Intelligent control and optimization for heating, ventilating, and air-conditioning systems

Guo, Chengyi

2007

Guo, C. (2007). Intelligent control and optimization for heating, ventilating, and air-conditioning systems. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/3487>

<https://doi.org/10.32657/10356/3487>

Nanyang Technological University

Downloaded on 26 Apr 2023 23:23:48 SGT

Intelligent Control and Optimization for Heating, Ventilating, and Air- Conditioning Systems

Guo Chengyi

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2007

Statement of Originality

I hereby certify that the content of this thesis is the result of work done by me and has not been submitted for a higher degree to any other University or Institution.

Date

Guo Chengyi

Acknowledgements

I would first like to thank my supervisor, Dr. Song Qing, for all the advice he has dispensed over the years. During the course of this study, he always took an active interest in my work and helped me to channel my sometimes very scattered thoughts in the right direction. Thank you, Dr. Song, for all your guidance and support.

I then take this chance to express my gratitude to Dr. Cai Wenjian for his enthusiastic encouragement and invaluable guidance.

Special thanks are also dedicated to my colleagues and technicians at Process and Instrumentation Laboratory for their help and encouragement during the course of my study.

Lately thanks to my friends who have made me stay in Singapore memorable. Last but definitely not least, I want to thank my parents and my wife. Without their steadfast love and understanding, I could never have achieved this goal.

Summary

This thesis presents the development of intelligent control and optimization technologies for Heating, Ventilating, and Air-Conditioning (HVAC) systems.

The HVAC industry expects the automation and control systems to perform well through the years without the requirement to re-tune the system. In this thesis, a novel neural network assisted control scheme is proposed. By taking advantage of neural network technology, the deficiency of traditional fixed controller (PID type) can be compensated to certain degree and better performance is achieved in term of set point tracking performance and disturbance rejection ability. Another important contribution of this thesis is that two robust neural network training algorithms are proposed. The neural network is trained in an online fashion and convergence of the network weights is guaranteed. For a neural network based control system, the stability issue is always the main concern in term of the closed control loop. In this thesis, we implemented the design and stability analysis for the neural controllers based on the conic sector theory. The viability and effectiveness of the proposed control approach is demonstrated with a series of real time experiments on an experimental HVAC system.

For the optimization strategy of HVAC system, A hybrid Genetic Algorithm (GA)/ Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm with its application in the condense water loop is presented in this thesis. Based on the predetermined system analysis models, first, the GA is employed to obtain the optimization results for both continuous and discrete variables offline. Considering the existents of the mismatch between the identified model and the real system, further optimization for the continuous variables is carried out using the SPSA algorithm in an online fashion. Testing on an experimental HVAC system shows that, with the hybrid

GA/SPSA optimization strategy, the optimization problem for condenser water loop of HVAC system can be solved in a more effective way and the operating cost of the condenser water loop can be substantially reduced compared with conventional operation strategy.

Table of Contents

Acknowledgements

Summary

List of Figures

List of Tables

Nomenclature in Chapter 6

Chapter 1 Introduction	1
1.1 Motivation	1
1.2 Objectives	2
1.3 Major Contributions	3
1.4 Organization of the Thesis.....	4
Chapter 2 Background and Previous Work.....	6
2.1 Overview of Building HVAC System.....	6
2.2 Review of HVAC Control Technology.....	8
2.3 Review of Neural Network for Control Application.....	10
2.4 Review of HVAC System Optimization.....	15
Chapter 3 Robust NN Assisted PI Controller for VAV System	17
3.1 Introduction	17
3.2 Neural Network Assisted PI control Scheme.....	18
3.3 Adaptive Dead Zone Training Algorithm.....	21
3.4 Stability Analysis.....	23

3.5 Application of the NNAPI Controller in VAV System	33
3.5.1 Overview of VAV Air-conditioning System	33
3.5.2 Experimental VAV Air-conditioning System	35
3.5.3 Experimental Studies.....	37
3.6 Conclusion	43
Chapter 4 SPSA Based Neural Controller for VAV System	45
4.1 Introduction	45
4.2 Neural Network Control Scheme.....	46
4.3 SPSA Based Training Algorithm	48
4.4 Stability Analysis.....	50
4.5 Experimental Studies	61
4.5.1 Experiment 1	61
4.5.2 Experiment 2	65
4.5.3 Experiment 3.....	67
4.6 Conclusion	70
Chapter 5 NN Assisted Cascade Control System for AHU System	71
5.1 Introduction	71
5.2 Description of AHU Control System	73
5.3 Neural Network Assisted Cascade Control Scheme	76
5.4 Simulation Study.....	77
5.5 Real-time Experiments and Results	79
5.5.1 Experiment Setup	79
5.5.2 Experiment 1	80
5.5.3 Experiment 2.....	84
5.6 Conclusion	86
Chapter 6 Optimization for Condenser Water Loop of HVAC System Using a Hybrid GA/SPSA Strategy	87
6.1 Introduction	87
6.2 Problem Formulation	91
6.3 Model Based Offline Optimization with GA	96

6.4 Online Optimization with SPSA	101
6.5 Experimental Studies	105
6.6 Conclusion	109
Chapter 7 Conclusions and future work	110
7.1 Conclusions	110
7.2 Recommendations for Future Work	111
 Author's Publication	 113
References	115

List of Figures

2.1 The schematic of a typical building HVAC system	7
2.2 Multilayer neural network	11
3.1 Structure of the control scheme	20
3.2 Equivalent error feedback system	24
3.3 Equivalent error feedback system	26
3.4 The region in which the K_I, K_P can be selected to make the H_2 satisfy the SPR condition	32
3.5 A Typical VAV air-conditioning system	34
3.6 Measurement and control apparatus of VAV air-conditioning system.....	35
3.7 Components of the supply air pressure control loop.....	36
3.8 VAV supply air pressure control loop	36
3.9 Performance of PI controller under different VAV damper status in experiment 1.....	39
3.10 Performance of NNAPI controller under different VAV damper status in experiment 1.....	39
3.11 Performance comparison for PI and NNAPI controller in experiment 2.....	41
3.12 Performance comparison for PI and NNAPI controller in experiment 3.....	43
4.1 Structure of the control scheme	47
4.2 The equivalent error feedback systems using the conic sector condition.....	51
4.3 Performance of PI controller under different VAV damper status.....	63
4.4 Performance of SPSA based neural controller under different VAV damper status	64
4.5 Performance of PI controller in Experiment 2.....	66
4.6 Performance of SPSA based neural controller in Experiment 2.....	66
4.7 Weight $W_{6,1}$ of the hidden layer using the BP training algorithm with a dead zone scheme.....	68

4.8 Weight $W_{6,1}$ of the hidden layer using the SPSA based training algorithm.....	68
4.9 Set point tracking performance of the neural controller trained using the BP training algorithm with a dead zone scheme	69
4.10 Set point tracking performance of the neural controller trained using the SPSA based training algorithm	69
5.1 Schematic diagram of conventional AHU control system.....	74
5.2 Block diagram of AHU's supply air temperature control.....	74
5.3 Typical chilled water distribution system	75
5.4 Schematic diagram of cascade control for supply air temperature.....	75
5.5 Block diagram of conventional cascade control	76
5.6 Block diagram of the outer control loop	76
5.7 Structure of the neural network assisted cascade control scheme.....	77
5.8 Performance of conventional cascade control	78
5.9 Performance of conventional cascade control	78
5.10 Performance of NN assisted cascade control	79
5.11 Performance of NN assisted cascade control	79
5.12 AHU control system	80
5.13 Speed of chilled water pump	82
5.14 Supply air temperature control performance of AHU in Experiment 1(Single loop PID control).....	82
5.15 Supply air temperature control performance of AHU in Experiment 1(Cascade control with PI inner loop controller and PID outer loop controller).....	83
5.16 Supply air temperature control performance of AHU in Experiment 1 (Cascade control with PI inner loop controller and NN outer loop controller).....	83
5.17 Supply air temperature control performance of AHU in Experiment 2 (Cascade control with PI inner loop controller and PID outer loop controller)	84
5.18 Supply air temperature control performance of AHU in Experiment 2 (Cascade control with PI inner loop controller and NN outer loop controller).....	85
6.1 Schematic of a typical HVAC system	88
6.2 The Performance of a Cooling Tower	92
6.3 Optimal Operating Points at Different Wet-Bulb Temperatures.....	95
6.4 Trade-offs Between Chiller Power and Fan Power	96
6.5 Implementation of the model based offline optimization using GA.....	100
6.6 Implementation of the online optimization using SPSA.....	104

6.7 Power Consumption of Chillers	106
6.8 Power Consumption of Pumps	107
6.9 Power Consumption of Fans	107
6.10 Total Power Consumption	108

List of Tables

3.1. Performance comparison for PI and NNAPI controller in experiment 1.....	40
3.2. Performance comparison for PI and NNAPI controller in experiment 2.....	42
4.1. Performance comparison (PI and SPSA based NN controller in experiment 1)...	65
4.2. Performance comparison (PI and SPSA based NN controller in experiment 2)...	67
5.1. Performance Comparison in Experiment 1.....	83
5.2. Performance Comparison in Experiment 2.....	86

Nomenclature in Chapter 6

a_1, a_2, a_3	the constant coefficients to determine Q_{rej}
b_0, b_1, b_2	the constant coefficients to determine $PLR_{adj,i}$
c	the empirical constant in Braun's model
$c_0 \dots c_5$	the constant coefficients to determine $Temp_{adj,i}$
C_{pw}	the specific heat of water under constant pressure
C_s	the derivative of saturation air enthalpy with respect to temperature
$COP_{nom,i}$	the nominal coefficient of performance of the i th chiller
$d_0 \dots d_3$	the constant coefficients for part-load operation of the pump
$e_0 \dots e_3$	the constant coefficients for part-load operation of the fan
$h_{a,in}$	the enthalpy of inlet air
$h_{s,w,i}$	the saturation air enthalpy at the temperature of inlet water
$h_{s,w,o}$	the saturation air enthalpy at the temperature of outlet water
i	the chiller number
j	the condenser water pump number
k	the cooling tower fan number
m_a	the total airflow rate of all the cooling towers
$m_{a,nom,k}$	the nominal airflow rate of the k th fan under full-load condition
$m_{a,k}$	the exact airflow rate provided by the k th operating tower fan
$m_{a,k,max}$	the maximum value of $m_{a,k}$
$m_{a,k,min}$	the minimum value of $m_{a,k}$
m_{CHW}	the water flow rate in the chilled water loop
m_w	the total water flow rate in the condenser water loop
$m_{w,k}$	the water flow rate through the k th cooling tower
$m_{w,nom,j}$	the nominal water flow rate of the j th pump under full-load condition
$m_{w,j}$	the exact water flow rate provided by the j th operating pump
$m_{w,j,max}$	the maximum value of $m_{w,j}$
$m_{w,j,min}$	the minimum value of $m_{w,j}$

m^*	the ratio of air to water effective capacitance rate in Braun's model
n	the empirical constant in Braun's model
NTU	the number of transfer unit
$P_{chiller}$	the power consumption of the chillers
P_{f1}	the value of the penalty function 1
P_{f2}	the value of the penalty function 2
P_{f3}	the value of the penalty function 3
P_{fan}	the power consumption of the fans
$P_{fan,nom,k}$	the k th nominal fan power consumption under full-load condition
P_{pump}	the power consumption of the pumps
$P_{pump,nom,j}$	the j th nominal pump power consumption under full-load condition
P	the total power consumption of the whole condenser water loop
$PLR_{adj,i}$	the adjustment factor of part-load ratio of i th the chiller
$Q_{cap,i}$	the nominal capacity of the i th chiller
Q	the real cooling load provided by all the chillers
Q_i	the real cooling load provided by the i th chiller
Q_{rej}	the heat rejection rate of all the cooling towers
T_{CHWS}	the chilled water supply temperature
T_{CHWR}	the chilled water return temperature
T_{CWS}	the condenser water supply temperature
$T_{CWS,max}$	the maximum value of T_{CWS}
$T_{CWS,min}$	the minimum value of T_{CWS}
T_{CWR}	the condenser water return temperature
T_{wb}	the ambient wet-bulb temperature
$Temp_{adj,i}$	the adjustment factor of temperature of the i th chiller
ν	the multipliers of penalty function
ε_a	the heat transfer effectiveness in Braun's model (1989)

Chapter 1

Introduction

1.1 Motivation

Heating, ventilating and air-conditioning (HVAC) system is a system for transporting heat and moisture from inside buildings to outside environments. For the building service system, the HVAC system is the most important from viewpoint of saving energy and improving the quality of the indoor environment. The consumption of energy by Heating, Ventilation and Air-Conditioning (HVAC) equipment in industrial and commercial buildings constitutes 30% of world energy consumption [1].

Designing good control strategies for the efficient operation of HVAC systems is an important issue. To decrease the total energy consumption, historically, new technologies have been introduced into the HVAC system, such as the variable airflow volume (VAV) system and the variable water flow distribution system. With these developments, the energy is utilized in a more efficient way for the modern HVAC system. However the processes of HVAC system became more and more complex because of these new changes and most of them become highly non-linear, these increase the difficulty of

control system design. In spite of the advancements made in microprocessor technology and its impact on the development of new control methodologies for HVAC systems, the process of operating HVAC equipment in commercial and industrial buildings is still an inefficient and high-energy consumption process [2]. Classical HVAC control techniques such as the ON/OFF controllers (thermostats) and the proportional-integral-derivative (PID) controllers are still very popular because of the low cost. In the long run, these controllers are expensive due to low-energy efficiency. In practice, application engineers have difficulties to design a well performing and stable control system because of the highly nonlinear processes and the time-varying working environment, at times, engineers have to resort to reduce functionality to ensure stable operation.

On the other hand, in term of energy saving, the optimization strategy of HVAC system also plays an important role. The HVAC optimization problem is formulated as the minimization of the total consumed energy, with constraints including mechanical limitations, component interactions, outdoor environment and indoor cooling load demands. The optimization result determines the optimal set points for each particular local control loops of HVAC system. The existing optimization methods used in HVAC industry are based on the predetermined mathematical models, the optimization have to be implemented offline. However, it may not be possible to achieve the accurate mathematical models for a complex system such as the HVAC in practice, and the character of system components usually will change after long use period because of the aging effect. Therefore, it is desired to develop a new optimization strategy, which not only can take advantage of existing mathematical models, but also can carry on online optimization to adapt the system and environment changes.

1.2 Objectives

The objective of the intelligent control in this thesis for HVAC system is to provide the desired indoor comfort with least energy consumption, under varying environment conditions and cooling requirement. One important factor affecting the efficiency of air conditioning systems is the fact that most HVAC systems are set to operate at design thermal loads while actual thermal loads affecting the system are time varying. Therefore, an intelligent control scheme that takes into consideration time varying loads should be able to operate efficiently and keep comfort conditions than conventional control schemes.

For optimization strategy, the objective of this thesis is to develop an algorithm that not only can take advantage of existing mathematical models, but also can adapt the system and environment change online, minimizing the total energy consumption during HVAC system' normal operation without scarifying the occupants comfort.

