43.81
	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00
$/Mwh	40.5	40.5	40.29	38.23	34.08	32.94	32.5	32.53	35.34
	18:00	19:00	20:00	21:00	22:00	23:00			
$/Mwh	51.31	44.68	43.65	42.74	41.1	34.39			

The real room model is expressed by the model built in the model section. Heat pump is used to provide heat into the room or absorb heat from the room. And the max power for heat pump is 1500W. The time interval used in the experiments is ten minutes. And the comfort temperature is 22℃ as the set point. The result of fuzzy logic control is shown in Fig. 5-7:

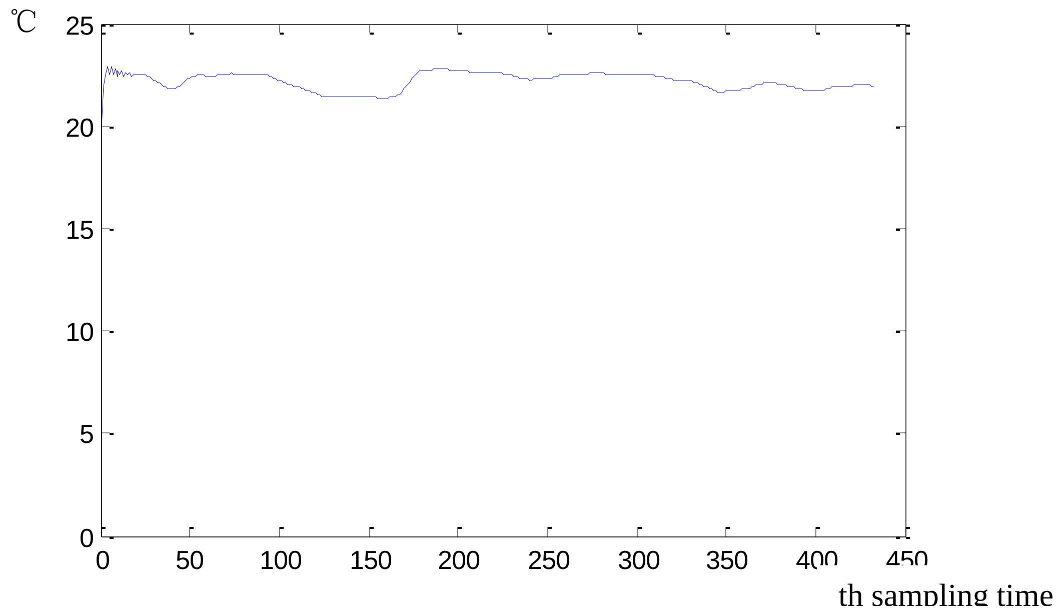

Fig. 5-7 Fuzzy logic result

As shown in the fig above, the temperature control is ok and the temperature is around 22℃. But the result is not good because the difference of temperature is a little big. The reason is that the fuzzy sets are not good. In summary, the result proves that the fuzzy logic can control the temperature well.

Chapter 6: Fuzzy Neural Network Controller

In Chapter 5, the fuzzy logic controller is successfully used to maintain the comfort temperature indoor. However, this method depends on the fuzzy rules from human experience. It is not enough sometimes because some rules may be not correct due to the misunderstanding from human. Due to this situation, tuning of fuzzy controller is necessary as in [65]. The target of the controller is to find the optimal fuzzy logic rules automatically.

6.1 Fuzzy Neural Networks (FNN)

In [66] the multi-layer neural network can be used to establish the fuzzy logic system. The schematic diagram of the FNN is shown in Fig. 6-1.

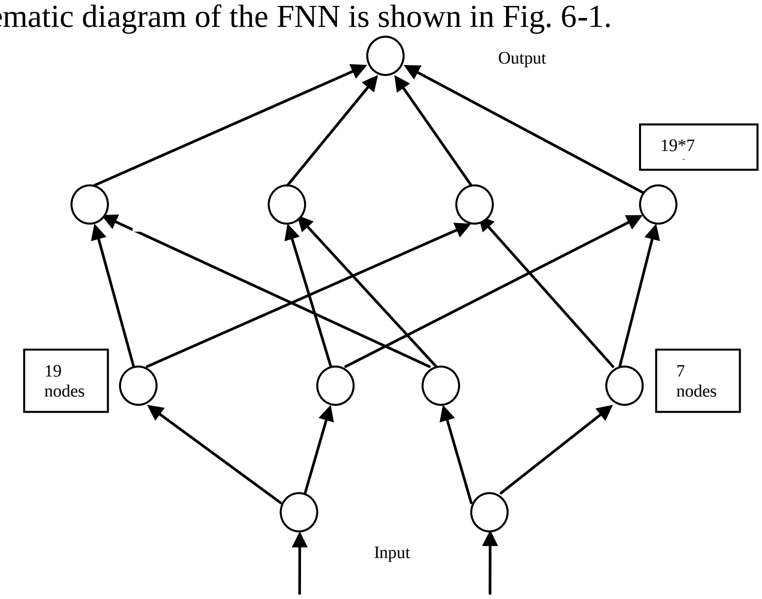

Fig. 6-1 Fuzzy neural network

As shown in the figure, there are two inputs and one output. Four layers are in the network. The first layer transmits the two inputs to the second layer using the connecting weights. The nodes in the second layer are for the membership functions. Every node in the second layer is used to lead the input to all possible positions. In the third layer, every node represents one fuzzy rule in the fuzzy inference table. The node in the last layer gives the final output by taking all the nodes from the fuzzy rules in the third layer.

The neural networks can learn themselves. In this chapter, a self-tuning fuzzy logic controller with neural networks is designed. The neural network provides the structure to fuzzy logic and the weights in neural network can represent the parameters of fuzzy logic system. So the self-tuning fuzzy controller is built by training of the neural networks.

In the FNN, the Min operator like in Chapter 5 is also used. And the weighted mean method is also applied in the step of defuzzification.

Define K is the weight between the second layer and the third layer, w is the result from the Min operator and the data A is the fuzzy set, x is the input in the first layer. The output y of the system is calculated using the weighted mean method. The inference of fuzzy logic is shown below:

If x_1 is A_{1i} and x_2 is A_{2j}, then K_{ij}

The output equation is shown below:

$$y = \sum K_{ij}\, w_{ij} / \sum w_{ij} \tag{6-1}$$

6.1.1 Nodes Operation

There are seven fuzzy sets for the linguistic variable for the temperature difference between set point and indoor (e_1), and there are nineteen fuzzy sets for the temperature difference between set point and outdoor (e_2). These decide the nodes in the neural network.

In each layer, the function is introduced below:

Layer 1: input layer

In the input layer, two nodes are set as the two inputs. Each of them sets an input variable to the next layer. There is not any change for the two inputs, and then the inputs are sent to the next layer.

Layer 2: membership layer

Because seven and nineteen membership functions for e_1 and e_2 are defined for inputs, there are 7+19 nodes in this layer. Each of these performs a membership function. Triangular membership functions are used. These are schematically shown in Fig. 6-2.

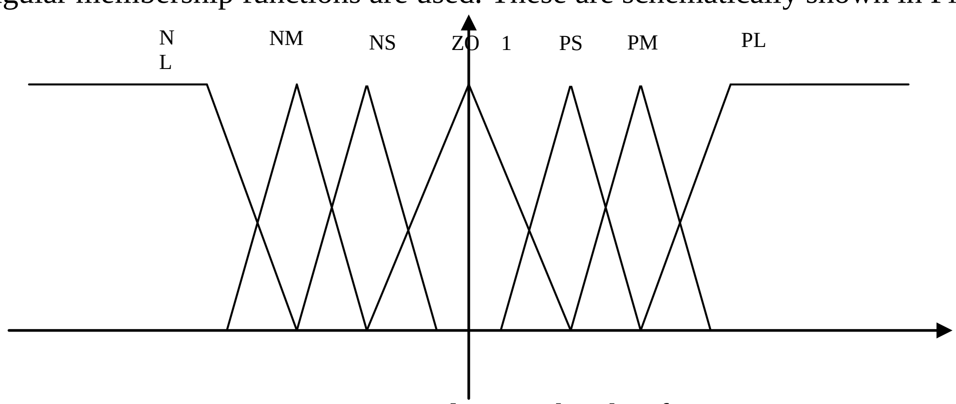

Fig. 6-2 Triangular membership functions

Layer 3: rule layer

There are 7*19 nodes in the layer for the antecedent matching because nineteen membership functions are set for one input and another seven membership functions are for another input. The Min operator is used in the layer, and then the outputs can be expressed as:

$$w_{ij} = \min(u_{1i}, u_{2j}) \quad (6\text{-}2)$$

Where

U is the degree of membership function.

There is the weight K between the second layer and the third layer. So the input to the last layer is K*w. And in order to design the FNN with learning process, η is used to modify K when the result is not good. The output equation for one node is shown below:

$$y = w_{ij}K_{ij} \quad (6\text{-}3)$$

When the result is bad, the new weight at next time with learning process is $K_{ij} + \eta * e1$.

Where

η is the learning rate

Layer 4: output layer

The final output is the weighted mean value of the all consequents in the previous layer. So the final output for the output layer is introduced below:

$$y = \sum_{i=1}\sum_{j=1} w_{ij}K_{ij} \,/ \sum_{i=1}\sum_{j=1} w_{ij} \quad (6\text{-}4)$$

Where w is the result from the Min operator and K is the weight or called the result according to the fuzzy inference table.

6.2 Fuzzy Neural Network Control System Structure

In [67] the model reference adaptive control (MRAC) is used in the control system. In the control method, though there is no model reference, the learning process is also good. The parameters in the control system are modified to meet the actual temperature system by using the difference between the set point and the actual output.

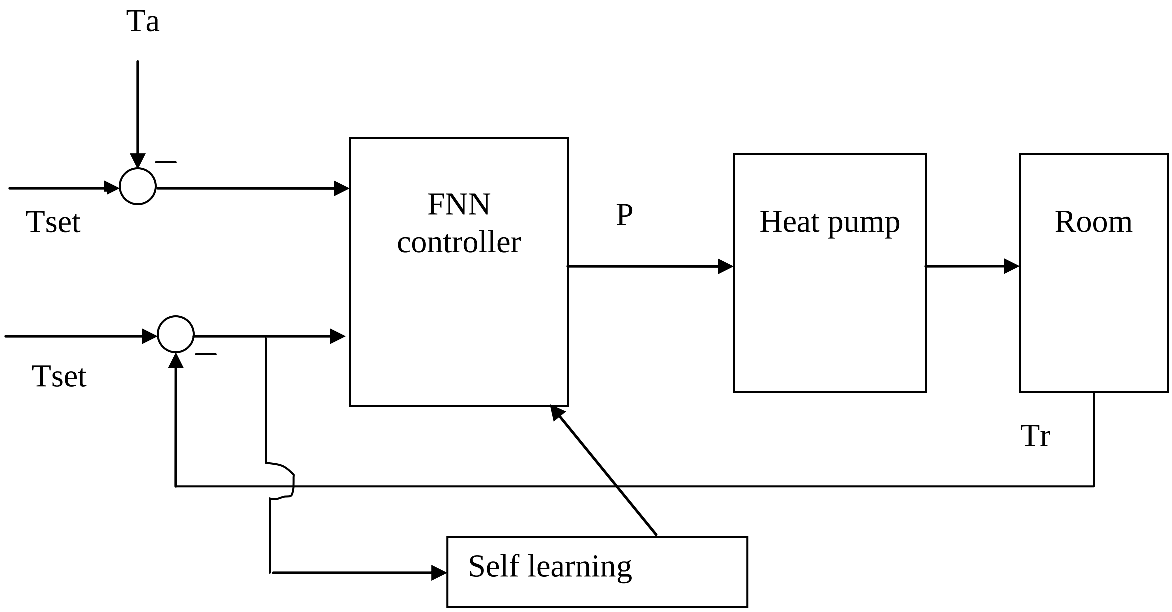

Fig. 6-3 Fuzzy neural network control

As shown in Fig. 6-3, the comfort condition provides the set point of the system; the feedback system is used to provide p to the system in order to get the actual output Tr tracking the set point. The fuzzy neural network (FNN) is used so that the system can learn itself and modify to meet the changes of system parameters.

The system of plant in the scheme is heat pump. The controlled variable in the system is the temperature indoor. The reference model provides the set comfort temperature and the FNN is used to provide operations to the heat pump in order to get the set point.

The same as in Chapter 5, here the FNN is also used to control the temperature indoor and inputs to the control system are the difference between the set temperature and actual temperature and the difference between the set temperature and the temperature outside.

6.3 Experiments Results

The result in the previous chapter is not good enough. In this section, the improved method is used with the same conditions.

The ANN is added into the control system and the new fuzzy inference is used to improve the result. There are more sets for the outside temperature to improve the fuzzy inference. The revised membership functions are shown below:

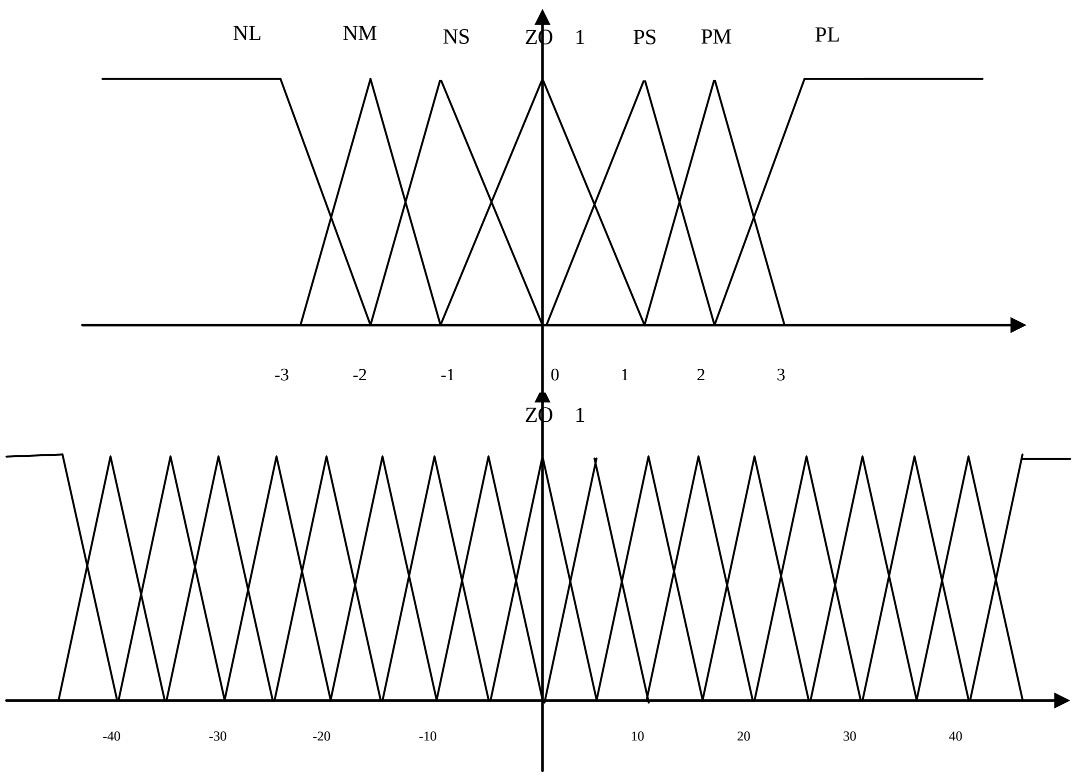

Fig. 6-4 Membership grade for fuzzy logic with ANN

The membership functions for e1(horizontal axis is for e1)

$$\text{NL: } u11 = \begin{cases} 0 & e1 \in [-2, \infty] \\ -2 - e1 & e1 \in [-3, -2] \\ 1 & e1 \in [-\infty, -3] \end{cases} \tag{6-5}$$

$$\text{NM: } u12 = \begin{cases} 1 - |e1 + 2| & e1 \in [-3, -1] \\ 0 & \text{otherwise} \end{cases} \tag{6-6}$$

$$\text{NS: } u13 = \begin{cases} 1 - |e1 + 1| & e1 \in [-2, 0] \\ 0 & \text{otherwise} \end{cases} \tag{6-7}$$

$$\text{ZO: } u14 = \begin{cases} 1 - |e1| & e1 \in [-1, 1] \\ 0 & \text{otherwise} \end{cases} \tag{6-8}$$

$$\text{PS: } u15 = \begin{cases} 1 - |e1 - 1| & e1 \in [0, 2] \\ 0 & \text{otherwise} \end{cases} \tag{6-9}$$

$$\text{PM: } u16 = \begin{cases} 1 - |e1 - 2| & e1 \in [1, 3] \\ 0 & \text{otherwise} \end{cases} \tag{6-10}$$

$$\text{PL: } u17 = \begin{cases} 0 & e1 \in [-\infty, 2] \\ -2 + e1 & e1 \in [2, 3] \\ 1 & e1 \in [3, \infty] \end{cases} \tag{6-11}$$

The membership functions for e2 (horizontal axis is for e2)

$$u21 = \begin{cases} 0 & e2 \in [-40, \infty] \\ -8 - e2/5 & e2 \in [-45, -40] \\ 1 & e2 \in [-\infty, -45] \end{cases} \tag{6-12}$$

$$u22 = \begin{cases} 1 - |e2 + 40|/5 & e2 \in [-45, -35] \\ 0 & \text{otherwise} \end{cases} \tag{6-13}$$

$$u23 = \begin{cases} 1 - |e2 + 35|/5 & e2 \in [-40, -30] \\ 0 & \text{otherwise} \end{cases} \tag{6-14}$$

$$u24 = \begin{cases} 1 - |e2 + 30|/5 & e2 \in [-35, -25] \\ 0 & \text{otherwise} \end{cases} \tag{6-15}$$

$$u25 = \begin{cases} 1 - |e2 + 25|/5 & e2 \in [-30, -20] \\ 0 & \text{otherwise} \end{cases} \tag{6-16}$$

$$u26 = \begin{cases} 1 - |e2 + 20|/5 & e2 \in [-25, -15] \\ 0 & \text{otherwise} \end{cases} \tag{6-17}$$

$$u27 = \begin{cases} 1 - |e2 + 15|/5 & e2 \in [-20, -10] \\ 0 & \text{otherwise} \end{cases} \tag{6-18}$$

$$u28 = \begin{cases} 1 - |e2 + 10|/5 & e2 \in [-15, -5] \\ 0 & \text{otherwise} \end{cases} \tag{6-19}$$

$$u29 = \begin{cases} 1 - |e2 + 5|/5 & e2 \in [-10, 0] \\ 0 & \text{otherwise} \end{cases} \tag{6-20}$$

$$u210 = \begin{cases} 1 - |e2|/5 & e2 \in [-5, 5] \\ 0 & \text{otherwise} \end{cases} \tag{6-21}$$

$$u211 = \begin{cases} 1 - |e2 - 5|/5 & e2 \in [0, 10] \\ 0 & \text{otherwise} \end{cases} \tag{6-22}$$

$$u212 = \begin{cases} 1 - |e2 - 10|/5 & e2 \in [5, 15] \\ 0 & \text{otherwise} \end{cases} \tag{6-23}$$

$$u213 = \begin{cases} 1 - |e2 - 15|/5 & e2 \in [10, 20] \\ 0 & \text{otherwise} \end{cases} \tag{6-24}$$

$$u214 = \begin{cases} 1 - |e2 - 20|/5 & e2 \in [15, 25] \\ 0 & \text{otherwise} \end{cases} \tag{6-25}$$

$$u215 = \begin{cases} 1 - |e2 - 25|/5 & e2 \in [20, 30] \\ 0 & \text{otherwise} \end{cases} \quad (6\text{-}26)$$

$$u216 = \begin{cases} 1 - |e2 - 30|/5 & e2 \in [25, 35] \\ 0 & \text{otherwise} \end{cases} \quad (6\text{-}27)$$

$$u217 = \begin{cases} 1 - |e2 - 35|/5 & e2 \in [30, 40] \\ 0 & \text{otherwise} \end{cases} \quad (6\text{-}28)$$

$$u218 = \begin{cases} 1 - |e2 - 40|/5 & e2 \in [35, 45] \\ 0 & \text{otherwise} \end{cases} \quad (6\text{-}29)$$

$$u219 = \begin{cases} 0 & e2 \in [-\infty, 40] \\ -8 + e2/5 & e2 \in [40, 45] \\ 1 & e2 \in [45, \infty] \end{cases} \quad (6\text{-}30)$$