1.3 Major Contributions

For the HVAC system, a novel neural network assisted control scheme is proposed. By taking advantage of neural network technology, the new control approach is capable of maintaining high control performance even though the actual cooling loading is time varying and process is highly nonlinear. In the proposed control scheme, the deficiency of traditional fixed controller (PID type) can be compensated to certain degree and better performance is achieved in term of set point tracking performance and disturbance rejection ability.

Another important contribution of this thesis is that two robust neural network training algorithms are proposed. To learn the non-linearity of the HVAC process and the time-varying environment, the neural network is trained in an online fashion. Moreover, convergence of the network weights is guaranteed with those two robust training algorithms. For a neural network based control system, the stability issue is always the

main concern in term of the closed control loop. In this thesis, we implemented the design and stability analysis for the neural controllers based on the conic sector theory.

In the previous studies, there were very few works reported on the neural network controller with successful implementation on the real HVAC system. We carried out a number of real time trials on an experimental HVAC system. The proposed neural network control systems proposed in this thesis were tested and the results demonstrated the effectiveness of the proposed algorithms.

In this thesis, a hybrid optimization strategy for condenser water loop of centralized Heating, Ventilation and Air-conditioning (HVAC) systems is also proposed. Based on the predetermined system analysis models, firstly, the genetic algorithm (GA) is employed to obtain the initial optimization results for both continuous and discrete controlled variables offline. Because it may not be possible to achieve the accurate mathematical models for a complex system such as HVAC in practice, further optimization for the continuous variables is carried out online with the simultaneous perturbation stochastic approximation (SPSA) algorithm. With the hybrid GA/SPSA optimization strategy, the optimization problem for condenser water loop of HVAC system can be solved in a more effective way. Experiments implemented on a centralized HVAC pilot plant shows that the operating cost of the condenser water loop can be substantially reduced compared with the conventional operation strategy.

1.4 Organization of the Thesis

The remainder of this thesis is organized as follows. In Chapter 2, background and previous research work on control and optimization for HVAC system are reviewed. Chapter 3 presents the robust neural network assisted PI control scheme for supply air pressure control in a typical variable air volume (VAV) HVAC system. For the same process of the HVAC system, in Chapter 4, a neural network controller, which is trained

online with the SPSA algorithm is proposed. As an application of the SPSA based neural controller, in Chapter 5, we introduced the neural network assisted cascade control scheme for air handling unit (AHU) of HVAC system. A new optimization method for HVAC system, i.e. the hybrid GA/SPAS optimization strategy with its application in condenser water loop of HVAC system is presented in Chapter 6. Conclusions and recommendations for future research are given in Chapter 7.

Chapter 2

Background and Previous Work

2.1 Overview of Building HVAC System

A building heating, ventilating and air-conditioning (HVAC) systems may be generally described as a system for transporting heat and moisture from inside buildings to outside environments. Centralized air-conditioning system is mostly adopted for large buildings with many zones of conditioned space for different sections of buildings. The schematic of a typical building HVAC system is shown in Figure 2.1. It can be divided into five heat transfer loops [3].

Indoor Air Loop includes fans, cooling coils, terminal units, dampers, ducts, and controls. The air in the conditioned space is driven by fans through cooling coils and then distributed to terminal units. Dampers are used to control airflows to terminal units and fans are used to keep certain air pressure in ducts. The cooling and ventilation loads are transferred from conditioned space to chilled water.

Figure 2.1: The schematic of a typical building HVAC system

Chilled Water Loop includes pipes, pumps, cooling coils, chiller evaporators, valves, and controls. The chilled water in pipes is driven by pumps to circulate between cooling coils and chiller evaporators. Valves are used to control water flow to cooling coils. The heat is transferred from air handling units (AHUs) to chiller evaporators.

Refrigerant Loop includes evaporators, compressors, condensers, expansion valves and controls. Refrigerant absorbs heat in chiller evaporators by changing phase from liquid to gas. The working of compressors makes the refrigerant a high pressure and high temperature state. The refrigerant with high temperature is cooled in chiller condensers. The high pressure refrigerant in gas is released by expansion valves back to evaporators again with phased change. The heat is transferred from the chiller evaporators to the chiller condensers.

Condenser Water Loop includes cooling towers, chiller condensers, pumps and controls. The condenser water is delivered to cooling towers by pumps. The heat is transferred from chiller condenser to cooling towers.

Out Door Air Loop includes fans, cooling towers, and controls. The outdoor air is driven by fans to go through cooling towers and to exchange heat with condenser water. The heat is transferred from cooling towers to ambient environment.

2.2 Review of HVAC Control Technology

The automation and control systems for the heating, ventilating, and air-conditioning (HVAC) system have gone through major changes. The change from the discrete analogy devices, pneumatic or electric, is just about to complete, and the digital electronic and software-based devices are the common practice. The microprocessor based control devices and systems are everywhere. All building automation and control system are using one form or another of this technology. Functionality has increased considerably on one hand but stayed stagnant on the other hand. All the control systems are still using the traditional control algorithm such as the Proportional, Integral and Derivative (PID) to execute the basic control algorithms. The control algorithms were invented many years ago, and were developed for linear processes since the state of the art of mathematics, at those days, was limited to the analysis of linear problems. In the past, HVAC and control designers went out of their way to linearize the system so that the control algorithm will yield the desired results. However, as the control technology progressed, the HVAC processes became more complex. In the early 1970's the VAV system was introduced. The VAV system increased the nonlinearity of the system and further increased the difficulty level to maintain stable control. In the early 1990's, the transition to variable water flow took place, and now the behavior of the HVAC system is severe. However, the age old PID control algorithm is still with us, and the application engineers have difficulty to maintain well performing systems, and sometimes they have to reduce the functionality to ensure the stable operation.

The early known application of automatic control was the flywheel governor. This was a simple feedback controller, adapted by James Watt in 1775 for controlling the speed of the steam engine in the presence of varying loads [4]. Broader use of feedback based automatic control began to appear in the late 1920's, and the first general theoretical treatment of the automatic control law (Proportional, Integral and Derivative) was

published in 1932 [5]. Initially, the PID control was implemented in very simple processes. The development of the control laws was based on a linear process even though the process are generally non-linear. This was due to the limitation of the mathematical analysis tools the designer had in that period. The non-linear characteristics of the process dictated the tuning of the PID controller as the result of load changes. Historically, in the HVAC industry, tuning was compromised by selecting the PID gains to satisfy the worst case. This situation is further affected by the introduction of VAV system and the variable water flow distribution systems. These trends increased the non-linear behavior of the HVAC systems, so that the field engineer introduced various control fixes to try to resolve the problem by relaxing the controller gains to such a degree that performance becomes sluggish.

In the recent past, there were a few interim solution such as PID parameter auto tuning technique [6], variable gain controllers [7], adaptive control algorithms [8] and variable techniques that helped to improve performance, however they did not satisfy the ultimate need: to provide continuous optimum control without tuning for the wide range of process load and working environment change.

The latest innovation in control system technology, neural networks, attempts to address this control performance problem [9,10]. The neural network has great capability to handle nonlinear functions and it also has the inherent adaptive ability. However, neural network training algorithms are sensitive to disturbances and may not be able to obtain robust performance, or even become unstable. On the other hand, there have been extensive researches in the theoretical area of robust neural control [11, 12, 13]. For example, the persistent exciting condition has been removed in the presence of disturbance [12]. Variable structure and dead zone scheme have been introduced to design robust adaptive algorithm of neural network control system to improve the tracking performance [12, 13, 14]. However, there are two main disadvantages of these

existing algorithms, which require both bounded input signal to the neural network and the knowledge of the upper bound of disturbance as a priori.

2.3 Review of Neural Network for Control Application

An artificial neural network is defined in [15] as a massively parallel-distributed processor made up of simple processing units, which has a natural property for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Inter neuron connection strings, known as synaptic weights, are used to store acquired knowledge.

The way in which the neurons of a neural network are interconnected determines its structure. And the structures mostly used are:

1. Single-layer Feed-forward networks.
2. Multilayer Feed-forward Networks.
3. Radial Basis Networks.
4. Dynamic (differential) or Recurrent Neural Networks.

Among the different neural network structures, the multilayer feed-forward neural networks are most commonly used in control applications. They distinguish themselves by the presence of one or more hidden layers (Figure 2.2) whose computation nodes are called hidden neurons. Typically the neurons in each layer have as their inputs the output signals of the preceding layer. If each neuron in each layer is connected to every neuron

in the adjacent forward layer, the neural network is named as fully connected, on the opposite called partly connected.

Figure 2.2: Multilayer neural network

A multilayer perception has three distinctive characteristics:

1. The activation function of each neuron is smooth as opposed to the hard limit used in the single layer perception. Usually, this nonlinear function is a sigmoidal one defined as:

$$h(x) = 1/(1 + e^{-\lambda x})$$

2. The network contains one or more layers of hidden neurons.
3. The network exhibits a high degree of connectivity.

Multilayer neural networks derive its computing power through the combination of these characteristics and its ability to learn from experience [16, 17]. However the presence of distributed nonlinearities and the high connectivity of the network make the theoretical analysis difficult.

Back-propagation (BP) Algorithm. The learning algorithm used to adjust the synaptic weights of a multilayer neural network is known as back-propagation. The basic idea was first described in [18]. Subsequently it was rediscovered in [19], similar generalization of the algorithm was derived in [20]. This algorithm provides an efficient method for the

training of multi-layer neural network. In [21], a complete derivation is presented. The BP algorithm has become the most popular one for training of the multilayer neural network. It is very efficient and able to classify information non-linearly separable. The algorithm is a gradient technique, implementing only one step search in the direction of the minimum, which could be a local one, and not an optimal one. So it is not possible to demonstrate its convergence to a global optimum.

Function Approximation. A multilayer neural network trained with the BP algorithm is able to perform a general nonlinear input-output mapping from R^n (dimension of input space) to R^l (dimension of the output space). Research interest in the capabilities of the multilayer neural network to approximate an arbitrary continuous function was first mentioned in [22]. It was Cybenko who first demonstrated that a single hidden layer is sufficient to uniformly approximate any continuous function with support in a unit hypercube [23] and [24].

The capability of multilayer neural network to approximate arbitrary continuous functions is established in the following theorem

Theorem 2.1 *Let $\sigma(\cdot)$ be a stationary, bounded, and monotone increasing function. Let I_n denote the n -dimensional unit hypercube. Let $C(I_n)$ be the space of continuous functions on I_n . Then for any $f \in C(I_n)$ and $\varepsilon > 0$, there exist an integer m and real constants α_i, ρ_i and w_{ij} , with $i=1, m$ and $j=1 \dots n$, such that, defining $F(u_1, u_2, \dots, u_n)$ as*

$$F(u_1, u_2, \dots, u_n) = \sum_{i=1}^m \alpha_i h\left(\sum_{j=1}^n w_{ij} u_j - \rho_i\right);$$

it is an approximate realization of $f(\cdot)$, that is,

$$|F(u_1, u_2, \dots, u_n) - f(u_1, u_2, \dots, u_n)| < \varepsilon, \forall (u_1, u_2, \dots, u_n) \in I_n$$

This theorem is directly applied to multilayer neural network, with the following characteristics:

1. The input nodes: $u_1, u_2, \dots, u_n$.
2. A hidden layer of m neurons completely connected to the input.
3. The activation function $h(\cdot)$, for the hidden neurons, is a constant, bounded, and is monotonically increasing.
4. The network output is linear combinations of the hidden neurons output.

This property is very useful for the applications of multilayer neural network to control.

Neural Networks in Control. The ultimate goal of control engineering is to implement an automatic system, which could operate with increasing independence from human actions in an unstructured and uncertain environment [25]. Such a system may be named as an autonomous or intelligent one. It would need only to be presented with a goal and would achieve its objective by continuous interaction with its environment through feedback about its behavior. It would continue to adapt and perform tasks with increasing efficiency under changing and unpredictable conditions. It would be also very useful when direct human interaction could be hazardous, prone to failures, or impossible.

Biological systems are a possible framework for the design of such an autonomous system. They provide several clues for the development of robust (highly stable) learning and adaptation algorithms required for this kind of systems. Biological systems process information differently than conventional control schemes; they are model free and are quite successful for dealing with uncertainty and complexity. They do not require the development of a mathematical model to execute complex tasks. Indeed, they can learn to perform new tasks and easily adapt to changing environments. If the fundamental principles of computation imbedded in the nervous systems are understood, an entirely new generation of control methods could be developed far beyond the capabilities of the present techniques based on explicit mathematical model. These new methods could serve to implement the ultimate intelligent systems.

A control system has the ability to learn if it acquires information, during operation, about the unknown features of the plant and its environment such that the overall performance is improved. By enhancing the controller with learning, it is possible to expand the operation region and ultimately implement autonomous system.

One class of models, which has the potential to implement this learning, is the artificial neural network. Indeed, the neural morphology of the nervous system is quite complex to analyze. Nevertheless, simplified analogies have developed, which could be applied to engineering applications. Based on these simplified understandings, artificial neural networks structures have been developed.

In reference to neural networks in control, the following characteristics and properties are important:

- 1. Applicable to non-linear processes** Neural networks offer a great promise in the realm of nonlinear control. This stems from their theoretical capability to approximate arbitrary nonlinear functions.
- 2. Parallel distributed processing.** Neural networks have a highly parallel structure, which allows immediately parallel implementations.
- 3. Learning and adaptation.** Neural networks are trained using data from the system under study. An adequately trained neural network has the ability to generalize for inputs not appearing in the training data. Moreover, they can also be adapted on-line.
- 4. Applicable to multivariable systems.** Neural networks have the ability to process many inputs and outputs, they are readily applicable to multivariable systems.

A modeling structure with all these features has a great promise for application in nonlinear identification and control. Due to the property of neural networks to implement input-output mappings, they are very suitable for applications on identification and control of nonlinear systems.

2.4 Review of HVAC System Optimization

Targeted at energy conservation, there have been many research works reported for either individual HVAC component or partial HVAC system efficiency optimization [26-30]. In terms of component-based optimization, House and Smith [31] studied optimization of two-zone variable air volume (VAV) heating system by traditional derivative-based methods, which would become very complicated if the number of zones is more than two. Assuming all the cooling loads of coils were same, Wepfer and Shelton [32] described the optimization of chilled water rate as a function of the air-water coil size and the refrigerant-water coil size. Braun [33] and Ahn [34] formulated indoor air loops and chilled water loops with quadratic functions, which is not accurate when the cooling loads of end users are changing diversely. In terms of system-based optimization, Austin [35] and Kirsner [36] used real systems for experiments and provided some general guidelines. Hartman [37][38] pointed out that an integrated DDC provides new approaches to improve energy efficiencies and comfort of typical facilities significantly. He also acknowledged that very large amount of data places huge burdens on communication network and processing capacities of DDC systems. In order to avoid the difficulties, some researchers [39, 40, 41, 42, 43, 44] considered some variables as constants, such as condenser water flow rate, chilled water supply temperature, nonetheless their researches are not overall system optimization.