And the idea of learning process in ANN is also applied in the control algorithm. It can modify the fuzzy inference close to the perfect point. The fuzzy inference for the new method with initial input is shown in Table 6-1:

Table 6-1

Fuzzy rules for fuzzy neural network with initial input

	U11	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**
U21	-1450	-1400	-1350	-1300	-1250	-1200	-1150
U22	-1350	-1300	-1250	-1200	-1150	-1100	-1050
U23	-1100	-1050	-1000	-910	-890	-850	-800
U24	-1050	-1000	-950	-900	-850	-800	-750

U25	-750	-700	-650	-600	-550	-500	-450
U26	-1000	-950	-900	-250	-200	-150	-100
U27	-160	-140	-120	-100	-80	-60	-40
U28	-130	-110	-90	-70	-50	-30	-10
U29	-90	-70	-50	-30	-10	10	20
U210	-30	-20	-10	0	10	20	30
U211	-20	-10	10	30	50	70	90
U212	10	30	50	70	90	110	130
U213	40	60	80	100	120	140	160
U214	100	150	200	250	900	950	1000
U215	450	500	550	600	650	700	750
U216	750	800	850	900	950	1000	1050
U217	800	850	890	910	1000	1050	1100
U218	1050	1100	1150	1200	1250	1300	1350
U219	1150	1200	1250	1300	1350	1400	1450

The inference table will be modified by the learning process to improve the control performance.

Fig. 6-5 shows the improved result.

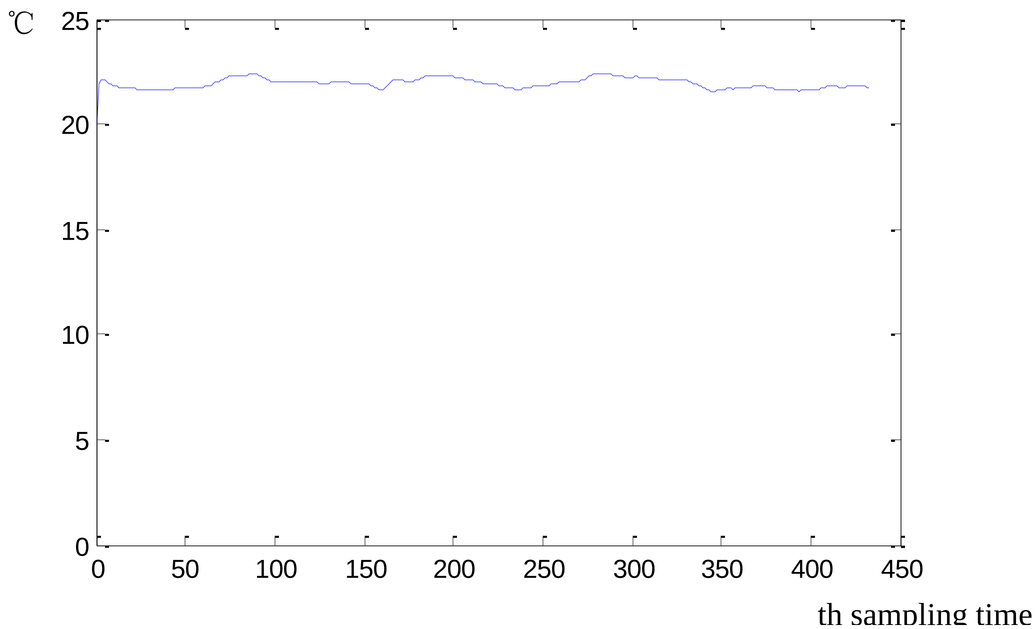

Fig. 6-5 Result for fuzzy logic with ANN

In the Fig. 6-5, the result for temperature control is improved. For the little peak at the beginning, the reason is that the initial input is chosen randomly so that the temperature in the wall is relative too high in winter. This is set for math theory as a big disturbance to check the performance of controller stability.

It is seen that the influence from wall with high temperature is eliminated quickly. And the rest result is close to 22℃ with small error. These results prove that the FNN controller is good for temperature control.

It proves that the fuzzy logic with ANN is a good method to control temperature. The next fig. 6-6 shows the power used in the heat pump.

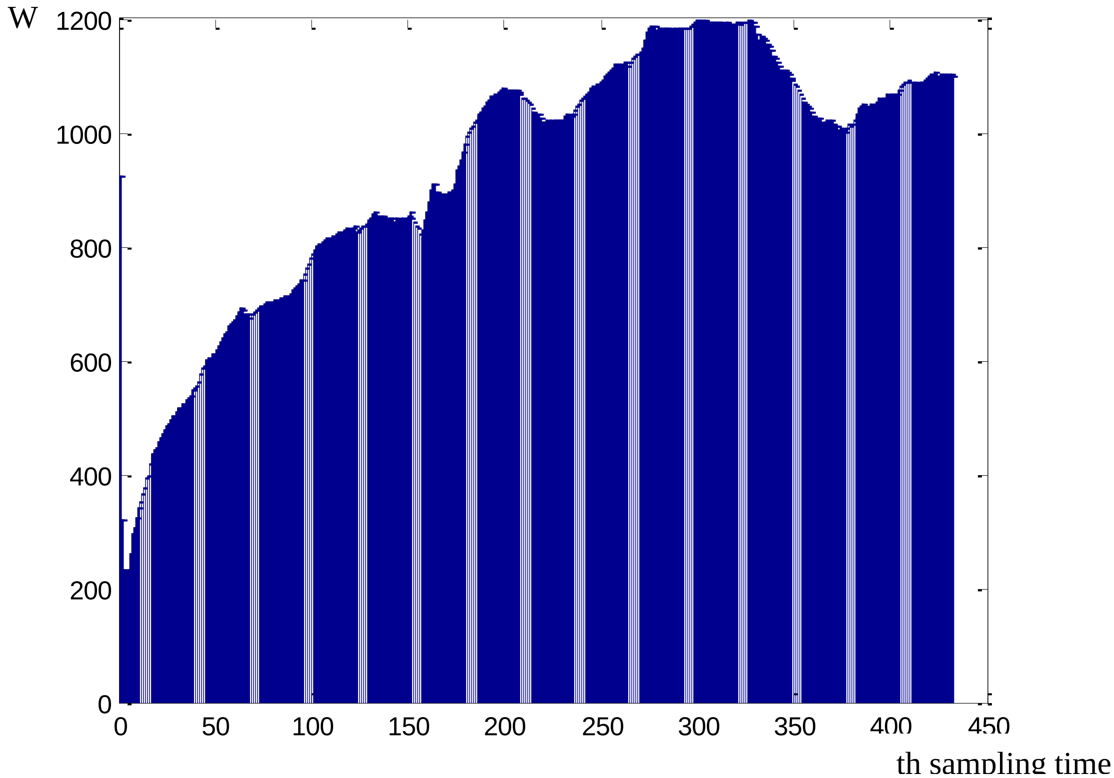

Fig. 6-6 power used in the heat pump with fuzzy neural network

Chapter 7: MPC Controller

In this Chapter, the MPC controller is designed to control the indoor temperature. To control the temperature, the MPC controller provides the control signal to the heat pump after predicting the temperature state in future by using weather forecast and building model.

The target of the system for heat pump is to control the indoor temperature at the comfort level. The diagram of the heat pump system is shown in Fig. 7-1.

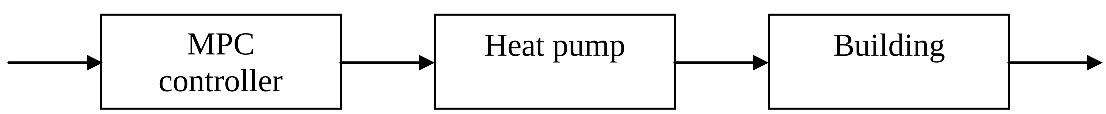

Fig. 7-1 MPC controller

The MPC controller is to calculate the supply heat with proper amount to the heat pump system in order to keep the comfort level indoor by using the weather forecast and building model. The control signal of heat is then sent to the heat pump system to provide heat. In the next step, the heat is sent to the building and it changes the temperature indoor.

7.1 MPC Controller Design

In the controller, MPC is applied to keep the temperature indoor at the comfort level. The inputs of the system are the set temperature, current temperature indoor and the temperature in wall. The temperature outside and solar radiation are the disturbances in the system model. The output of the controller is the power or heat which the heat pump needs to produce in order to change the temperature indoor.

The control strategy used can be expressed as in Fig. 7-2:

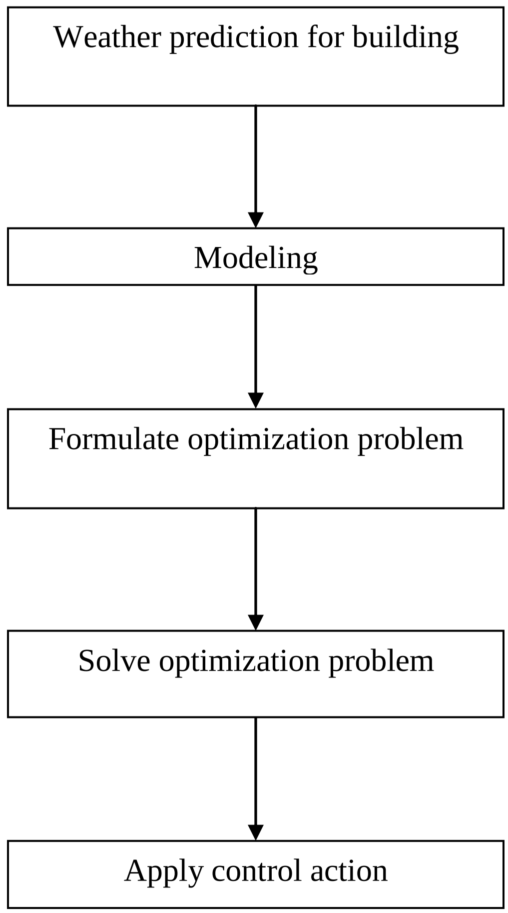

Fig. 7-2 Flow chart of temperature MPC

The first step of MPC is to get the weather forecast for the building; the forecast is for temperature outside and solar radiation and so on. The next step is building the model for heat transformation in the system. And it also needs some data in the building such as heat capacity in the building and the coefficient of heat transformation between different places. The third step is to formulate the optimization problem. In the problem, there should be optimization equation, cost function and relative constraints. Then the problem should be solved with some software in order to get the power for heat pump to produce in the future sampling instant. At last, heat pump actually produces the heat to the building.

7.2 Weather prediction

Temperature forecast

In MPC, the forecast may be the most important part because the quality of forecast determines the performance of the control system if the model of building is good enough. In the thesis, there are two forecasts as shown in Fig. 7-3 and Fig. 7-4. One is for the temperature outside and the other one is for solar radiation. They are from JRibal Environmental eXchange network. And the price signal is the local marginal price from PJM. The period time used in the experiment is from 12/29/2013 to 12/31/2013. Because the data is for winter, so the temperature is low and the target of heat pump is to provide heat to the building.

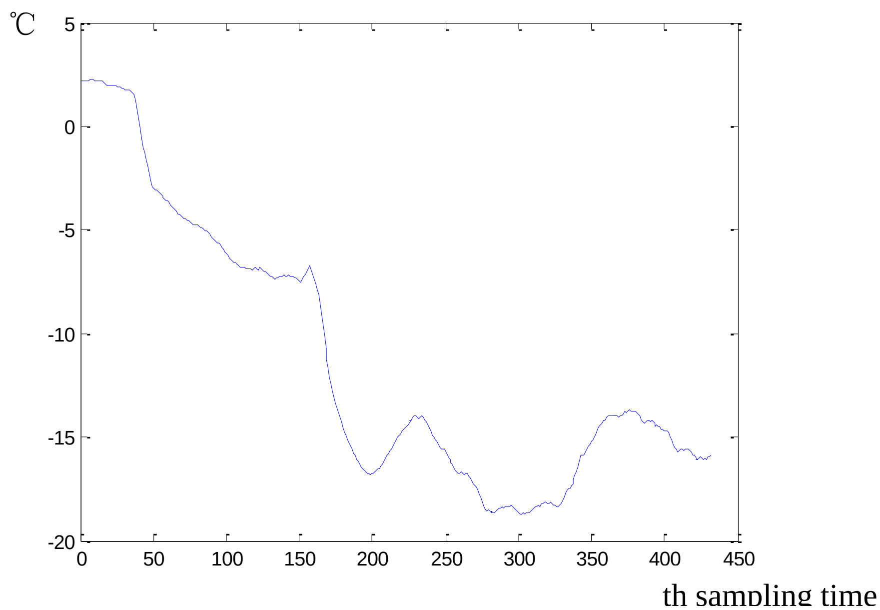

Fig. 7-3 Temperature forecast from 12/29/2013 to 12/31/2013

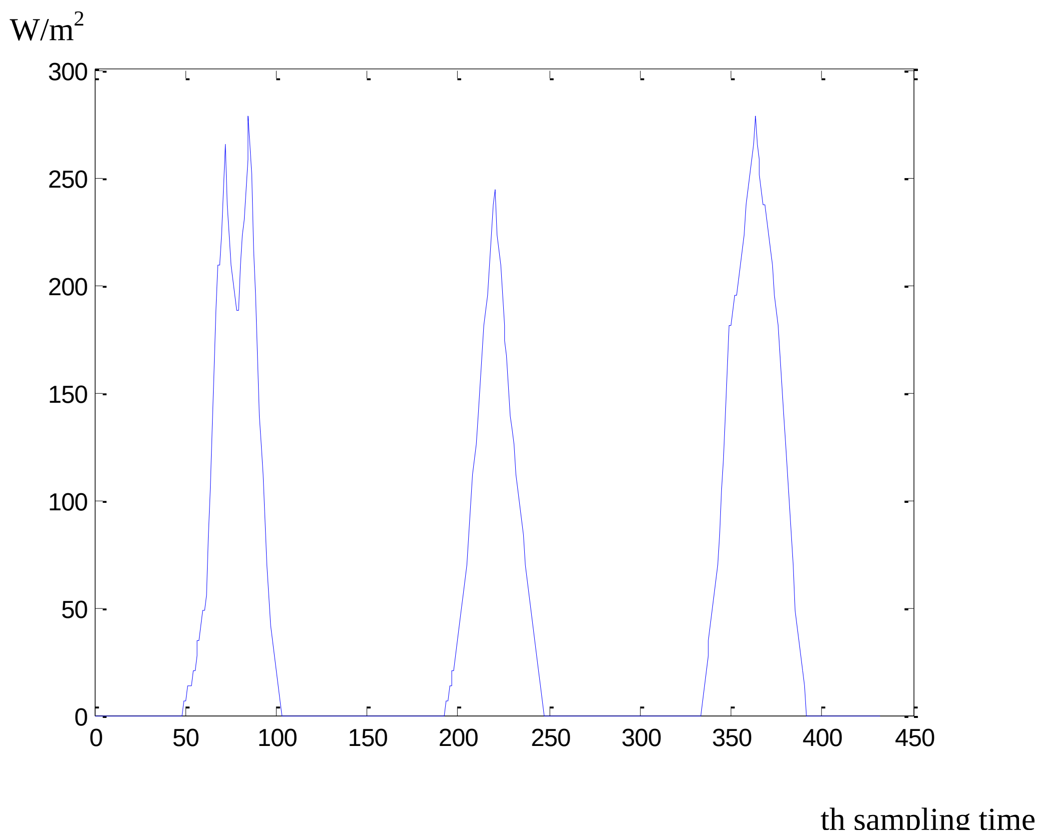

Fig. 7-4 Solar irradiation forecast from 12/29/2013 to 12/31/2013

In the experiment, the data for temperature outside and solar radiation is used as the disturbance in the system. There are some assumptions in the model: no wind influence for heat; no influence from the people activities in the room. So in the forecast part, there is no data for wind and the influence from human activities in the building. The reason is to build the building model easily.

7.3 Modeling of MPC

Building model data

Before the model of building is built, the relative data of building should be collected such as the heat capacity of the building, the coefficient and rate of heat transformation between different places.

Model building

In the building model section, the model used in the thesis has been introduced. The heat balance model in the room can be expressed as:

$$\alpha W - UA_{indoor-wall} * (T_{indoor} - T_{wall}) + \beta P_s = C_{building} T_{bc} \tag{7-1}$$

$$UA_{indoor-wall} * (T_{indoor} - T_{wall}) + \gamma P_s - UA_{wall-outside} * (T_{wall} - T_{outside}) = C_{wall} T_{wc} \tag{7-2}$$

The continuous-time state space model is:

$$\dot{x} = Ax + Bu + Ed \tag{7-3}$$

$$y = Cx \tag{7-4}$$

And in the experiment, the state space model is converted to a discrete-time model which can be expressed as:

$$x_{k+1} = A_d x_k + B_d u_k + E_d d_k \tag{7-5}$$

$$y_k = C_d x_k \tag{7-6}$$

Where

X is the temperature states vector for the temperature indoor and the temperature in wall $[T_{indoor}\ T_{wall}]^T$, k means the kth sampling instant, u is the power used in heat pump to provide heat to the building, and d is the vector for disturbances about the temperature outside and the solar radiation $[T_{outside}\ P_s]^T$ And y is the output for controlled variable $y = T_{indoor}$.

A, B, E and C are the matrices for the coefficients shown below:

$$A = \begin{bmatrix} \frac{-UA_{indoor-wall}}{C_{building}} & \frac{UA_{indoor-wall}}{C_{building}} \\ \frac{UA_{indoor-wall}}{C_{wall}} & \frac{-UA_{indoor-wall}-UA_{wall-outside}}{C_{wall}} \end{bmatrix} \tag{7-7}$$

$$B = \begin{bmatrix} \frac{\alpha}{C_{building}} \\ 0 \end{bmatrix} \tag{7-8}$$

$$E = \begin{bmatrix} 0 & \frac{\beta}{C_{building}} \\ \frac{UA_{wall-outside}}{C_{wall}} & \frac{\gamma}{C_{wall}} \end{bmatrix} \tag{7-9}$$

$$C = [1\ 0] \tag{7-10}$$

7.4 Optimization Problem

With the prediction for the future outputs using the state space model, the optimization problem is to minimize the cost for energy consumption in order to keep the comfort level indoor.

Cost function

$$\min J = \textstyle\sum_{k\in N} \tau_k u_k \qquad k \in N \tag{7-11}$$

$$x_{k+1} = A_d x_k + B_d u_k + E_d d_k \quad k \in N \tag{7-12}$$

$$y_k = C_d x_k \qquad k \in N \tag{7-13}$$

$$u_{min} \le u_k \le u_{max} \qquad k \in N \tag{7-14}$$

Where

N is the prediction horizon. And it should be big enough to reduce the discrepancies between the open loop and closed loop control methods. However, big horizon means the large computation and the high risk in the forecast because the forecast is not perfect and the error becomes bigger when the time is long. The cost coefficient $\boldsymbol{\tau}$ is the electricity prices which are also from the forecast. The MPC cost function consists some constraints on power in heat and the comfort level.