As for optimization algorithms, the classic derivative-based methods are widely used [45] and [31, 32, 34], but they are incapable of dealing with mixed-integer nonlinear optimization [46]. Thanks to the newly developed evolutionary computation techniques, genetic algorithms have been successfully used in many areas [47, 48, 49, 50, 51, 52]. In order to relieve huge burdens on DDC systems, original optimization problem is simplified to reduce number of independent variables and computation time. However,

the existing methods are still based on the predetermined system analysis models, the optimization is implemented offline. Therefore, the results obtain usually not the optimal one because it is not possible to achieve the accurate mathematical models for such a complex system as HVAC system in practice, and the character of system components usually will change after long term running because of the aging effect.

Chapter 3

Robust NN Assisted PI Controller for VAV System

3.1 Introduction

Recently, there has been an interest in applying neural networks in the context of adaptive control [53, 54, 55]. However, most efforts have been directed towards designing indirect adaptive control. This is because indirect adaptive control can be realized, at least conceptually, in a straightforward manner. It does not require adjusting the controller parameters based on the error between the desired value and plant output. Generally, it is implemented using two networks, one network is trained offline for the purpose of identification of either the plant or its inverse and the other network is trained online for the purpose of control. As is obvious, the performance of indirect adaptive neural controller is related to the quality of the offline-training.

By applying direct adaptive control, the neural controller works in a feed-forward fashion just like a conventional PID controller. The controller takes the process error signal and produces a control action on-line. But there is a main challenge, which is how to train the

neural controller, since the desired control action is not available. To address this problem, we propose in this chapter the neural network assisted proportional and integral control (NNAPI) scheme.

To design a neural network assisted controller in HVAC industry, such as the VAV system we studied in this work, one of the key problems is the controller's robust stability. For the neural network controller, the stability issue is related directly to the neural network's convergence property. However, a conventional training algorithm of neural network may become divergent in the presence of noise [56]. Some of the original results are examined in [57, 58, 59, 60], in which the control algorithms guarantee that both the tracking error and the NN weight error are convergent in the presence of disturbance [57, 58, 59, 60]. However there are certain limitations in these studies. For example, in the approach of [58] and [59], it was reported that a smaller robot tracking error leads to a larger NN weight error, and vice versa. This will affect the overall performance of the NN controller. To assure the convergence of the multiplayer NN in practical controller design, a robust back-propagation training algorithm with an adaptive dead zone scheme is proposed. The main advantage of this neural network assisted controller is that the upper bound of the system disturbance can be estimated on-line by updating the size of dead zone.

To demonstrate the applicability of the proposed control scheme and neural network training algorithm, real-time tests are implemented on a pilot VAV air-conditioning system and good experimental results are obtained.

3.2 Neural Network Assisted PI Control Scheme

Considering the dynamical control systems, which can be represented as a single-input-single-output form as the following:

$$y(k) = f[y(k-1), y(k-2), \dots, y(k-m_y), u(k-d-1), u(k-d-2), \dots, u(k-d-m_u)] + u(k-d) + \varepsilon(k) \quad (3.1)$$

where y is the output, u is the control input, d is the relative degree of the system. Particularly, for the supply air pressure control loop studied in this chapter, y is the static pressure in the supply air duct, and u is the input voltage of supply air fan motor. $f(\cdot)$ is a unknown dynamic nonlinear function, $\varepsilon(k)$ demotes a bounded overall noise signal of the control system. m_y, m_u are integers and $m_y \geq m_u$.

The set-point tracking error is:

$$s(k) = y(k) - y^*(k) \quad (3.2)$$

where $y^*(k)$ is the command input. Define the control signal as

$$u(k-d) = -\hat{f}(\cdot) + y^*(k) + G_{PI}(z^{-1})s(k-1) \quad (3.3)$$

where $\hat{f}(\cdot)$ is estimate of the nonlinear function $f(\cdot)$ by the neural network to be defined later, $G_{PI}(z^{-1})$ denotes the proportional-plus-integral control algorithm. We have the control signal at time step k as

$$\begin{aligned} u(k) &= -\hat{f}(\cdot) + y^*(k+d) + G_{PI}(z^{-1})s(k-1+d) \\ &= -\hat{f}[y(k+d-1), y(k+d-2), \dots, y(k+d-m_y), u(k-1), u(k-2), \dots, u(k-m_u)] \\ &\quad + y^*(k+d) + G_{PI}(z^{-1})s(k-1+d) \end{aligned} \quad (3.4)$$

Note that the equation above shows that the control system becomes non-causal when $d > 1$. However, for the proposed controller design, this issue can be typically addressed by introducing a linear observer with the extra observation of the difference signals.

$$y(k-1+d) = \dot{y}(k+d-2)T + y(k+d-3)$$

where T is the sampling time. $\dot{y}$ is the differential signal of output y .

For example, when $d = 2$, the non-causal term $y(k-1+d)$ can be obtained by

$$y(k-1+d) = y(k+1) = \dot{y}(k)T + y(k-1)$$

For the fixed PI controller, we employ the following discrete time algorithm:

$$G_{PI}(z^{-1}) = k_p + k_i \cdot \frac{Tz^{-1}}{1 - z^{-1}}$$

where z^{-1} is the time delay factor, k_p is the proportional gain, k_i is the integral gain and T is the sampling time. To simplify the PI algorithm above, let $K_p = k_p$ and $K_i = k_i T$, we have the discrete time PI controller as:

$$G_{PI}(z^{-1}) = K_p + K_i \cdot \frac{z^{-1}}{1 - z^{-1}} \quad (3.5)$$

Then, the estimation error vector of the neural network can be presented as

$$e(k) = f(k) - \hat{f}(k) + \varepsilon(k) \quad (3.6)$$

Figure 3.1: Structure of the control scheme (with $m_y = 2, m_u = 0, d = 2$)

The neural network control structure is shown in Figure 3.1 (For any other arbitrary m, n , the diagram can be changed accordingly in an obvious way). Note that for the neural network training, the estimation error e_k may not be directly measurable, so we should use the tracking error to generate it using the closed-loop relationship via (3.1), (3.2), (3.3), (3.6).

$$e(k) = [1 - z^{-1}G_{PI}(z^{-1})]s(k) \quad (3.7)$$

The output of a three-layered neural network can be presented as

$$\hat{f}(k) = v^T(k)H(w(k), x(k))$$

where the input vector $x(k) \in R^m$ of the neural network is

$$x(k) = [y(k-1), y(k-2), \dots, y(k-m_y), u(k-d-1), u(k-d-2), \dots, u(k-d-m_u)]^T \quad (3.8)$$

with $m = m_y + m_u$. $v(k) = [v_1(k), v_2(k), \dots, v_{n_h}(k)]^T \in R^{n_h}$ is the weight vector of the output layer, n_h is the numbers of neurons in the hidden layers of the network. The adjustable weight matrix $w(k) \in R^{n_h \times m}$ of the hidden layer is

$$w(k) = [w_1(k), w_2(k), \dots, w_{n_h}(k)]^T$$

where $w_j(k) = [w_{j1}(k) \ w_{j2}(k) \ \dots w_{ji}(k) \ \dots w_{jm}(k)]^T \in R^m$ with $j = 1, 2, \dots, n_h$, w_{ji} is the adjustable weight from the i th neuron of the input layer to the j th neuron of the hidden layer, $H(w(k), x(k))$ is the nonlinear activation function raw vector.

$$H(w(k), x(k)) = [h(w_1^T(k)x(k)) \ h(w_2^T(k)x(k)) \ \dots \ h(w_{n_h}^T(k)x(k))] \quad (3.9)$$

where $h(\cdot)$ is the nonlinear activation function

$$h(x) = 1 / (1 + e^{-4\lambda x}) \quad (3.10)$$

where $\lambda > 0$ is the so called gain parameter of the threshold function.

3.3 Adaptive Dead Zone Training Algorithm

To deal with the disturbance, an adaptive dead-zone function is defined as

$$g(e(k), \Delta_v(k)) = \begin{cases} \|e(k)\| - \Delta_v(k) & \text{if } \|e(k)\| > \Delta_v(k) \\ 0 & \text{if } \|e(k)\| \leq \Delta_v(k) \end{cases} \quad (3.11)$$

where $\Delta_v(k)$ is the size of the adaptive dead-zone to be estimated.

The cost function is

$$E(k) = (1/2)e^2(k) \quad (3.12)$$

Now we can define a normalized gradient decent algorithm to update $w(k)$

$$w(k+1) = w(k) - \frac{\partial E(k)}{\partial w(k)} \frac{\beta(k)}{2[1 + (\|H'(k)v(k)\| \|x(k)\|)^2]} \quad (3.13)$$

$$= w(k) + \frac{\beta(k)H'(k)v(k)e(k)x^T(k)}{2[1 + (\|H'(k)v(k)\| \|x(k)\|)^2]}$$

$$\Delta_w(k+1) = \Delta_w(k) + \frac{\beta(k) \|e(k)\|}{2[1 + (\|H'(k)v(k)\| \|x(k)\|)^2]} \quad (3.14)$$

where $\beta(k)$ is a variable learning rate based on the adaptive dead zone scheme defined as

$$\beta(k) = \begin{cases} g(e(k), \Delta_w(k)) / \|e(k)\| & \text{if } \|e(k)\| \frac{h'_{\min}}{\lambda} > \Delta_w(k) \\ 0 & \text{if } \|e(k)\| \frac{h'_{\min}}{\lambda} \leq \Delta_w(k) \end{cases} \quad (3.15)$$

$$\begin{aligned} H'(k) &= \text{diag}[h'_1(k), \dots, h'_{n_h}(k)] \\ &= \text{diag}[h'(w_1(k), x(k)), \dots, h'(w_{n_h}(k), x(k))] \in R^{n_h \times n_h} \end{aligned}$$

where $h'_i(k)$ is the first derivative of the threshold function in equation (3.10), and $h'_{\min}(k) = \min[h'_1(k), \dots, h'_{n_h}(k)] > 0$ (assume that $h'_i(k)$ is not simultaneously zero) is a positive constant.

Similarly, a normalized gradient descent algorithm can be written in the matrix form

$$\begin{aligned} v(k+1) &= v(k) - \frac{\partial E(k)}{\partial v(k)} \frac{\alpha(k)}{1 + \|H(w(k), x(k))\|^2} \\ &= v(k) + \frac{\alpha(k)H(w(k), x(k))e^T(k)}{1 + \|H(w(k), x(k))\|^2} \end{aligned} \quad (3.16)$$

$$\Delta_v(k+1) = \Delta_v(k) + \frac{\alpha(k) \|e(k)\|}{1 + \|H(w(k), x(k))\|^2} \quad (3.17)$$

where $\alpha(k)$ is a variable learning rate based on the dead zone scheme defined as

$$\alpha(k) = \begin{cases} g(e(k), \Delta_v(k)) / \|e(k)\| & \text{if } \|e(k)\| > \Delta_v(k) \\ 0 & \text{if } \|e(k)\| \leq \Delta_v(k) \end{cases} \quad (3.18)$$

Refer to the structure of control scheme (Figure 3.1), the whole algorithm can be summarized as follows:

1. Form the new input vector $x(k)$ of the neural network based on Equation (3.8).
2. Calculate the neural network output $\hat{f}(k)$ using the input $x(k)$ and the existing weights of the network.
3. The control input $u(k)$ is calculated based on Equation (3.3).
4. The new plant output is taken and the new tracking error signal $s(k+1)$ is fed through a fixed filter to produce the training error signal $e(k)$ of the network according to Equation (3.7).
5. The training error $e(k)$ is used to train the neural network and calculates the new weights $w(k+1)$ and $v(k+1)$.
6. Go back to step 1 to continue the iteration.

Remark 3.1: The main advantage of this robust training algorithm of the neural network is the online estimation of the width $\Delta_w(k)$ and $\Delta_v(k)$ of the adaptive dead-zone in (3.14) and (3.17). It should be noted that the adaptive algorithm aims at looking for an upper bound of system uncertainty automatically to ensure convergence of the weight-tuning algorithm and the stability of the closed-loop system. This means $v(k)$ and $w(k)$ may not be able to approach the ideal weight vector v^* and w^* as long as it enters the dead zone. However, the adaptive dead zone algorithm makes sense in term that it estimates the upper bound of the uncertainty and minimized the width of the dead zone on-line (compared to the one using fixed dead zone algorithm). This is the main advantage of the adaptive dead zone over the fixed dead zone algorithm since the latter can only select a very conservative bound in the presence of system uncertainty, which leads to a larger size of the dead zone, i.e. the bigger tracking error $s(k)$.

3.4 Stability Analysis

Stability is the most important issue in the practical design of neural network based control system. In this work, the stability analysis is based on the sector theory [61,62,63]. To apply the sector theory, the feedback system in Figure 3.1 should be reformed as an equivalent feedback structure as shown in Figure 3.2. Then neural network training algorithm can be proved to meet the certainty dissipative condition to obtain guaranteed stability of the tracking error signal $s(k)$.

Figure 3.2: Equivalent error feedback system

The operator H_1 represents the adaptive dead zone training algorithm, its input signal is the tracking error $s(k)$ defined in (3.2). The output is $\Phi(k)$, which will be defined later and is related to the weight error vectors, and in turn, the estimation parameter error vector and tracking error $s(k)$ through (3.7). The operator H_2 usually represents the mismatched linear model uncertainty in a typical adaptive linear control system [61]. Here, the operator H_2 represents the fixed PI controller dynamics (refer to Figure 3.1), i.e.

$$H_2 = (1 - z^{-1}) / [1 - (1 + K_p)z^{-1} - (K_I - K_p)z^{-2}]$$

And now we can establish the relationship between the tracking error signal $s(k)$ and the parameter estimate vectors of the neural network.

$$\begin{aligned} s(k) &= H_2 e(k) \\ &= H_2 (f(k) - \hat{f}(k) + \varepsilon(k)) \end{aligned}$$

$$\begin{aligned}
&= H_2[v^T(k)\tilde{H}(k) + \tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)] \\
&= H_2[v^T(k)(H(w^*, x(k)) - H(w(k), x(k))) + \tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)] \\
&= H_2[v^T(k)[h(w_1^{*T}x(k)) - h(w^T(k)x(k)) \\
&\quad \dots h(w_{n_h}^{*T}x(k)) - h(w_{n_h}^T(k)x(k))]]^T + \tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)]
\end{aligned} \tag{3.19}$$

where $\tilde{H}(k) = H(w^*, x(k)) - H(w(k), x(k))$, $\tilde{v} = v^* - v(k) \in R^{n_h}$ is the weight error matrix of the output layer. Note that the activation function $h(\cdot)$ in Equation (3.10) is non-decreasing function. According to the mean value theorem, there exists a unique positive number $\mu(\cdot)$ with $\lambda \geq \mu(\cdot) \geq 0$, the equation (3.19) can be rewritten as the following

$$\begin{aligned}
s(k) &= H_2\{v^T(k)[\mu(w_1^*, w_1(k), x(k))(w_1^{*T} - w_1^T(k))x(k) \\
&\quad \dots \mu(w_{n_h}^*, w_{n_h}(k), x(k))(w_{n_h}^{*T} - w_{n_h}^T(k))x(k)]^T + \tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)\} \\
&= H_2v^T(k)\mu(k)\tilde{w}(k)x(k) + H_2[\tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)]
\end{aligned} \tag{3.20}$$

Let $\Phi(k) = -v^T(k)\mu(k)\tilde{w}(k)x(k)$ and $\tilde{e}(k) = H_2[\tilde{v}^T(k)H(w^*, x(k)) + \varepsilon(k)]$, which is an equivalent disturbance term. We have

$$s(k) = -H_2\Phi(k) + \tilde{e}(k) \tag{3.21}$$

Theorem 3.1: Consider the error feedback system (as shown in Figure 3.2)

$$s(k) = \tilde{e}(k) - P(k)$$

$$\Phi(k) = H_1s(k)$$

$$P(k) = H_2\Phi(k)$$

with operators $H_1, H_2 : L_{2e} \rightarrow L_{2e}$ and discrete time signal $s(k), P(k), \Phi(k) \in L_{2e}$ and $\tilde{e}(k) \in L_2$. If

(a) $H_1 : s(k) \rightarrow \Phi(k)$ satisfies

$$\sum_{k=0}^N [s^T(k)\Phi(k) + \sigma \|s(k)\|^2 / 2] \geq -\gamma$$

(b) $H_2 : \Phi(k) \rightarrow P(k)$ satisfies

$$\sum_{k=0}^N [\sigma P^T(k)P(k)/2 - P^T(k)\Phi(k)] \leq -\eta \| (P(k), \Phi(k)) \|_N^2$$

for some $\sigma, \gamma, \eta > 0$, then the above feedback system is stable with $s(k), \Phi(k) \in L_2$.