7.5 Experiments results

In the section, the software Matlab is also used to simulate the MPC process. The target is to do the temperature control for 12/29/2013-12/31/2013. The location data used is from Akwesasne in New York State. All the environmental data are from JRibal Environmental eXchange network. And the price signal is the local marginal price from PJM. Heat pump is used to provide heat into the room or absorb heat from the room. The limit of heat pump is the same as that in above chapters. The time interval used in the experiments is ten minutes. And the comfort temperature is 22℃ as the set point.

The first situation is when the forecast is very well. The result is shown in Fig. 7-5:

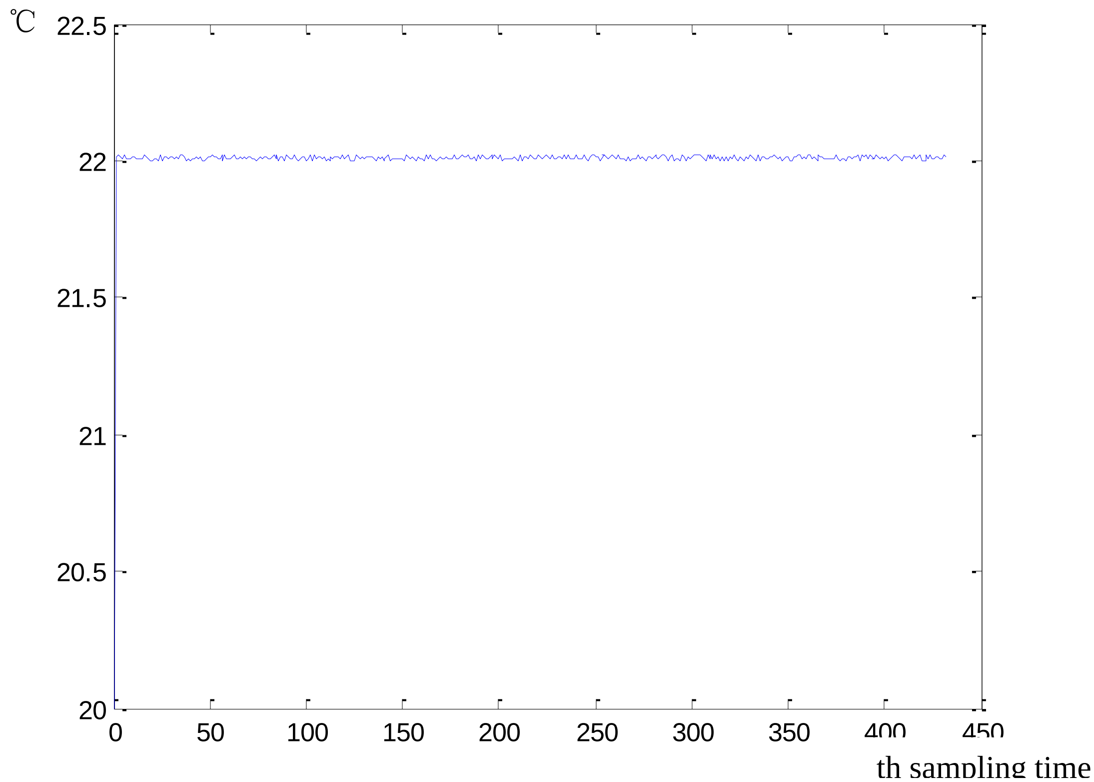

Fig. 7-5 MPC control with good forecast

In the above fig, it is can be seen that the result is very good by using MPC. The temperature is very close to the set point. For the big disturbance mentioned in FNN, there is no influence for MPC control because the temperature in wall is concerned in the model built in MPC.

For above situation, the forecast is very good. However the real forecast is not good so the result can’t be good as above. In addition, when the forecast is longer, the error is bigger.

The Fig. 7-6 shows the result when the forecast is updated every 12 hours.

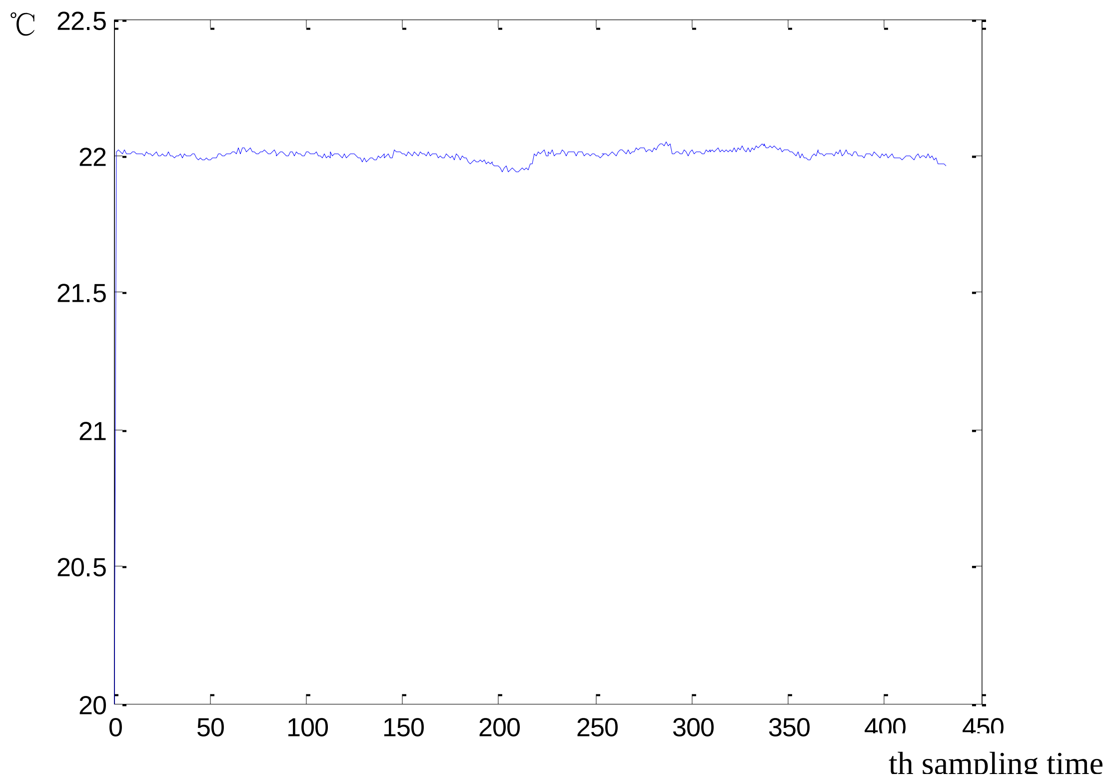

Fig. 7-6 MPC result with real forecast (update every 12 hours)

In Fig. 7-6, the result is better and the difference is becoming less. So MPC is based on the quality of forecast.

Fig. 7-7 shows the power used in heat pump in MPC control period.

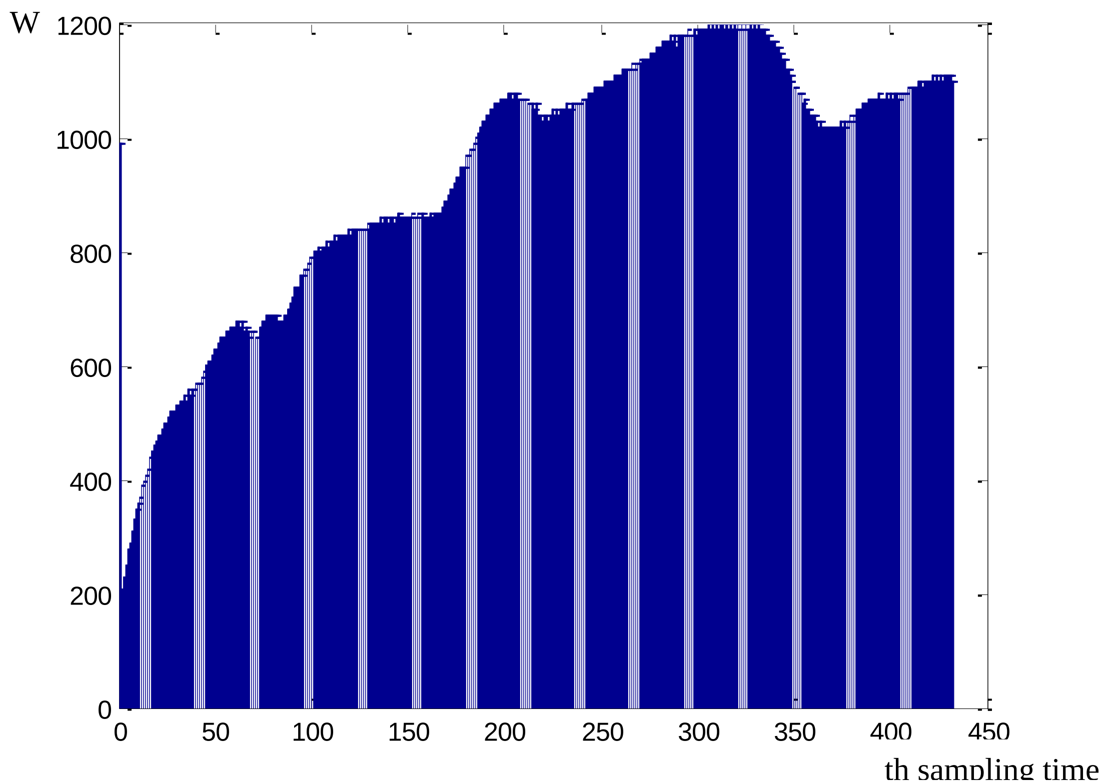

Fig. 7-7 Power used in MPC

Chapter 8: Optimization with GA

In practical control systems, the system with good control performance and low cost will be applied finally. In the thesis, fuzzy logic with ANN and MPC are both good for the performance and cost. But it is better if the cost can be saved more, and now many researchers are working with it.

For MPC, there is a method to save more money if there is a good energy storage system in the building. MPC can predict the power used in future, and if there is a energy storage system which can store the energy for future, the working period can be moved to the time with lower price to save more cost.

GA is a good method to optimize the working period with different price signal. GA can solve many optimization problems with the process of crossover and mutation in chromosomes.

8.1 Fitness Function and Constraints

The cost function in MPC can be used as the fitness function shown below in GA to solve the optimization problem.

$$\text{Fitness function} = \sum_{k \in N} \tau_k {u'}_k \qquad k \in N \tag{8-1}$$

Constraints:

$$u_{min} \le {u'}_k \le u_{max} \qquad k \in N \tag{8-2}$$

In each 12 hour period

$$\sum u'_k = \sum u_k \qquad k \in N \qquad (8\text{-}3)$$

Where

τ_k is the price signal at kth sample time, u'_k is the optimized power with GA. And for each 12 hours, the total amount of used energy is not changed.

8.2 Experiments Results

During MPC in the above section, every 12 hours is one working period. Therefore MPC can predict the power for 12 hours once. So in this section, GA can optimize the working time for every 12 hours. The results are shown in fig.8-1 to fig. 8-12. And there are 6 results for the 6 periods in MPC.

Fig. 8-1 shows the original power used in MPC in the first 12 hours. And Fig. 8-2 shows the result with GA for the first period.

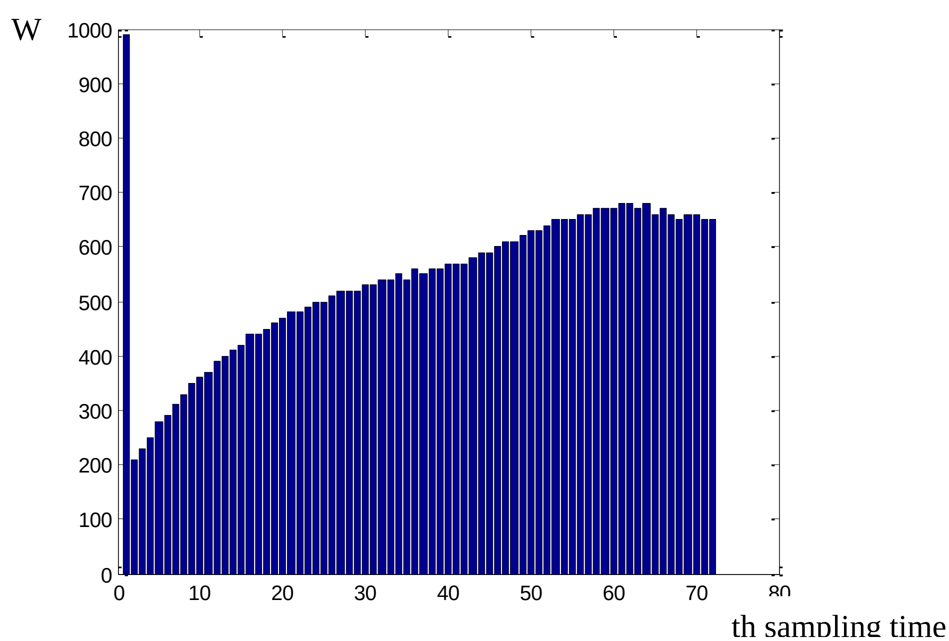

Fig. 8-1 Power for the first period in MPC

With the price from PJM, the cost is $0.183741.

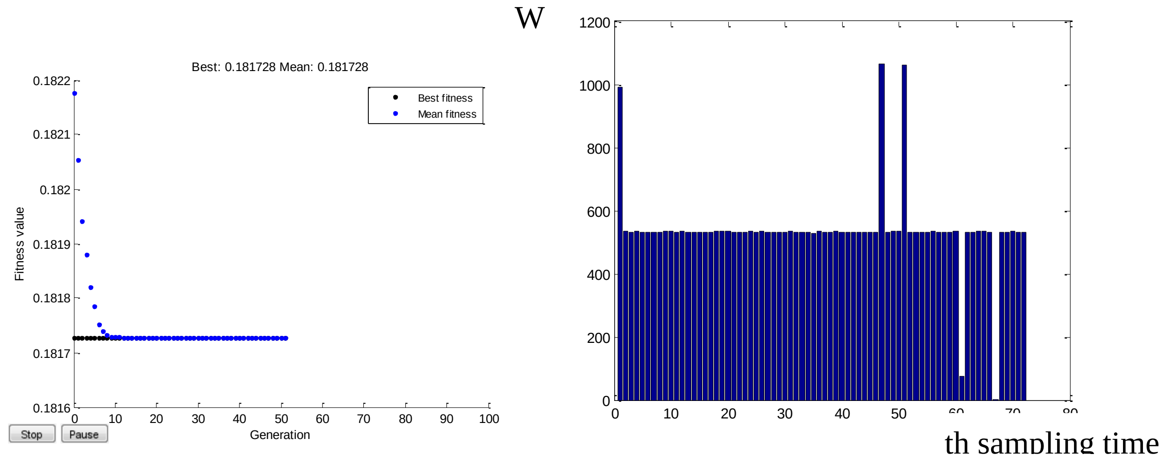

Fig. 8-2 GA result and the changed power for the first period

The cost with GA for the first period is $0.181472 and it saves about 1.23%.

Fig. 8-3 shows the original power used in MPC in the second 12 hours. And Fig. 8-4 shows the result with GA for the period.

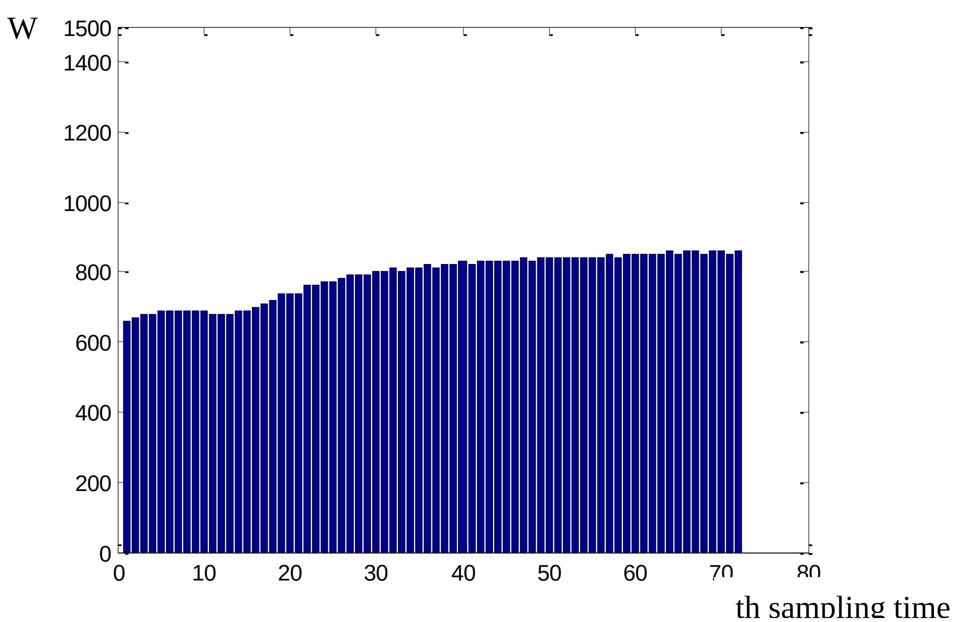

Fig. 8-3 Power for the second period in MPC

With the price from PJM, the cost is $0.319716.

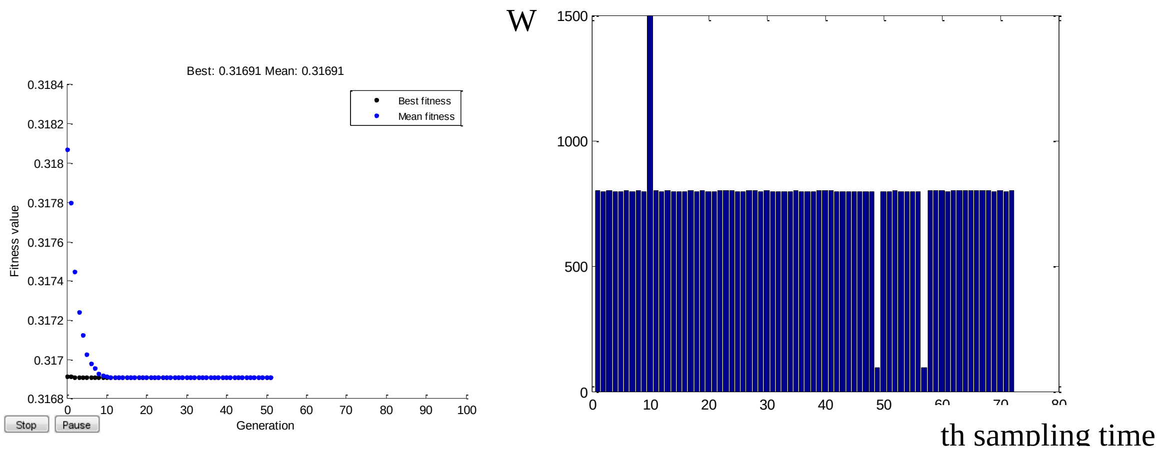

Fig. 8-4 GA result and the changed power for the second period

The cost with GA for the period is $0.31691 and it saves about 0.88%.

Fig. 8-5 shows the original power used in MPC in the third 12 hours. And Fig. 8-6 shows the result with GA for the period.