Proof: see Corollary 2.1 of [63].

Remark 3.2: It should be noted that the condition (b) of the Theorem 3.1 can be treated as positive real function, i.e. the plot of H_2 should be in the positive half of a complex plane as shown in [62].

Lemma 3.1: The operator $H_1 : s(k) \rightarrow \Phi(k)$, which represents the training algorithm for hidden layer, satisfies the condition (a) of Theorem 3.1.

Proof:

First we establish the conic sector condition between the estimate error $e(k)$ and the output $\Phi(k) = -v^T(k)\mu(k)\tilde{w}(k)x(k)$ (see Figure 3.3) and then extend to the tracking error $s(k)$.

Figure 3.3: Equivalent error feedback system

Define $V_w(k) = \text{tr}\{\tilde{w}^T(k)\tilde{w}(k)\}$, we have

$$\begin{aligned} & V_w(k+1) - V_w(k) \\ &= -2\beta(k) \frac{\text{tr}\{H^T(k)v(k)e(k)x^T(k)\tilde{w}^T(k)\}}{\rho(k)} \\ &+ \beta(k)^2 \frac{\|H^T(k)v(k)e(k)x^T(k)\|^2}{\rho^2(k)} \end{aligned} \tag{3.22}$$

Consider the property of the matrix trace, we have

$$\begin{aligned}
& \text{tr}\{H'(k)v(k)e(k)x^T(k)\tilde{w}^T(k)\} \\
&= [h_1'(k)e^T(k)v_1(k)x^T(k)\tilde{w}^T(k) + \dots \\
&+ h_{m_1}'(k)e^T(k)v_{n_h}(k)x^T(k)\tilde{w}_{n_h}^T(k) \\
&\geq \frac{h_{\min}'}{\lambda} \text{tr}\{e^T(k)v^T(k)\mu(k)\tilde{w}(k)x(k)\}
\end{aligned}$$

Then we have

$$\begin{aligned}
& V_w(k+1) - V_w(k) \\
&\leq -2\left(\frac{h_{\min}'}{\lambda}\right)\beta(k)\frac{\text{tr}\{e^T(k)v^T(k)\mu(k)\tilde{w}(k)x(k)\}}{\rho(k)} \\
&+ \beta(k)^2 \frac{\|H'(k)v(k)e(k)x^T(k)\|^2}{\rho^2(k)} \\
&= \beta(k)\left(2\frac{h_{\min}'}{\lambda}\rho^{-1}(k)e(k)\Phi(k) + \rho^{-2}(k)\|H'(k)v(k)\|^2\|x(k)\|^2\beta(k)\|e(k)\|^2\right) \\
&= \beta(k)\left(2\frac{h_{\min}'}{\lambda}e^{nT}(k)\Phi^n(k) + \sigma(k)\|e^n(k)\|^2\right)
\end{aligned} \tag{3.23}$$

where $\sigma(k) = \rho^{-1}(k)\|H'(k)v(k)\|^2\|x(k)\|^2\beta(k)$

Summing the above equation upon to $N+1$ step, we are able to establish the conic condition with a constant $\hat{\sigma}$ for the estimate error $e(k)$ as the input conic sector theory (Refer to Figure 3.3) and the output $\Phi(k)$.

$$\begin{aligned}
& \sum_{k=0}^N \left[2\frac{h_{\min}'}{\lambda}e^{nT}(k)\Phi^n(k) + \rho^{-1}(k)\|H'(k)v(k)\|^2\|x(k)\|^2\beta(k)\|e^n(k)\|^2 \right] \geq -V_w(0) \\
& \sum_{k=0}^N [e^{nT}(k)\Phi^n(k) + \frac{\hat{\sigma}}{2}\|e^n(k)\|^2] \geq -\frac{\lambda V_w(0)}{2h_{\min}'}
\end{aligned} \tag{3.24}$$

by selecting a suitable normalized factor $\hat{\rho}(k)$ to obtain the constant number $\hat{\sigma}$, such that $\hat{\sigma}$ satisfy

$$1 > \hat{\sigma} \geq \rho^{-1}(k)\|H'(k)v(k)\|^2\|x(k)\|^2\beta(k)\lambda/h_{\min}' \tag{3.25}$$

and here we select $\hat{\rho}(k)$ as

$$\hat{\rho}(k) = 1 + \|H'(k)v(k)\|^2 \|x(k)\|^2 \quad (3.26)$$

Note that the conic sector condition guarantees that the estimate error $e(k)$ and the output $\Phi(k) = -v^T(k)\mu(k)\tilde{w}(k)x(k)$ are bounded according to the extended conic sector theory. So is the parameter estimate error $\tilde{w}(k)$. Next, we establish the conic sector condition of the tracking error $s(k)$.

Note that, the PI controller have following structure:

$$G_p(z^{-1}) = \frac{K_p + (K_I - K_p)z^{-1}}{1 - z^{-1}} \quad (3.27)$$

$$s(k) = \frac{1 - z^{-1}}{1 - (1 + K_p)z^{-1} - (K_I - K_p)z^{-2}} e(k) = H_2 e(k)$$

$$e(k) = s(k) - [(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1)] \quad (3.28)$$

After substituting $e^n(k)$, (3.23) can be rewritten as

$$\begin{aligned} & V_w(k+1) - V_w(k) \\ & \leq -2\left(\frac{h_{\min}}{\lambda}\right)\beta(k)\frac{\text{tr}\{e^T(k)v^T(k)\mu(k)\tilde{w}(k)x(k)\}}{\rho(k)} \\ & \quad + \beta(k)^2\frac{\|H'(k)v(k)e(k)x^T(k)\|^2}{\rho^2(k)} \\ & = 2\beta(k)\frac{h_{\min}}{\rho(k)\lambda}\{s(k) - [(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1)]\}\Phi(k) \\ & \quad + \beta(k)\sigma(k)\rho^{-1}(k)\|e(k)\|^2 \\ & \leq 2\beta(k)\frac{h_{\min}}{\rho(k)\lambda}s(k)\Phi(k) \\ & \quad + \beta(k)\frac{h_{\min}}{\rho^2(k)\lambda}\|(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1)\|^2 \\ & \quad + \beta(k)\frac{h_{\min}}{\lambda}\Phi^2(k) \\ & \quad + \beta(k)\sigma(k)\rho^{-1}(k)\|e(k)\|^2 \end{aligned} \quad (3.29)$$

Above inequality is due to the fact:

$$\begin{aligned} & \frac{2}{\rho(k)} [(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1)]\Phi(k) \\ & \leq \frac{1}{\rho^2(k)} \|(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1)\|^2 + \Phi^2(k) \end{aligned}$$

Recall the PI control algorithm, we have:

$$(1 + K_p)s(k-1) + (K_I - K_p)s(k-2) - e(k-1) = s(k) - e(k) \quad (3.30)$$

Then we have:

$$\begin{aligned} & V_w(k+1) - V_w(k) - \beta(k) \frac{h_{\min}'}{\lambda} \Phi^2(k) \\ & \leq 2\beta(k) \frac{h_{\min}'}{\rho(k)\lambda} s(k)\Phi(k) + \beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|s(k) - e(k)\|^2 \\ & \quad + \beta(k)\sigma(k)\rho^{-1}(k) \|e(k)\|^2 \\ & = 2\beta(k) \frac{h_{\min}'}{\rho(k)\lambda} s(k)\Phi(k) - 2\beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} s(k)e(k) + \beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|s(k)\|^2 \\ & \quad + \beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|e(k)\|^2 + \beta(k)\sigma(k)\rho^{-1}(k) \|e(k)\|^2 \\ & \leq 2\beta(k) \frac{h_{\min}'}{\rho(k)\lambda} s(k)\Phi(k) + 2\beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|s(k)\|^2 + 2\beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|e(k)\|^2 \\ & \quad + \beta(k)\sigma(k)\rho^{-1}(k) \|e(k)\|^2 \end{aligned} \quad (3.31)$$

Then we have:

$$\begin{aligned} & V_w(k+1) - V_w(k) - \beta(k) \frac{h_{\min}'}{\lambda} \Phi^2(k) - 2\beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|e(k)\|^2 - \beta(k)\sigma(k)\rho^{-1}(k) \|e(k)\|^2 \\ & \leq 2\beta(k) \frac{h_{\min}'}{\rho(k)\lambda} s(k)\Phi(k) + 2\beta(k) \frac{h_{\min}'}{\rho^2(k)\lambda} \|s(k)\|^2 \\ & \quad \frac{V_w(k+1) - V_w(k)}{2\beta(k) \frac{h_{\min}'}{\lambda}} - \frac{\Phi(k)^2}{2} - \frac{\|e^n(k)\|^2}{\rho(k)} - \frac{\|H'(k)v(k)\|^2 \|x(k)\|^2 \beta(k) \|e^n(k)\|^2 \lambda}{2h_{\min}'\rho(k)} \\ & \leq s^n(k)\Phi^n(k) + \frac{2}{\rho(k)} \frac{\|s^n(k)\|^2}{2} = s^n(k)\Phi^n(k) + \sigma \frac{\|s^n(k)\|^2}{2} \end{aligned} \quad (3.32)$$

With the normalized tracking error $s^n(k) = s(k)/\sqrt{\rho(k)}$, and the normalized output $\Phi^n(k) = \Phi(k)/\sqrt{\rho(k)} = -v^T(k)\mu(k)\tilde{w}(k)x(k)/\sqrt{\rho(k)}$ by choosing the normalized factor $\rho(k)$ to guarantee that there exists a constant σ such that

$$1 > \sigma \geq 2\rho^{-1}(k) > 0 \quad \text{i.e. } \rho(k) > 2$$

We can select

$$\rho(k) = 2(1 + \|H'(k)v(k)\|^2 \|x(k)\|^2)$$

Summing above inequality $N+1$ steps, we have

$$\begin{aligned} & \sum_{k=0}^N [s^n(k)\Phi^n(k) + \frac{\sigma}{2} \|s^n(k)\|^2] \\ & \geq -\frac{\lambda V_w(0)}{2\beta(k)h'_{\min}} - \sum_{k=0}^N \left\{ \frac{\Phi(k)^2}{2} + \frac{\|e^n(k)\|^2}{\rho(k)} + \frac{\|H'(k)v(k)\|^2 \|x(k)\|^2 \beta(k) \|e^n(k)\|^2 \lambda}{2h'_{\min}\rho(k)} \right\} \end{aligned} \quad (3.33)$$

Remark 3.3: Note that the last item in the R.H.S of (3.33) is bounded as shown in (3.23) (obviously, we have $\rho(k) > \hat{\rho}(k)$, which implies that the normalization factor $\rho(k)$ will guarantee the conic sector condition. Furthermore, the specified normalized factor $\rho(k)$ plays two important roles. Firstly, it guarantees $\sigma < 1$ to avoid the so-called vanished cone problem [63]. Secondly, it guarantees the sector conditions to be simultaneously satisfied by both the original feedback system in Figure 3.1 and the equivalent feedback system in Figure 3.2 [61,62,63]. And this result satisfies the condition (a) of Theorem 3.1.

Lemma 3.2: For the PI control algorithm employed in this controller design (refer to equation (3.5)), there exists one region, when the values of K_I, K_P are inside this region, the property of H_2 satisfy the strictly positive real (SPR) condition.

Proof:

$$\begin{aligned} s(k) &= \frac{1 - z^{-1}}{1 - (1 + K_p)z^{-1} - (K_I - K_p)z^{-2}} e(k) = H_2 e(k) \\ H_2 &= \frac{z^2 - z}{z^2 - (1 + K_p)z - (K_I - K_p)} \end{aligned} \quad (3.34)$$

note that $z = e^{j\omega} = \cos \omega + j \sin \omega$

$$\forall \omega \in [0, 2\pi), \quad i = \sqrt{-1}$$

we have

$$\begin{aligned} H_2(e^{j\omega}) &= \frac{(\cos \omega + j \sin \omega)^2 - (\cos \omega + j \sin \omega)}{(\cos \omega + j \sin \omega)^2 - (1 + K_p)(\cos \omega + j \sin \omega) - (K_I - K_p)} \\ &= \frac{(\cos 2\omega - \cos \omega) + j(\sin 2\omega - \sin \omega)}{(\cos 2\omega - (1 + K_p) \cos \omega + (K_p - K_I)) + j[\sin 2\omega - (1 + K_p) \sin \omega]} \end{aligned} \quad (3.35)$$

we have

$$\begin{aligned} \text{Re}[H_2(e^{j\omega})] &= \frac{(2 + K_p) - (2 + K_p) \cos \omega + (K_p - K_I) \cos 2\omega - (K_p - K_I) \cos \omega}{[\cos 2\omega - (1 + K_p) \cos \omega + (K_p - K_I)]^2 + [\sin 2\omega - (1 + K_p) \sin \omega]^2} \\ &= \frac{(2 + K_p) - (2 + K_p) \cos \omega + (K_p - K_I)(2 \cos^2 \omega - 1) - (K_p - K_I) \cos \omega}{[\cos 2\omega - (1 + K_p) \cos \omega + (K_p - K_I)]^2 + [\sin 2\omega - (1 + K_p) \sin \omega]^2} \\ &= \frac{2(K_p - K_I) \cos^2 \omega - (2 + 2K_p - K_I) \cos \omega + 2 + K_I}{[\cos 2\omega - (1 + K_p) \cos \omega + (K_p - K_I)]^2 + [\sin 2\omega - (1 + K_p) \sin \omega]^2} \end{aligned} \quad (3.36)$$

To make H_2 satisfy the SPR condition, i.e. $\text{Re}[H_2(e^{j\omega})] > 0 \quad \forall \omega \in [0, 2\pi)$

We have

$$2(K_p - K_I) \cos^2 \omega - (2 + 2K_p - K_I) \cos \omega + 2 + K_I > 0 \quad (3.37)$$

note that $|\cos \omega| \leq 1$, and $K_p, K_I > 0$. The above inequality can be solved as the result shown in Figure 3.4's shadow area, which means that when the values of K_I, K_p is inside this region, the property of H_2 satisfy the strictly positive real condition (SPR.)