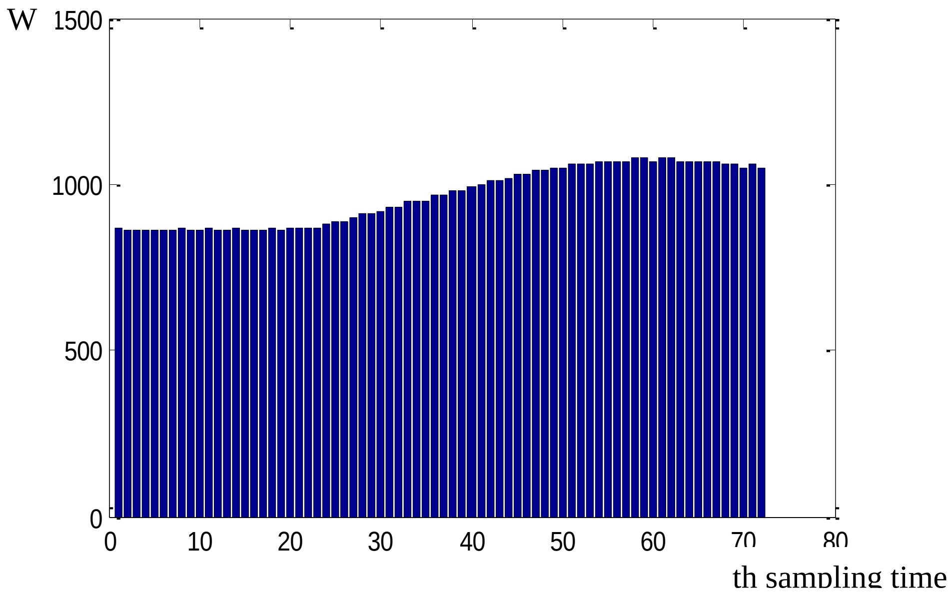

Fig. 8-5 Power for the third period in MPC

With the price from PJM, the cost is $0.388239.

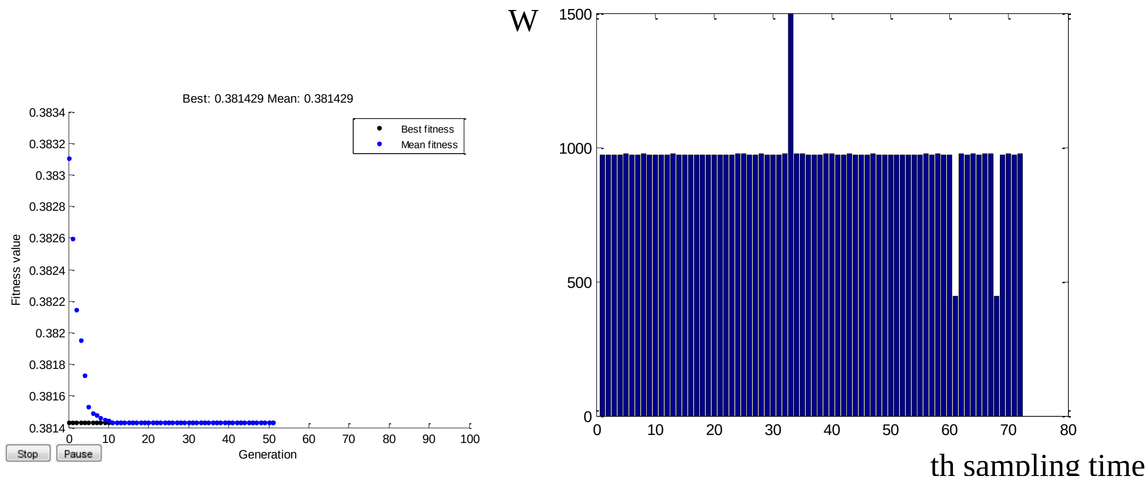

Fig. 8-6 GA result and the changed power for the third period

The cost with GA for the period is $0.381429 and it saves about 1.75%.

Fig. 8-7 shows the original power used in MPC in the fourth 12 hours. And Fig. 8-8 shows the result with GA for the period.

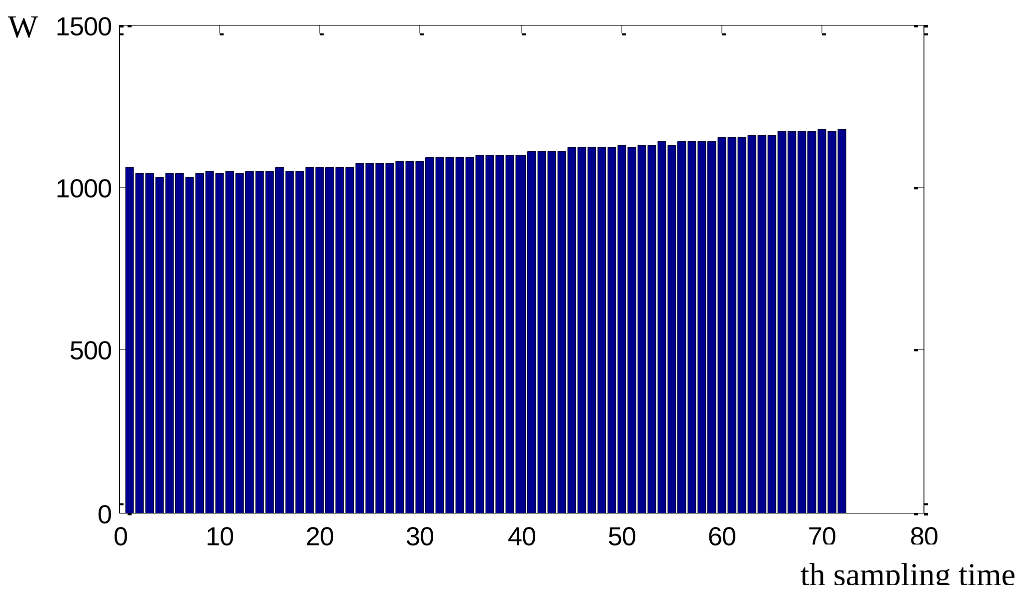

Fig. 8-7 Power for the fourth period in MPC

With the price from PJM, the cost is $0.59718.

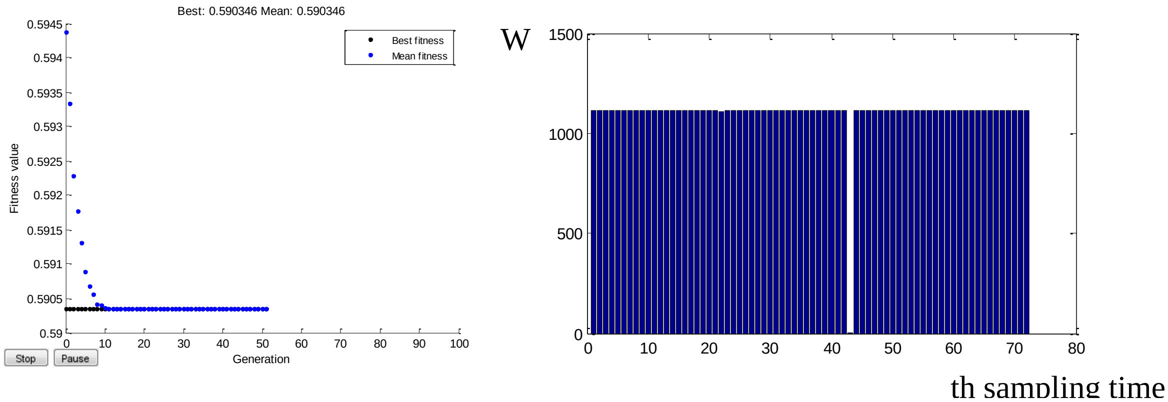

Fig. 8-8 GA result and the changed power for the fourth period

The cost with GA for the period is $0.590346 and it saves about 1.14%.

Fig. 8-9 shows the original power used in MPC in the fifth 12 hours. And Fig. 8-10 shows the result with GA for the period.

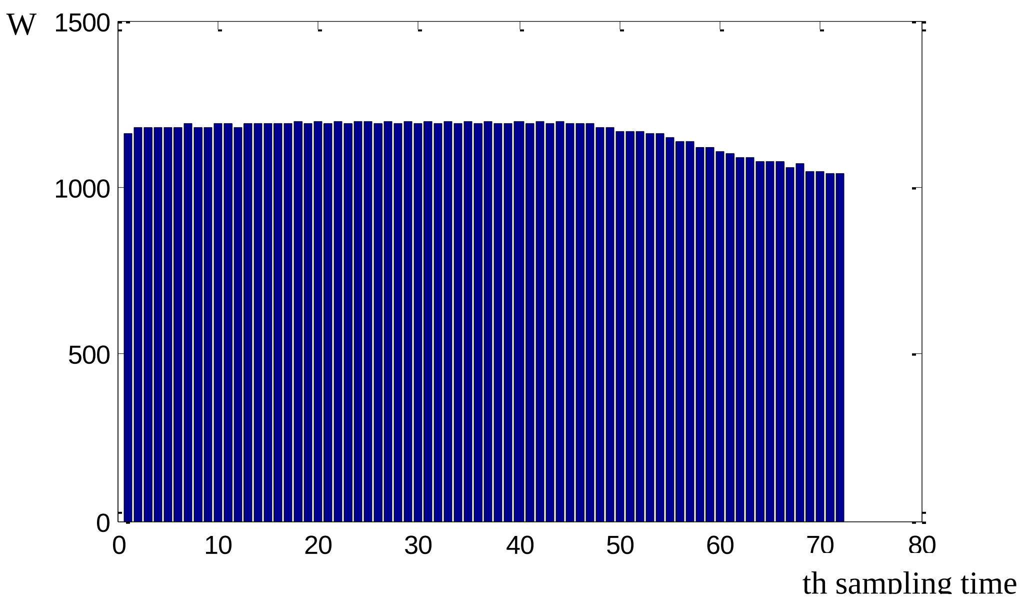

Fig. 8-9 Power for the fifth period in MPC

With the price from PJM, the cost is $0.492064.

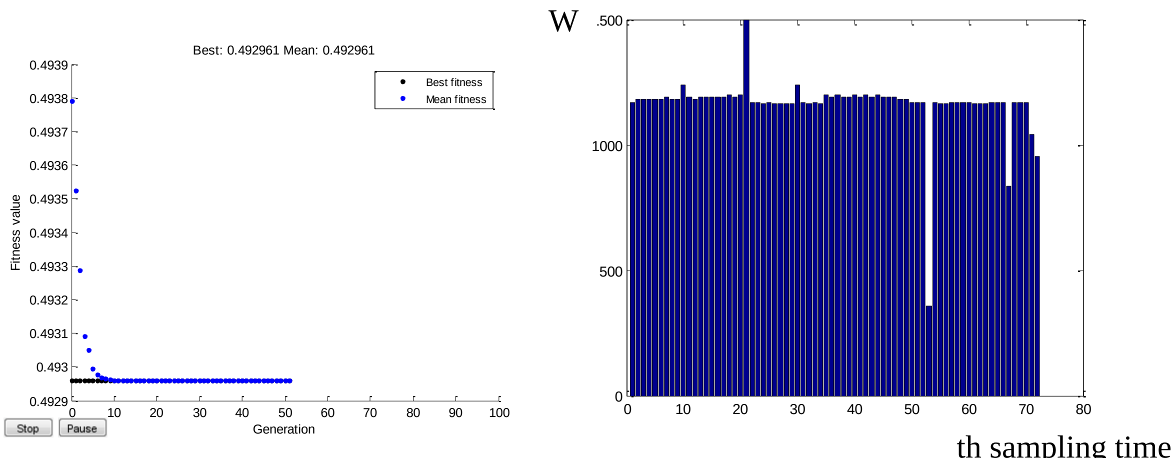

Fig. 8-10 GA result and the changed power for the fifth period

The cost with GA for the period is $0.491523 and it saves about 0.11%.

Fig. 8-11 shows the original power used in MPC in the sixth 12 hours. And Fig. 8-12 shows the result with GA for the period.

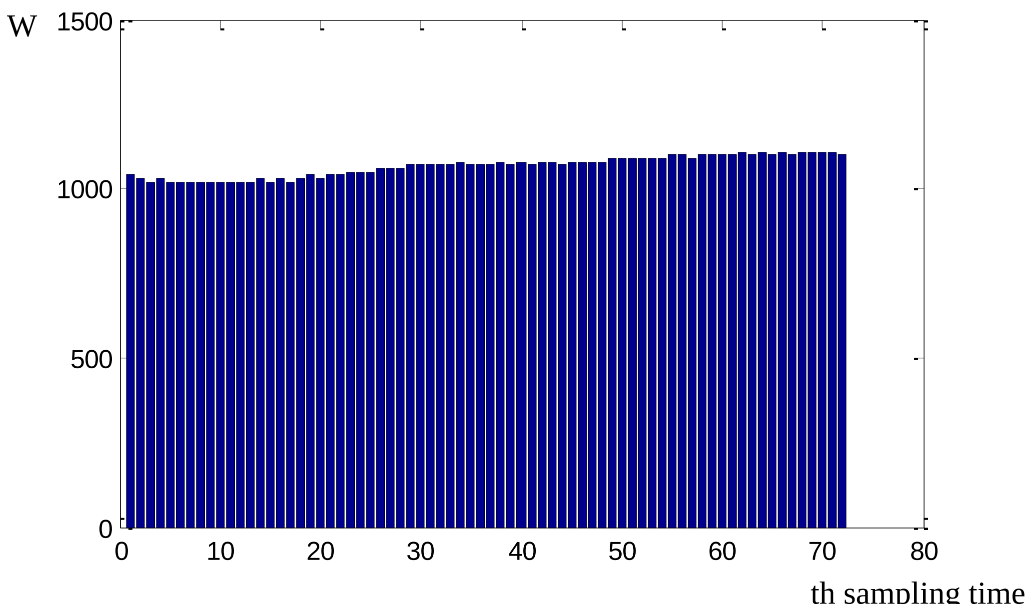

Fig. 8-11 Power for the sixth period in MPC

With the price from PJM, the cost is $0.495459.

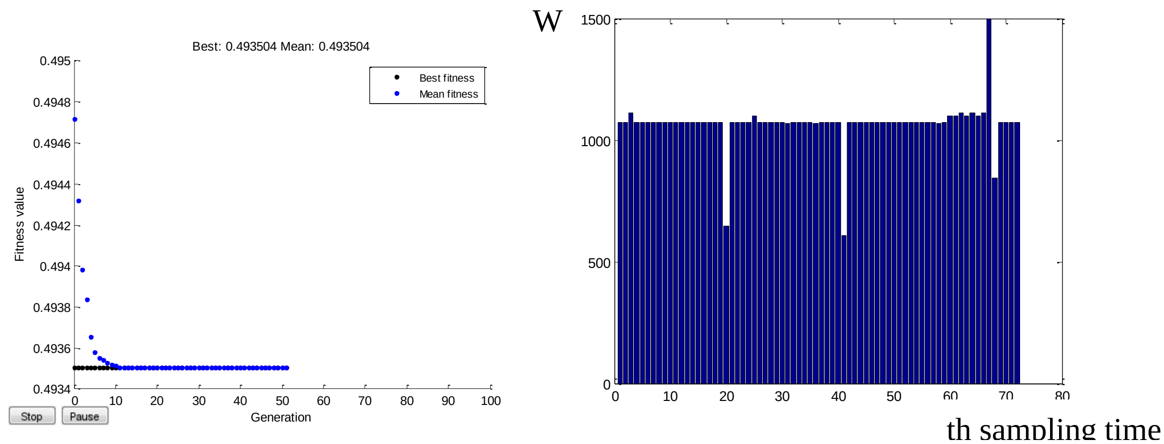

Fig. 8-12 GA result and the changed power for the sixth period

The cost with GA for the period is $0.493854 and it saves about 0.32%.

Total cost with GA is $2.4555. And the original total cost in MPC is $2.4764.

In summary, the total cost in MPC can be saved by 0.84% with GA. The saving performance is not very obvious and the reason is that the control is in the winter with very low temperature. That means the original power is high for each hour so that there is no big space for moving the power at the time with low price. GA may not achieve the best result and it gets different result, however it leads to close the best point. It is shown that MPC with GA is a good method to control the temperature.

Chapter 9: Summary

In the thesis, there are two methods to control the temperature in room. One is fuzzy logic with neural network and another one is MPC with GA. The results of both methods are good, so these two methods are good for temperature control.

The first method is fuzzy logic control. There are some fuzzy sets, membership functions and fuzzy inference designed in the thesis. They are used to achieve the control behavior in order to regulate the temperature in the room.

This method is used with the human beings experience. So there are advantages when human beings are involved. For example in the thesis, the temperature is important for people and human beings have good feelings about the comfort temperature, therefore it is easy for designer when build the fuzzy sets for inputs. The fuzzy logic is mostly used when the system does not need very critical control because the performance does not degrade very much even when the parameters are not optimal.

In summary, the advantages of fuzzy logic are shown below:

- The fuzzy logic takes a combination of numerics and linguistics. And it is better than the pure numerical method or pure linguistic method
- The fuzzy logic can use approximate data, so it is easy to get the data
- The fuzzy logic do not need many data to build the fuzzy sets

- The fuzzy logic is easy to understand for people
- The fuzzy logic is usually robust even it is not very sensitive to the changes
- The reasoning process is simple, so the computing time is saved. It is good in the real time systems
- It is shorter to get results when using fuzzy logic than other common methods
- The fuzzy logic is easily used with other common methods
- The fuzzy logic does not need to build model for the system

There are also some disadvantages shown below:

- When there is not enough mathematical description, the fuzzy logic is hard to use.
- Manual tuning is necessary even when the system is similar. One fuzzy logic design is usually used for only one system.
- The control of fuzzy logic is not accurate. It can’t be used with highly restricted conditions

When using the fuzzy logic to control the temperature in the thesis, the result is ok but not very good. To improve the result, a new fuzzy logic with neural network is used.

The neural network is used as the tool of fuzzy logic in order to improve the control design. With the structure of neural network, the design of fuzzy logic is easy to build. And the process of weight in the neural network can be used in the fuzzy logic to realize the learning process. If the result is not fit the trend, the control data is then changed by using the idea of adjusting weight in neural network. Therefore the result of temperature control is improved. But if there is a big disturbance, FNN can't handle it very well because there is no model for it so that the disturbance is not concerned in the controller.

The next method used in the thesis is MPC. In the temperature control, MPC is used to predict the power used in the prediction horizon. First develop a model of temperature in the room, and then at the time t, predict the output temperature in the future. Next the control signal is calculated and then sent to the heat pump to provide heat or absorb heat. At the next interval, repeat the procedure from the prediction of temperature.

In summary, MPC builds a mathematical model to simulate any process. It predicts the behavior of system with inputs and it is great to perfect the system to the desired output. Common controllers are based on error from the set point but for MPC it is based on the set point, constraints and optimization.

There are also some disadvantages for MPC shown below:

- The model in MPC is for only one system. It can't be used for other systems.
- MPC needs a lot of number of model coefficients.
- Some MPCs can't deal with input disturbances.
- If the prediction is not correct, the performance is bad.
- The forecast decides the performance of MPC. If the forecast is bad, the result of MPC is poor.

To control the temperature, MPC is very well in the thesis and the amount of power is optimized. However, the cost problem can be optimized more if there is a good energy storage system. GA is a good method to solve the optimization problems. For the advantages of GA, it can solve optimization problems if they can be described with chromosome encoding. It is not based on the error. And it is easy to understand as the fuzzy logic. So GA is used to improve the optimization problem of cost saving in MPC. And the result is that cost of MPC is reduced.

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