Remark 3.4: Based on lemma 3.1 and lemma 3.2, both condition (a) and (b) of Theorem 3.1 are fulfilled, i.e. $s(k), \Phi(k) \in L_2$. It should be noted that the SPR restriction for H_2 is only sufficient condition, which will lead to the conclusions in Theorem 3.1 [63, 64, 65]. So, in term of the closed control loop stability, the restriction for K_I, K_p is actually much milder than the region shown in Figure 3.4.

Figure 3.4: The region in which the K_I, K_P can be selected to make the H_2 satisfy the SPR condition

For the convergence of the adaptive dead zone training algorithm, we have following theorem.

Theorem 3.2: *The weight-tuning algorithm in equation (3.16) and (3.17) using the adaptive dead-zone scheme has the following properties:*

$$\begin{aligned} \|\tilde{v}(k+1)\| &\leq \|\tilde{v}(k)\| & \text{for } k = 0, 1, \dots, \\ \|\tilde{\Delta}_v(k+1)\| &\leq \|\tilde{\Delta}_v(k)\| & \text{for } k = 0, 1, \dots, \\ \limsup_{k \rightarrow \infty} |e(k)| &\leq \Delta_v \end{aligned}$$

where $\tilde{v}(k) = v^* - v(k)$ and $\tilde{\Delta}_v(k) = \Delta_v - \Delta_v(k)$

Proof:

Define Lyapunov function

$$\begin{aligned} V_v(k) &= \|\tilde{v}(k)\|^2 + \tilde{\Delta}_v^2(k) \\ &= \text{tr}\{\tilde{v}^T(k)\tilde{v}(k)\} + \tilde{\Delta}_v^T(k)\tilde{\Delta}_v(k) \end{aligned} \tag{3.38}$$

$$\begin{aligned} e(k) &= f(k) - \hat{f}(k) + \varepsilon(k) \\ &= v^T(k)(H(w^*, x(k)) - H(w(k), x(k))) + \varepsilon(k) \\ &= v^T(k)\tilde{H}(k) + \tilde{V}^T(k)H(w^*, x(k)) + \varepsilon(k) \end{aligned}$$

And use (3.19) to give

$$|e(k)|^2 - |e(k)| \tau_v(k) \leq \text{tr}\{e(k) \tilde{v}^T H(w(k), x(k))\}$$

where $\tau_v(k) = v^{*T} \tilde{H}(k) + \varepsilon(k) \leq \Delta_v$. According to the definition of the adaptive learning rate in (3.18), (3.38) can be rewritten as

$$\begin{aligned} & V_v(k+1) - V_v(k) \\ & \leq \frac{2\alpha(k) |e(k)| (\Delta_v(k) - |e(k)|)}{1 + (\|H(w(k), x(k))\|^2)} \\ & \quad + \frac{|\alpha(k)e(k)|^2 (1 + \|H(w(k), x(k))\|^2)}{1 + (\|H(w(k), x(k))\|^2)} \\ & \leq (-2) \frac{g(e(k), \Delta_v(k)) (|e(k)| - \Delta_v(k))}{1 + (\|H(w(k), x(k))\|^2)} \\ & \quad + \frac{g^2(e(k), \Delta_v(k))}{1 + (\|H(w(k), x(k))\|^2)} \\ & \leq - \frac{g^2(e(k), \Delta_v(k))}{1 + (\|H(w(k), x(k))\|^2)} \end{aligned} \tag{3.39}$$

Then $V_v(k)$ is bounded below by zero and is not increasing. The limit exists and the last term in (3.39) will go to zero. Since $H(w(k), x(k))$ is a bounded signal, we have

$$\limsup_{k \rightarrow \infty} \|e(k)\| = \limsup_{k \rightarrow \infty} \|\Delta_v(k)\| \leq \Delta_v$$

This completes the proof.

3.5 Application of the NNAPI Controller in VAV System

3.5.1 Overview of VAV Air-conditioning System

The energy crisis of the 1970s and the need to improve interior environmental control in a more cost-effective, high-quality manner have increased the popularity of variable air volume (VAV) air-conditioning system. The VAV system changes the supply airflow rate to match the variation of space load to maintain the predetermined space parameters and conserve the energy at reduced volume airflow. The counterpart of VAV is the

constant air volume system (CAV) in which the airflow rate is fixed at a constant speed by changing supply air temperature for varying load conditions, which need reheat of the air and consume more energy.

Figure 3.5: A Typical VAV air-conditioning system

A typical VAV air-conditioning system is shown in Figure 3.5. In the system, the outside air is mixed with the building return air, and the mixed air (supply air) is sucked through the cooling coil by a supply air fan. The cooled air is subsequently supplied to different zones. In the system, the temperature of the off-coil air, T_{OCA} , can be controlled at a pre-specified value by the regulation valve VLV of chilled water supply (or return). To ensure that each loop is working properly, the supply air pressure, P_{Duct} , is kept at a constant value, which is realized by regulating the supply air fan speed. Each zone temperature can be fine tuned by the damper of the VAV box in each zone. The supply air pressure control is an important control task for VAV system, which performance affects directly the whole system's energy efficiency. To model the dynamic behavior of the VAV system, some research work has been done [66, 67] based on the physical

principles (the analysis motor-fan model developed in [66]). The mathematic models developed in these works reveal that high non-linearity of the process is the main challenge for the VAV control system design.

3.5.2 Experimental VAV air-conditioning system

To develop a superior controller with robust stability performance for VAV system, a VAV air-conditioning pilot plant was built for the experimental purpose. As shown in Figure 3.6, number 1, 2, 3 and 4 indicate the components of computer controller, air-conditioning pilot plant, signal process board and signal transmission cables, respectively. The system has three chillers, three zones with three air-handling units (AHU), three cooling towers and flexible partitions up to twelve rooms (four rooms for each zone). All motors (fans, pumps and compressors) are controlled by variable speed drives (VSD). The system is designed to be flexible for different combinations of three units to form various VAV air-conditioning schemes.

The main components for the supply air pressure control loop are shown in Figure 3.7. Here, number 1, 2, 3 and 4 indicate the location of the supply air fan, the ductwork, static pressure sensor and VAV terminal box.

Figure 3.6: Measurement and control apparatus of VAV air-conditioning system

Figure 3.7: Components of the supply air pressure control loop

Figure 3.8: VAV supply air pressure control loop

Figure 3.8 shows a simplified diagram of the supply air pressure control loop in this experimental VAV system. It can be seen from this figure that one air supply fan feeds fresh air into four different rooms. Each room has one VAV box which can regulate the air volume flowing into the room by adjusting the damper's position, the VAV dampers'

position may change according to the cooling or heating requirement in each room. The designed controller is expected to maintain the supply air pressure at the set point in spite of dampers' constant change. A static pressure sensor with measurement range from 0 Pa to 250 Pa is mounted near the end of the main supply air duct. The controller issues commands to a variable speed drive (VSD) that is connected to the supply air fan motor, such that the pressure can be controlled by the fan speed. The National Instrument Data Acquisition Card 6064E is used for the control system with a sampling interval set to 0.1s.

3.5.3 Experimental Studies

The performance of the neural network assisted PI controller is compared to that of a conventional PI controller on the experimental VAV air-conditioning system described in section 3.5.2. The experiments conducted are listed as follows.

Experiment 1: Performance comparison of these two controllers under different control load subject to different VAV damper status.

Experiment 2: Performance comparison of these two controllers under different operating points and external disturbances subject to supply airflow rate change.

Experiment 3: Evaluation of the NNAPI controller's performance under long working hours.

For a linear process, the PI controller is typically tuned to produce a fast plant respecting to set-point changes without overshoot. For a system with a static non-linearity, the tuning procedure is more complex, since the controlled response varies with operating points. One commonly used technique is to tune the controller when the process is operating in the region of the highest gain, so that the response may have damped performance at other operating points [68]. In this real-time VAV system experiments, for the experiment 1 and 2, the optimal PI controller's parameters are tuned under the

condition that only one damper is completely open while others are closed, and the supply air pressure set point is around 80Pa . The PI controller tuning method used is the well-known Ziegler-Nichols method and minor adjustments with the trial and error method are made to obtain the best response without overshoot at the operating point. For experiment 3, the integral gain of the well-tuned PI controller is decreased to simulate the PI control performance after system degradation due to the aging effect of long working hours. It should be noted that, for a fair comparison, for each test, the NNAPI controller uses the same parameters as its counterpart PI controller.

Experiment 1

With the tuning method mentioned above, the proportional and integral gains for PI and NNAPI controller are obtained as $K_p = 1.5$, $K_i = 0.9$.

In this experiment, for each controller, the tests are carried out two times with different VAV damper positions. For the first time, the dampers' position status: room 1 is completely opened, rooms 2,3,4 are completely closed. And for the second time, the dampers' position status: room 1, 2, 3, 4 are all completely opened.

The experiment steps are described as follows.

1. Stabilize the supply air static pressure at 60 Pa .
2. Reset the supply air static pressure set-point to 80 Pa at the time step $t=4000$.
3. Reset the supply air static pressure set-point back to 60 Pa at the time step $t=6000$.

Figure 3.9: Performance of PI controller under different VAV damper status in experiment 1 Above: The damper of room 1 is completely open, those of room 2,3,4 are completely closed. Below: The dampers of room 1, 2, 3, 4 are all completely opened.

Figure 3.10: Performance of NNAPI controller under different VAV damper status in experiment 1. Above: The damper of room 1 is completely open, those of room 2,3,4 are completely closed. Below: The dampers of room 1, 2, 3, 4 are all completely opened.

VAV dampers position	TESTING	CRITERIA	PI controller	NNAPI controller
One open, the other three closed	Set-point change from 60 Pa to 80 Pa	Settling time (s)	15	10
	Set-point change from 80 Pa to 60 Pa	Settling time (s)	25	12
All open	Set-point change from 60 Pa to 80 Pa	Settling time (s)	65	15
	Set-point change from 80 Pa to 60 Pa	Settling time (s)	70	20

Table 3.1: Performance comparison for PI and NNAPI controller in experiment 1

Figure 3.9, Figure 3.10 and Table 3.1 show the first experiment result. Before the change of damper positions, the PI controller was set around the operation points where the PI controller is well tuned. After the change of damper positions (with more VAV dampers opened), the PI controller's performance degrades a lot in term of the response time. However, the NNAPI controller has overall superior performance compared to the standard PI controller in term of fast settling time.

Experiment 2

The proportional and integral gains for PI and NNAPI controller are still the well-tuned values for PI control algorithm at $K_p = 1.5$, $K_I = 0.9$. The VAV dampers status for the four rooms: room 1, 2 is completely open, room 3, 4 are completely closed.

These two different controllers go through the same test as follows:

1. Stabilize the supply air static pressure at 40 Pa.
2. Reset the supply air static pressure set-point to 60 Pa at the time step $t=2000$.

3. Reset the supply air static pressure set-point to 80 Pa at the time step $t=4000$.
4. Reset the supply air static pressure set-point to 100 Pa at the time step $t=6000$.
5. Close the damper of room1 to generate a disturbance which will decrease the air flow rate in the duct at the time step $t=7000$.

Figure 3.11 and the Table 3.2 give the experiment 2 results. It shows that, because of the nonlinearity of the plant, the performance degrades a lot in term of the response time for the fixed PI controller when the operating point changes, while the NNAPI control maintains a good performance. For the disturbance rejection ability, the NNAPI controller is also superior over the fixed PI controller.

Figure 3.11: Performance comparison for PI and NNAPI controller in experiment 2

TESTING	CRITERIA	PI controller	NNAPI controller
Set-point change from 40 Pa to 60 Pa	Settling time (s)	42	13
Set-point change from 60 Pa to 80 Pa	Settling time (s)	22	11
Set-point change from 80 Pa to 100 Pa	Settling time (s)	39	15
Disturbance (Airflow rate decrease)	Settling time (s)	40	22

Table 3.2: Performance comparison for PI and NNAPI controller in experiment 2

Experiment 3

In this experiment, the integral gain of the well-tuned PI controller is decreased to simulate the PI control performance after system degradation due to the aging effect of long working hours. The proportional and integral gains are: $K_p = 1.5$, $K_i = 0.4$. The VAV damper status for the four rooms: room 1, 2 are completely open, room 3, 4 are completely closed.

These two different controllers go through the same test as follows:

1. Stabilize the supply air static pressure at 140 Pa.
2. Begin at time step $t=3000$, the set-point changes as a pulse signal, with period=100s and amplitude 15 Pa.

From Figure 3.12 we can easily see that when the set point changes from a higher level to a lower level, it takes the PI controller longer time to catch up with the set-point wave change than the NNAPI controller. The NNAPI controller inherits the same parameters

with the PI controller, which means, by integrating with the neural network trained by the adaptive dead zone train algorithm, the PI controller's performance degradation for aging effect is compensated to certain degrees.

Figure 3.12: Performance comparison for PI and NNAPI controller in experiment 3

3.6 Conclusion

The focus of this chapter is to design and demonstrate the robust performance of a neural network assisted PI control strategy for VAV air-conditioning system. A simplified formulation of the control signal is obtained by summing up outputs of the PI controller and neural network. The neural network is trained online to estimate the system nonlinear dynamic. To ensure the convergence of the learning algorithm and enhance the robust performance of the controller, an adaptive dead zone scheme is used. The system stability

issue of the proposed control scheme is guaranteed based on the conic sector theory. Real-time experiments are implemented in a laboratory environment and the experiment results demonstrate the applicability of the proposed method.

Chapter 4

SPSA Based Neural Controller for VAV System

4.1 Introduction

The neural network assistant PI controller proposed in Chapter 3 is trained by the adaptive dead zone training algorithm which is able to guarantee the convergence of weight. This chapter presents a simultaneous perturbation stochastic approximation (SPSA) algorithm based neural network to control the supply air pressure of VAV air-conditioning system. The SPSA based neural controller is capable of maintaining good control performance in spite that the actual cooling load is time-varying and process is highly nonlinear. The neural network is trained online by the SPSA algorithm in the closed-loop to provide an improved control performance over the standard methods, such as the back-propagation algorithm, in term of guaranteed stability of the weights. The main motivation to use the SPSA is its excellent convergence property. The SPSA algorithm, which is proposed by Spall [69], provides inherent drift-free parameter estimation through simultaneous perturbation of the weights.

Since the stability is a crucial feature in the practical design of control system based on neural networks, we implement the design and stability analysis for this neural controller based on the conic sector theory with theoretical proofs. No accurate process model is needed for the system design and better performance is achieved in term of robust stability, adaptive ability of system dynamic change and set point tracking. To evaluate the applicability of the proposed neural control system, real-time experiments are carried out on the experimental VAV air-conditioning system to control the static supply air pressure, and good experimental results are obtained.

4.2 Neural Network Control Scheme

Figure 4.1 shows the schematic of the neural control scheme, which comprise the outer control loop with a fixed proportional feedback controller and a neural network controller that is trained to approximate the inverse dynamics of the plant. With the k as the time index, the dynamical control system can be represented as a single-input-single-output form as the following:

$$y_k = f(y_{k-1}, y_{k-2}, \dots, y_{k-m_y}, u_{k-d-1}, u_{k-d-2}, \dots, u_{k-d-m_u}) + u_{k-d} + \varepsilon_k \quad (4.1)$$

where y is the output, u is the control input, d is the relative degree of the system. Particularly, for the supply air pressure control loop studied in this chapter, y is the static pressure in the supply air duct, and u is the input voltage of supply air fan motor. $f(\cdot)$ is a unknown dynamic nonlinear function, ε_k demotes a bounded overall noise signal of the control system. m_y, m_u are integers and $m_y \geq m_u$.

The set point tracking error is:

$$s_k = y_k - y_k^* \quad (4.2)$$

where y_k^* is the command input. Define the control signal as

$$u_{k-d} = -\hat{f}(\cdot) + y_k^* + K_P s_{k-1} \quad (4.3)$$

where $\hat{f}(\cdot)$ is estimate of the nonlinear function $f(\cdot)$ by the neural network to be defined later, K_p denotes the proportional gain of the fixed controller. We have the control signal at time step k as

$$\begin{aligned} u_k &= -\hat{f}(\cdot) + y_{k+d}^* + K_p s_{k+d-1} \\ &= -\hat{f}(y_{k+d-1}, y_{k+d-2}, \dots, y_{k+d-m_y}, u_{k-1}, u_{k-2}, \dots, u_{k-m_u}) \\ &\quad + y_{k+d}^* + K_p s_{k+d-1} \end{aligned} \quad (4.4)$$

Note that the equation above shows that the control system becomes non-causal when $d > 1$. However, for the proposed controller design, this issue can be typically addressed by introducing a linear observer with the extra observation of the difference signals.

$$y_{k-1+d} = \dot{y}_{k+d-2}T + y_{k+d-3} \quad (4.5)$$

where T is the sampling time. $\dot{y}$ is the differential signal of output y .

For example, when $d = 2$, the non-causal term y_{k-1+d} can be obtained by

$$y_{k-1+d} = y_{k+1} = \dot{y}_k T + y_{k-1}$$

Figure 4.1: Structure of the control scheme (with $m_y = 2, m_u = 0, d = 2$)

The estimation error vector of the neural network can be presented as

$$e_k = f_{k-1} - \hat{f}_{k-1} + \varepsilon_k \quad (4.6)$$

Note that, for the neural network training, the estimation error e_k may not be directly measurable, so we should use the tracking error to generate it basing on the closed-loop relationship via (4.1), (4.2), (4.3), (4.6).

$$e_k = [1 - z^{-1}K_P]s_k \quad (4.7)$$

The output of a three-layered neural network can be presented as

$$\hat{f}_k = H(w_k, x_k)v_k^T$$

where the input vector $x_k \in R^m$ of the neural network is

$$x_k = [y_{k-1}, y_{k-2}, \dots, y_{k-m_y}, u_{k-d-1}, u_{k-d-2}, \dots, u_{k-d-m_u}]^T \quad (4.8)$$

with $m = m_y + m_u$.

$v_k \in R^{n_h}$ is the weight vector of the output layer, n_h is the numbers of neurons in the hidden layers of the network. $w_k \in R^{n_h \times m}$ is the adjustable weight matrix of the hidden layer. $H(w_k, x_k)$ is the nonlinear activation function vector.

$$H(w_k, x_k) = [h(w_{k,1}^T x_k) \ h(w_{k,2}^T x_k) \ \dots \ h(w_{k,n_h}^T x_k)] \quad (4.9)$$

where $h(\cdot)$ is the nonlinear activation function

$$h(x) = 1 / (1 + e^{-4\lambda x}) \quad (4.10)$$

where $\lambda > 0$ is the so called gain parameter of the threshold function.

4.3 SPSA Based Training Algorithm

The SPSA algorithm proposed by Spall [69] [70] is a numerically efficient stochastic optimization algorithm. Unlike the conventional gradient-based optimization methods,

which evaluate the gradient of the objective function by perturbing each decision variable separately (as in the standard two-sided finite difference approximation), the SPSA formalism approximates the gradient by perturbing all the variables simultaneously. The optimization objective underlying the SPSA is defined as: find the optimal decision variable vector, θ^* , such that it simultaneously minimize the objective function $L(\theta)$. The SPSA implementation is iterative that begins with a randomly initialized solution vector. The basic SPSA formalism stipulates that the objective function to be minimized should be differentiable. For the minimum point, θ^* , the gradient of the objective function, $L(\theta)$, attains zero magnitude. That is

$$g(\theta^*) = \left. \frac{\partial L(\theta)}{\partial \theta} \right|_{\theta=\theta^*} = 0 \quad (4.11)$$

The estimate of the decision variable vector θ is updated iteratively as

$$\hat{\theta}_k = \hat{\theta}_{k-1} - a_k \hat{g}_k(\hat{\theta}_{k-1}) \quad (4.12)$$

where a_k is the learning rate and $\hat{g}_k(\hat{\theta}_{k-1})$ is the approximation of the gradient function with

$$\hat{g}_k(\hat{\theta}_{k-1}) = \frac{L(\hat{\theta}_{k-1} + c_k \Delta_k) - L(\hat{\theta}_{k-1} - c_k \Delta_k) + \varepsilon_k^\theta}{2c_k} r_k \quad (4.13)$$

and where ε_k^θ is the measurement disturbance as defined in [69]. In the above equation, $\Delta_k \in R^p$ is a random directional vector that is used to stimulate the weight vector simultaneously, $c_k > 0$ is a sequence of positive number satisfying certain regularity conditions [69,70]. The random vector Δ_k is generated via Monte Carlo according to conditions specified in [69] or [70]. If the i th element of Δ_k is denoted as Δ_{ki} , then the sequence of $r_k \in R^p$ is defined as

$$r_k = \left[\frac{1}{\Delta_{k_1}} \dots \frac{1}{\Delta_{k_p}} \right], \quad (4.14)$$

When applying the SPSA to the three-layer neural network training, we define the overall estimate decision vector as

$$\hat{\theta}_k = [\hat{\theta}_k^{vT} \ \hat{\theta}_k^{wT}]^T \in R^p \text{ with } p = n_h + n_h m,$$

Where $\hat{\theta}_k^v = v_k$ and $\hat{\theta}_k^w = [w_{k,1}^T \ w_{k,2}^T \ \dots \ w_{k,n_h}^T]$. Then the output of a three-layer neural network can be presented as

$$\hat{f}_k = H(\hat{\theta}_k^w, x_k) \hat{\theta}_k^v \quad (4.15)$$

It should be noted that, for a multi-layered neural network, it might not be possible to update all the estimated parameters with a single gradient approximation function (4.13) to meet the stability requirement. Therefore, it is better that the estimate parameter vectors $\hat{\theta}_k^v$ and $\hat{\theta}_k^w$ are updated separately in the SPSA algorithm using different gradient approximation functions as in the standard back-propagation training algorithm. This point will be explored further in the robust stability analysis in the next section.

4.4 Stability Analysis

We use $\|\bullet\|$ to denote the Frobenius norm of a matrix and Euclidean norm of a vector in this chapter. For an $m \times n$ matrix A ,

$$\|A\| = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2}$$

The stability of the input-output neural control system can be analyzed by the conic sector theory [61,62,63]. The main concern is with the discrete time tracking error signal s_k , which is an infinite sequence of real vectors. Consider, following [71], the extended space L_{2e} , consisting of those elements whose truncations lie in L_2 , e.g. s belongs to the extended space L_{2e} if

$$\|s\|_{2e} = \left\{ \sum_{k=1}^t s_k^T s_k \right\}^{1/2} < \infty$$

$\forall t \in Z_+$ (the set of positive integer).

Based on Theorem 3.1, the operator H_1 represents the SPSA training algorithm, the input error signal is the tracking error s_k defined in (4.2) and the output is Φ_k , which will be defined later and is related to the weight error vectors, and in turn, the estimation parameter error vector e_k and tracking error s_k through (4.7). H_2 usually represents the mismatched linear model uncertainty in a typical adaptive linear control system and will be defined later [61].

The first step to use the conic sector stability Theorem 3.1 is to restructure the control system in Figure 4.1 into an equivalent error feedback system as shown in Figure 4.2(a).

Figure 4.2: The equivalent error feedback systems using the conic sector condition:

- (a) For the tracking error s_k and the output $\Phi_k^v = -H(\hat{\theta}_{k-1}^w, x_{k-1})\tilde{\theta}_k^v$
- (b) For the estimate error e_k and the output $\Phi_k^v = -H(\hat{\theta}_{k-1}^w, x_{k-1})\tilde{\theta}_k^v$

The parameter estimation error vector should be derived and referred to the output signal Φ_k . For this purpose, define the desired output of the neural network as the plant nonlinear function in (4.1), i.e.

$$f_{k-1} = H(\hat{\theta}_{k-1}^{w^*}, x_{k-1})\theta^{v^*} \quad (4.16)$$

where $\theta^{v^*} \in R^{n_h}$ is an ideal weight vector in the output layer of the neural network and $\theta^{w^*} \in R^{n_{hm}}$ is the desired weight vector of the hidden layer. Therefore, the parameter estimate error vectors can be defined as $\tilde{\theta}_k^v = \theta^{v^*} - \theta_k^v \in R^{n_h}$ and $\tilde{\theta}_k^w = \theta^{w^*} - \hat{\theta}_k^w \in R^{n_{hm}}$, for the output and hidden layers, respectively.

Assumptions:

- The system disturbance ε_k is L_2 norm bounded.
- The ideal weight vectors θ^{v^*} and θ^{w^*} are also L_2 bounded.

Now, we are ready to establish the relationship between the tracking error signal s_k and the parameter estimate vectors of the neural network, which is referred to as the operator H_1 in Theorem 3.1, i.e. the SPSA based training algorithm. According to equations (4.6) and (4.7) the error signals can be extended as

$$\begin{aligned} s_k &= H_2 e_k = H_2 (f_{k-1} - \hat{f}_{k-1} + s_k) \\ &= H_2 \left(\frac{1}{2} (f_{k-1} - \hat{f}_{k-1}^{v+}) + \frac{1}{2} (f_{k-1} - \hat{f}_{k-1}^{v-}) + \varepsilon_k \right) \\ &= H_2 H(\hat{\theta}_{k-1}^w, x_{k-1}) \tilde{\theta}_{k-1}^v + \tilde{e}_k^v \\ &= -H_2 \Phi_k^v + \tilde{e}_k^v \end{aligned} \quad (4.17)$$

where the operator $H_2 = \frac{1}{1 - K_p z^{-1}}$ and

$$\Phi_k^v = -H(\hat{\theta}_{k-1}^w, x_{k-1}) \tilde{\theta}_{k-1}^v \quad (4.18)$$

$$\tilde{H}(\hat{\theta}_{k-1}^w, \theta^{w^*}, x_{k-1}) = (H(\theta^{w^*}, x_{k-1}) - H(\hat{\theta}_{k-1}^w, x_{k-1}))\theta^{v^*} \quad (4.19)$$

$$\tilde{e}_k^v = H_2 (\tilde{H}(\hat{\theta}_{k-1}^w, \theta^{w^*}, x_{k-1}) + \varepsilon_k) \quad (4.20)$$

$$\begin{aligned} \hat{f}_{k-1}^{v+} &= H(\hat{\theta}_{k-1}^w, x_{k-1})(\hat{\theta}_{k-1}^v + c_k \Delta_v^k) \\ \hat{f}_{k-1}^{v-} &= H(\hat{\theta}_{k-1}^w, x_{k-1})(\hat{\theta}_{k-1}^v - c_k \Delta_v^k) \end{aligned} \quad (4.21)$$

with Δ_k^v and $r_k^v \in R^{n_h}$ which can be viewed as the first n_h components of Δ_k and r_k defined in (4.13) and (4.14) for the SPSA, respectively.

Remark 4.1: There is an important implication in equation (4.17). The tracking error signal s_k is directly linked to the output signal Φ_k in equation (4.18), and in turn, the parameter estimation error vector $\tilde{\theta}_k^v$ of the output layer of the neural network, which implies that the training procedure of the output layer of the neural network should be treated separately from the hidden layer of the network to obtain a bounded disturbance term $\tilde{e}_k^v$ as defined in (4.20), $\tilde{e}_k^v \in L_2$ as required by Theorem 3.1 (defined as e_k^*). Therefore, using equation (4.17), we are able to form an equivalent error feedback system (Figure 4.2(a)) as the one in Theorem 3.1. Note that H_2 usually represents the mismatched linear model uncertainty in a typical adaptive linear control system [61]. Since the neural network has powerful approximation ability to match the nonlinear function without the need to worry about the linear model mismatch, therefore, the operator $H_2 = \frac{1}{1 - K_p z^{-1}}$ represents only the fixed controller and is always stable as $K_p < 1$. Furthermore, the condition (b) of Theorem 3.1 can be treated as positive real function, i.e. the plot of H_2 should be in the positive half of a complex plane as shown in [62].

We define the operator H_1^v , which represents the SPSA training algorithm of the output layer. Also define the loss function as

$$L(\hat{\theta}_{k-1}^v, \hat{\theta}_{k-1}^w) = \|f_k - \hat{f}_k\|^2 \quad (4.22)$$

With definitions in equation (4.13) and (4.20), we have a normalized gradient approximation using the simultaneous perturbation vector $\Delta_k^v \in R^{n_h}$ to stimulate the weight of the output layer:

$$\begin{aligned}
\hat{g}(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v, \Delta_k^v) &= \frac{L(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v + c_k \Delta_k^v) - L(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v - c_k \Delta_k^v) + \varepsilon_k^v}{2c_k \rho_k^v} r_k^v \\
&= \frac{(f_{k-1} - \hat{f}_{k-1}^{v+})^2 - (f_{k-1} - \hat{f}_{k-1}^{v-})^2 + \varepsilon_k^v}{2c_k \rho_k^v} r_k^v \\
&= \frac{(f_{k-1} - \hat{f}_{k-1}^{v+} + f_{k-1} - \hat{f}_{k-1}^{v-})^T (\hat{f}_{k-1}^{v-} - \hat{f}_{k-1}^{v+}) + \varepsilon_k^v}{2c_k \rho_k^v} r_k^v \\
&= \frac{e_k^T (\hat{f}_{k-1}^{v-} - \hat{f}_{k-1}^{v+})}{2c_k \rho_k^v} r_k^v = -\frac{s_k^T (1 - K_P z^{-1}) H(\hat{\theta}_{k-1}^w, x_{k-1}) 2\Delta_k^v}{\rho_k^v} r_k^v
\end{aligned} \tag{4.23}$$

Where the bounded normalization factor, which is traditionally used in adaptive control system to bound the signals in learning algorithms [63], is

$$\rho_k^v = \mu \rho_{k-1}^v + \max(4 \|H(\hat{\theta}_{k-1}^w, x_{k-1})\|^2 \|\Delta_k^v\|^2 \|r_k^v\|^2, \bar{\rho}) \quad \text{with } \bar{\rho} > 0, \mu \in (0, 1). \tag{4.24}$$

ε_k^v is the bounded measurement error and has a relationship with the overall system disturbance ε_k in (4.1) as

$$\varepsilon_k = \left\| \hat{f}_{k-1}^{v+} - \hat{f}_{k-1}^{v-} \right\|^{-2} (\hat{f}_{k-1}^{v+} - \hat{f}_{k-1}^{v-}) \varepsilon_k^v = \frac{(H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v) \varepsilon_k}{\left\| H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v \right\|^2 2c_k}$$

which is also bounded.

Note that the gradient approximation function in (4.23) can be used only for the output layer as justified in Remark 4.1. Therefore, the parameter vector $\hat{\theta}_k^v$ can be estimated by the SPSA training algorithm in equation (4.12) with the gradient approximation $\hat{g}(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v, \Delta_k^v)$, i.e.

$$\begin{aligned}
\hat{\theta}_k^v &= \hat{\theta}_k^v - a_k \hat{g}(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v, \Delta_k^v) \\
&= \hat{\theta}_{k-1}^v + a_k \frac{s_k^T (1 - K_P z^{-1}) H(\hat{\theta}_{k-1}^w, x_{k-1}) 2\Delta_k^v}{\rho_k^v} r_k^v
\end{aligned} \tag{4.25}$$

Then stability analysis of the robust neural controller can be justified by the conic sector condition, which requires the feedback system in Figure 4.1 to meet certain dissipative condition as in Theorem 3.1 and can be justified as in the following theorem.

Theorem 4.1: The operator $H_1^v : s_k \rightarrow \Phi_k^v$, which represents the SPSSA learning algorithm of the output layer (see Figure 4.2 (a)), satisfies the conditions (a) of Theorem 3.1.

Proof: As an easy starting point, we establish the conic sector condition between the estimate error e_k and the output $\Phi_k^v = -H(\hat{\theta}_{k-1}^w, x_{k-1})\tilde{\theta}_{k-1}^v$ first (see Figure 4.2(b)), and then extend to the tracking error s_k later (both relationships can be basically derived from equation (4.25)).

Using the iteration equation (4.25), we have

$$\begin{aligned} \|\tilde{\theta}_k^v\|^2 - \|\tilde{\theta}_{k-1}^v\|^2 &= -2\{a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\Delta_k^v r_k^{vT} \tilde{\theta}_{k-1}^v\}(\rho_k^v)^{-1} + \{a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\Delta_k^v r_k^v \tilde{\theta}_{k-1}^v (\rho_k^v)^{-1}\}^2 \\ &\leq 2\{a_k\}|-e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\tilde{\theta}_{k-1}^v| \|\tilde{\theta}_{k-1}^v\| (\tilde{\theta}_{k-1}^v \tilde{\theta}_{k-1}^{vT})^{-1} \Delta_k^v r_k^v \tilde{\theta}_{k-1}^v|(\rho_k^v)^{-1} \\ &\quad + \{a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\Delta_k^v r_k^v (\rho_k^v)^{-1}\}^2 \end{aligned} \quad (4.26)$$

Consider the property of gradient of the square error signal around the attractor basin [13].

$$-\frac{\partial(e_k^T e_k)}{\partial(\hat{\theta}_{k-1}^v)^T} \tilde{\theta}_{k-1}^v = -e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\tilde{\theta}_{k-1}^v = e_k^T \Phi_k^v \geq 0 \quad (4.27)$$

and the trace property

$$\begin{aligned} |\tilde{\theta}_{k-1}^{vT} (\tilde{\theta}_{k-1}^v \tilde{\theta}_{k-1}^{vT})^{-1} \Delta_k^v r_k^{vT} \tilde{\theta}_{k-1}^v| &\triangleq \text{tr}\{\tilde{\theta}_{k-1}^{vT} (\tilde{\theta}_{k-1}^v \tilde{\theta}_{k-1}^{vT})^{-1} \Delta_k^v r_k^{vT} \tilde{\theta}_{k-1}^v\} \\ &\triangleq \text{tr}\{\tilde{\theta}_{k-1}^v \tilde{\theta}_{k-1}^{vT} (\tilde{\theta}_{k-1}^v \tilde{\theta}_{k-1}^{vT})^{-1} \Delta_k^v r_k^{vT} \tilde{\theta}_{k-1}^v\} \triangleq \text{tr}\{\Delta_k^v r_k^{vT}\} \triangleq n_h \end{aligned} \quad (4.28)$$

Equation (4.26) can be rewritten as

$$\|\tilde{\theta}_k^v\|^2 - \|\tilde{\theta}_{k-1}^v\|^2 \leq 2a_k n_h \{e_k^T \Phi_k^v\}(\rho_k^v)^{-1} + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1})\Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \quad (4.29)$$

Summing the above equation upon to N steps, we are able to establish the conic condition with a constant $\hat{\sigma}^v$ for the estimate error e_k as the input in Theorem 3.1 (refer to Figure 4.2 (b)) and the output Φ_k^v similar to reference [72]:

$$\sum_{k=0}^N \left[e_k^T \Phi_k^v + e_k^T e_k \frac{\bar{\sigma}^v}{2} / 2 \right] > -(\tilde{\theta}_0^v)^2 \frac{\bar{\rho}_v^k}{(2a_k n_h)} \quad (4.30)$$

by selecting a suitable normalized factor $\bar{\rho}_k^v$ to obtain the constant number $\bar{\sigma}^v$ such that

$$1 > \bar{\sigma}^v \geq \frac{a_k}{n_h} \|\Delta_k^v\|^2 \|r_k^v\|^2 (\bar{\rho}_k^v)^{-1} > \frac{a_k}{n_h} \|H(\hat{\theta}_{k-1}^w, x_{k-1})\|^2 \|\Delta_k^v\|^2 \|r_k^v\|^2 (\bar{\rho}_k^v)^{-1} > 0 \quad (4.31)$$

Note that the conic sector condition (4.30) guarantees that the estimate error e_k and the output $\Phi_k^v = -H(\hat{\theta}_{k-1}^w, x_{k-1}) \tilde{\theta}_{k-1}^v$ are bounded according to the Theorem 3.1, and in turn, the parameter estimate error $\tilde{\theta}_k^v$. To establish the conic sector condition of the tracking error s_k we can further expend equation (4.26) into

$$\begin{aligned} \|\tilde{\theta}_k^v\|^2 - \|\tilde{\theta}_{k-1}^v\|^2 &\leq 2a_k n_h \{e_k^T \Phi_k^v\} (\rho_k^v)^{-1} + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \\ &= 2a_k n_h \{s_k^T \Phi_k^v - K_p s_{k-1}^T \Phi_k^v\} (\rho_k^v)^{-1} + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \\ &\leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} + 2a_k n_h \|K_p s_{k-1}^T \Phi_k^v (\rho_k^v)^{-1}\| + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \\ &\leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} + a_k n_h \|K_p s_{k-1}^T (\rho_k^v)^{-1}\|^2 + a_k n_h K_p \|\Phi_k^v\|^2 + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \end{aligned} \quad (4.32)$$

Above inequality is due to the fact

$$2a_k n_h \|K_p s_{k-1}^T \Phi_k^v (\rho_k^v)^{-1}\| \leq a_k n_h \|K_p s_{k-1}^T (\rho_k^v)^{-1}\|^2 + a_k n_h K_p \|\Phi_k^v\|^2$$

(4.32) can be rewritten as

$$\begin{aligned} \|\tilde{\theta}_k^v\|^2 - \|\tilde{\theta}_{k-1}^v\|^2 - a_k n_h K_p \|\Phi_k^v\|^2 &\leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} + a_k n_h \|(s_k^T - e_k^T) (\rho_k^v)^{-1}\|^2 \\ &\quad + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \end{aligned} \quad (4.33)$$

Then we have

$$\begin{aligned} \|\tilde{\theta}_k^v\|^2 - \|\tilde{\theta}_{k-1}^v\|^2 - a_k n_h K_p \|\Phi_k^v\|^2 &\leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} - 2a_k n_h \|s_k^T e_k^T\| (\rho_k^v)^{-2} \\ &\quad + a_k n_h \|s_k^T\|^2 (\rho_k^v)^{-2} + a_k n_h \|e_k^T\|^2 (\rho_k^v)^{-2} + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \\ &\leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} + 2a_k n_h \|s_k^T\|^2 (\rho_k^v)^{-2} + 2a_k n_h \|e_k^T\|^2 (\rho_k^v)^{-2} \\ &\quad + \|a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1}\|^2 \end{aligned}$$

we have

$$\begin{aligned} & \left\| \tilde{\theta}_k^v \right\|^2 - \left\| \tilde{\theta}_{k-1}^v \right\|^2 - a_k n_h K_P \left\| \Phi_k^v \right\|^2 - 2a_k n_h \left\| e_k^T \right\|^2 (\rho_k^v)^{-2} - \left\| a_k e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1} \right\|^2 \\ & \leq 2a_k n_h s_k^T \Phi_k^v (\rho_k^v)^{-1} + 2a_k n_h \left\| s_k^T \right\|^2 (\rho_k^v)^{-2} \end{aligned}$$

Above inequality can be rewritten as

$$\begin{aligned} & \frac{\left\| \tilde{\theta}_k^v \right\|^2 - \left\| \tilde{\theta}_{k-1}^v \right\|^2}{2a_k n_h} - \frac{K_P \left\| \Phi_k^v \right\|^2}{2} - \left\| e_k^T \right\|^2 (\rho_k^v)^{-2} - \frac{a_k \left\| e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1} \right\|^2}{2n_h} \\ & \leq s_k^T \Phi_k^v (\rho_k^v)^{-1} + \left\| s_k^T \right\|^2 (\rho_k^v)^{-2} \end{aligned}$$

Then we have

$$\begin{aligned} & \frac{\left\| \tilde{\theta}_k^v \right\|^2 - \left\| \tilde{\theta}_{k-1}^v \right\|^2}{2a_k n_h} - \frac{K_P \left\| \Phi_k^v \right\|^2}{2} - \frac{\left\| e_k^T \right\|^2}{(\rho_k^v)^2} - \frac{a_k \left\| e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1} \right\|^2}{2n_h (\rho_k^v)^2} \\ & \leq \bar{s}_k^T \bar{\Phi}_k^v + \frac{2}{\rho_k^v} \frac{\left\| \bar{s}_k^T \right\|^2}{2} \leq \bar{s}_k^T \bar{\Phi}_k^v + \sigma^v \frac{\left\| \bar{s}_k^T \right\|^2}{2} \end{aligned} \quad (4.34)$$

with the normalized tracking error $\bar{s}_k = s_k / \sqrt{\rho_k^v}$, and the normalized output $\bar{\Phi}_k^v = \Phi_k^v / \sqrt{\rho_k^v}$.

And the choice of the normalized factor ρ_k^v guarantees that there exists a constant σ^v such that $1 > \sigma^v \geq 2\rho_k^v > 0$.

As shown in equation (4.24)

$$\rho_k^v = \mu \rho_{k-1}^v + \max(4 \left\| H(\hat{\theta}_{k-1}^w, x_{k-1}) \right\|^2 \left\| \Delta_k^v \right\|^2 \left\| r_k^v \right\|^2, \bar{\rho}) \quad \text{with } \bar{\rho} > 0, \mu \in (0, 1).$$

Summing inequality (4.34) $N+1$ steps, we have

$$\begin{aligned} & \sum_{k=0}^N \left[\bar{s}_k^T \bar{\Phi}_k^v + \sigma^v \frac{\left\| \bar{s}_k^T \right\|^2}{2} \right] \\ & \geq - \frac{\left\| \tilde{\theta}_0^v \right\|^2}{2a_k n_h} - \sum_{k=0}^N \left\{ \frac{K_P \left\| \Phi_k^v \right\|^2}{2} - \frac{\left\| e_k^T \right\|^2}{(\rho_k^v)^2} - \frac{a_k \left\| e_k^T H(\hat{\theta}_{k-1}^w, x_{k-1}) \Delta_k^v r_k^v (\rho_k^v)^{-1} \right\|^2}{2n_h (\rho_k^v)^2} \right\} \end{aligned} \quad (4.35)$$

The specified normalized factor ρ_k^v , plays two important roles. Firstly, it guarantees $\sigma^v < 1$ to avoid the so-called vanished cone problem [63]. Secondly, it guarantees the sector conditions of Theorem 3.1 to be simultaneously satisfied by both the original feedback system in Figure 4.1 and the normalized equivalent feedback system in Figure 4.2. [61,62,63]. The last item in the right hand side of equation (4.35) is bounded as shown in (4.30). Therefore the condition (a) of Theorem 3.1 is fulfilled.

Remark 4.2: Based on the Theorem 3.1 and the discussion on operator H_2 in Remark 4.1, both the condition (a) and (b) are fulfilled. Therefore the feedback system is stable with $s_k, \Phi_k^v \in L_2$

As justified in Remark 4.1, the hidden layer parameter of the network is estimated separately. Therefore, a conic sector condition should be established for the hidden layer training to grantee the stability of the whole system.

Similar to the error equation (4.17), we can rewrite it as

$$\begin{aligned} s_k &= H_2 e_k = H_2 (f_{k-1} - \hat{f}_{k-1} + s_k) \\ &= H_2 [H(\theta^{w*}, x_{k-1}) \theta^{*v} - H(\hat{\theta}_{k-1}^w, x_{k-1}) \hat{\theta}_{k-1}^v + \varepsilon_k] \\ &= H_2 [H(\theta^{w*}, x_{k-1}) \theta^{*v} - H(\theta^{w*}, x_{k-1}) \hat{\theta}_{k-1}^v + H(\theta^{w*}, x_{k-1}) \hat{\theta}_{k-1}^v - H(\hat{\theta}_{k-1}^w, x_{k-1}) \hat{\theta}_{k-1}^v + \varepsilon_k] \\ &= H_2 [\tilde{H}(\hat{\theta}_{k-1}^w, x_{k-1}) \hat{\theta}_{k-1}^v + H(\theta^{w*}, x_{k-1}) \tilde{\theta}_{k-1}^v + \varepsilon_k] \\ &= -H_2 \Phi_k^w + \tilde{e}_k^w \end{aligned}$$

with

$$\tilde{e}_k^w = H_2 [H(\theta^{w*}, x_{k-1}) \tilde{\theta}_{k-1}^v + \varepsilon_k]$$

$$\Phi_k^w = -\tilde{\Omega}_{k-1} \tilde{\theta}_{k-1}^w$$

where $\tilde{H}(\hat{\theta}_{k-1}^w, x_{k-1}) = H(\hat{\theta}_{k-1}^{w*}, x_{k-1}) - H(\hat{\theta}_{k-1}^w, x_{k-1})$, $\tilde{\theta}_{k-1}^w = \theta_{k-1}^{w*} - \hat{\theta}_{k-1}^w$ and $\tilde{\Omega}_{k-1} \in R^{mn_h}$ is following vector

$$\tilde{\Omega}_{k-1} = \left[\underbrace{\tilde{\mu}_{k-1,1} \hat{\theta}_{k-1,1}^v x_{k-1,1} \cdots \tilde{\mu}_{k-1,1} \hat{\theta}_{k-1,1}^v x_{k-1,1}}_m \cdots \tilde{\mu}_{k-1,i} \hat{\theta}_{k-1,i}^v x_{k-1,i} \cdots \tilde{\mu}_{k-1,n_h} \hat{\theta}_{k-1,n_h}^v x_{k-1,n_h} \right] \quad (4.36)$$

note that equation (4.36) is derived from the mean value theorem. The activation function in equation (4.10) is a non-decreasing function, so there exist unique positive numbers $\tilde{\mu}_{k-1,i}$ such that

$$h(\theta_{k-1,i}^{w*}, x_{k-1}) - h(\hat{\theta}_{k-1,i}^w, x_{k-1}) = \tilde{\mu}_{k-1,i} (\theta_{k-1,i}^{w*} - \hat{\theta}_{k-1,i}^w) \quad (4.37)$$

where $\theta_{k-1,i}^{w*}$, $\hat{\theta}_{k-1,i}^w$ are the ideal and estimation vectors linked to the i th hidden layer neuron, respectively. The maximum value of the derivative h' is λ (see the definition of $h(\cdot)$ in (4.10), therefore

$$\lambda \geq \tilde{\mu}_{k-1,i} \geq 0 \quad (1 \leq i \leq n_h) \quad (4.38)$$

Note that $\tilde{e}_k^w$ is a bounded signal, since $\hat{\theta}_{k-1}^v$ has been proven to be bounded in Theorem 4.1. Then similar to equation (4.23), the normalized gradient approximation of the hidden layer can be written as

$$\begin{aligned} \hat{g}(\hat{\theta}_{k-1}^v, \hat{\theta}_{k-1}^w, \Delta_k^w) &= \frac{L(\hat{\theta}_{k-1}^v, \hat{\theta}_{k-1}^w + c_k \Delta_k^w) - L(\hat{\theta}_{k-1}^v, \hat{\theta}_{k-1}^w - c_k \Delta_k^w) + \varepsilon_k^v}{2c_k \rho_k^v} r_k^w \\ &= \frac{(f_{k-1} - \hat{f}_{k-1}^{w+})^2 - (f_{k-1} - \hat{f}_{k-1}^{w-})^2 + \varepsilon_k^w}{2c_k \rho_k^v} r_k^w \\ &= \frac{(f_{k-1} - \hat{f}_{k-1}^{w+} + f_{k-1} - \hat{f}_{k-1}^{w-})^T (\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+}) + \varepsilon_k^w}{2c_k \rho_k^v} r_k^w \\ &= \frac{[2(f_{k-1} - \hat{f}_{k-1}) + (\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+}) + (\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+})]^T (\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+}) + \varepsilon_k^w}{2c_k \rho_k^w} r_k^w \\ &= \frac{e_k^T (\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+})}{2c_k \rho_k^w} r_k^w = -\frac{s_k^T (1 - K_P z^{-1})(\hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+})}{c_k \rho_k^w} r_k^w \end{aligned} \quad (4.39)$$

where Δ_k^w and $r_k^w \in R^{mn_h}$,

the normalized factor

$$\rho_k^w = \mu \rho_{k-1}^w + \max \left(\left\| \hat{f}_{k-1}^{w-} - \hat{f}_{k-1}^{w+} \right\|^2 \left\| r_k^w \right\|^2, \bar{\rho} \right)$$

and

$$s_k = H_2 e_k = H_2 (f_{k-1} - \hat{f}_{k-1} + \varepsilon_k)$$

$$\hat{f}_{k-1}^{w+} = H(\hat{\theta}_{k-1}^w + c_k \Delta_k^w, x_{k-1}) \hat{\theta}_{k-1}^v$$

$$\hat{f}_{k-1}^{w-} = H(\hat{\theta}_{k-1}^w - c_k \Delta_k^w, x_{k-1}) \hat{\theta}_{k-1}^v$$

ε_k^w is the bounded measurement error and has a relationship with the overall system disturbance ε_k as

$$s_k = [(f_{k-1} - \hat{f}_{k-1}) + (\hat{f}_{k-1} - \hat{f}_{k-1}^{w+}) + (\hat{f}_{k-1} - \hat{f}_{k-1}^{w-})]^T - \|\hat{f}_{k-1}^{w+} - \hat{f}_{k-1}^{w-}\|^{-2} (\hat{f}_{k-1}^{w+} - \hat{f}_{k-1}^{w-}) \varepsilon_k^w \quad (4.40)$$

Note that s_k is a bounded signal. Then the SPSA algorithm of the hidden layer becomes

$$\begin{aligned} \hat{\theta}_k^w &= \hat{\theta}_k^w - a_k \hat{g}(\hat{\theta}_{k-1}^w, \hat{\theta}_{k-1}^v, \Delta_k^v) \\ &= \hat{\theta}_{k-1}^w + a_k \frac{s_k^T (1 - K_P z^{-1})(f_{k-1}^{w+} - f_{k-1}^{w-})}{c_k \rho_k^w} r_k^w \end{aligned} \quad (4.41)$$

and following theorem holds.

Theorem 4.2: The operator $H_1^w : s_k \rightarrow \Phi_k^w$, which represents the SPSA learning algorithm of the hidden layer, and H_2 satisfy the condition (a) and (b) of Theorem 3.1.

Proof: (The proof follows the same approach as that in Theorem 4.1 and the discussion in Remark 4.1).

The robust neural controller algorithm can be summarized as (refer to Figure 4.1):

Step 1: Form the new input vector x_{k-1} of the neural network defined in equation (4.8).

Step 2: Calculate the neural network output $\hat{f}_{k-1}$ by using the input state x_{k-1} and the existing or initial weights of the network in the first iteration. (The weights of the neural network can be randomly initialized.)

Step 3: The control input u_{k-1} is calculated based on equation (4.3).

Step 4: The new measurement of the system dynamics is taken and the measurable tracking error signal s_k is fed through a fixed filter to produce the implicit training error signal e_k of the network according to equation (4.7).

Step 5: The tracking error s_k is used directly to train the neural network and calculates the new weights $\hat{\theta}_k^v$ and $\hat{\theta}_k^w$ by using learning law in (4.25) and (4.41) for the output and hidden layers, respectively, the updated new weights will be used in the next training iteration.

Step 6: Go back to Step 1 to continue the training iteration.

4.5 Experimental Studies

To evaluate the control performance of the SPSA based neural controller proposed, three experiments are implemented on the experimental VAV air-conditioning system described in section 3.5 of Chapter 3.

4.5.1 Experiment 1

The first experiment is to compare the performance of the proposed controller with the conventional PI controller under different control loads caused by different VAV damper statuses. A three-layer neural network as defined in section 4.2 is used for this experiment study with 12 hidden layer neurons, all the initial weight values are chosen to be zero, the gain parameter of the fixed controller is given as $K_p = 0.8$ and sampling interval set to 0.1s. For a linear process, the PI controller is typically tuned to produce a fast plant response to set point changes without overshoot. For a plant with a static non-linearity, the tuning procedure is more complex, since the controlled response varies with operating points. One commonly used technique is to tune the controller when the plant is operating in the region of the highest gain, so that the response may have damped performance at other operating points. In our real-time VAV system experiments, the optimal PI

controller's parameters are tuned under the conditions that only one damper is completely open while others are closed. The PI controller tuning used the well-known Ziegler-Nichols method and minor adjustments are made to obtain the best response without overshoot.

With the tuning method mentioned above, the proportional and integral gains for PI controller are obtained as $K_p = 1.5$, $K_I = 0.9$.

In this experiment, for each controller, the tests are carried out two times with different VAV damper positions. For the first time, the dampers' position status: room 1 is completely opened, rooms 2,3,4 are completely closed. And for the second time, the dampers' position status: room 1, 2, 3, 4 are all completely opened.

The experiment steps are described as follows.

1. Stabilize the supply air static pressure at 60 Pa.
2. Reset the supply air static pressure set point to 80 Pa at the time step $t=4000$.
3. Reset the supply air static pressure set point back to 60 Pa at the time step $t=6000$.

Figure 4.3: Performance of PI controller under different VAV damper status
 (a) The damper of room 1 is completely open, those of room 2,3,4 are completely closed.
 (b) The dampers of room 1, 2, 3, 4 are all completely opened.

Figure 4.4: Performance of SPSA based neural controller under different VAV damper status

- (a) The damper of room 1 is completely open, those of room 2,3,4 are completely closed.
(b) The dampers of room 1, 2, 3, 4 are all completely opened.

VAV dampers position	TESTING	CRITERIA	PI Controller	NN Controller
One open, the other three closed	Set-point change from 60 Pa to 80 Pa	Settling time (s)	10	7
	Set-point change from 80 Pa to 60 Pa	Settling time (s)	22	11
All open	Set-point change from 60 Pa to 80 Pa	Settling time (s)	12	8
	Set-point change from 80 Pa to 60 Pa	Settling time (s)	24	9

Table 4.1: Performance comparison (PI and SPSA based NN controller in experiment 1)

Figure 4.3, Figure 4.4 and Table 4.1 show the first experiment result. Before the change of damper positions, the PI controller is set around the operation points where the PI controller is well tuned. After the change of damper positions (with more VAV dampers opened), the PI controller's performance degrades a lot in term of the response time. However, the SPSA based neural controller has overall superior performance compared to the standard PI controller in term of fast settling time. The performance is not affected significantly by the system dynamic and control load change.

4.5.2 Experiment 2

For HVAC control system, in practice, an originally well tuned PI controller, after long-term running, because of the aging effect and system components degradation, the control performance of the controller will be greatly affected. In the second Experiment, we continue to compare the performance between SPSA based neural controller and PI controller. The integral gain in the two control system are both decreased to 0.4 (i.e.

$K_f = 0.4$) to simulate the control performance degradation due to the aging effect of long working hours, The VAV dampers status: The damper of room 1 is completely open, those of room 2,3,4 are completely closed. The other parameters of these two control system and test steps remain the same with the first experiment.

Figure 4.5: Performance of PI controller in Experiment 2

Figure 4.6: Performance of SPSA based neural controller in Experiment 2

VAV dampers position	TESTING	CRITERIA	PI controller	NNAPI controller
One open, the other three closed	Set-point change from 60 Pa to 80 Pa	Settling time (s)	28	10
	Set-point change from 80 Pa to 60 Pa	Settling time (s)	30	12

Table 4.2: Performance comparison (PI and SPSA based NN controller in experiment 2)

The experiment results are shown in Figure 4.5, Figure 4.6 and summarized in Table 4.2. Comparing experiment the result with experiment 1, for SPSA based neural controller, the control performance change is little in term of the set-point tracking ability. While the performance of PI controller is degraded a lot because of the integral gain's decrease, which means, by integrating with the neural network trained by the SPSA based algorithm, the conventional PI controller's performance degradation for aging effect can be compensated to certain degree.

4.5.3 Experiment 3

In the third experiment, two different online training algorithms are investigated. A conventional BP training algorithm of neural network (NN) may become divergent in the presence of noise. This issue has been investigated concretely in [10][13]. To solve this problem, a dead zone scheme is proposed in [13] to modify the conventional BP training algorithm and guarantee the convergence of weight. Because of salient nature of SPSA algorithm, the weight drifting is inherently prevented in the SPSA based training algorithm proposed in this work. Both the dead zone and SPSA based training algorithm are applied to the same control structure in Figure 4.1. The testing results are shown in Figure 4.7, 4.8, 4.9 and 4.10. We can see that the dead zone training algorithm guarantees the weight drift-free by stopping training when the training error is smaller than some

threshold. While the SPSA based training algorithm guarantees the drift-free of weights by persist exciting and a continuous learning is achieved. As a result shown in Figure 4.9 and 4.10, the tracking errors are relatively smaller compared with the neural controller trained with the BP algorithm with a dead zone scheme.

Figure 4.7: Weight $W_{6,1}$ of the hidden layer using the BP training algorithm with a dead zone scheme

Figure 4.8: Weight $W_{6,1}$ of the hidden layer using the SPSA based training algorithm

Figure 4.9: Set point tracking performance of the neural controller trained using the BP training algorithm with a dead zone scheme

Figure 4.10: Set point tracking performance of the neural controller trained using the SPSA based training algorithm

4.6 Conclusion

The focus of this chapter is to design and demonstrate the robust performance of a SPSA based neural network control strategy for VAV air-conditioning system. A simplified formulation of the control signal is obtained by summing up outputs of a fixed controller and neural network. The neural network is trained online to estimate the system nonlinear dynamic. The closed-loop control stability is proved based on the conic sector theory. Real-time experiments are implemented in a laboratory environment and the experiment results show that the proposed robust neural controller performs better than a neural controller based on the standard back-propagation algorithm with dead zone modification and the PI controller.

Chapter 5

NN Assisted Cascade Control System for AHU System

5.1. Introduction

With the simultaneous perturbation stochastic approximation based training algorithm proposed in Chapter 4, in this chapter, we propose neural network assisted cascade control system to control air handling units (AHU). In Heating, Ventilating, and Air-Conditioning (HVAC) systems, the function of AHU is to transfer cooling load from air loop to chilled water loop by forcing airflow flow over the cooling coil and into the space to be conditioned. The performance of AHU directly influences the performance of HVAC systems. Traditionally, AHUs are controlled by single loop Proportional-Integral-Derivative (PID) type controllers [73] due to the relatively simple structure. However, in cases where requirements of the environment for equipments are very high, such as cleanrooms (typically, temperature and humidity specifications require error tolerances of $\pm 0.50^\circ\text{C}$ and 2% RH, respectively), it would be desirable to integrate PID controllers into complex control structures to achieve better performance.

In this chapter, we propose a cascade control strategy for AHU temperature control system. Cascade control algorithms are constructed by two control loops: an inner loop with fast dynamic to eliminate input disturbances and an outer loop to regulate output performance [74] [75]. It is particularly useful when there are significant dynamic differences between the control and process variables, tight control actions can be achieved by using an intermediate signal that responds faster than the original control signal. The cascade temperature control strategy of AHU can be implemented by selecting the chilled water flowrate as an intermediate control signal that has the fast response to the valve position change. Traditionally, the cascade control scheme is constructed as: a P or PI controller for the inner loop and a PI or PID controller for the outer loop. However, in most practical cases, such a cascade control system cannot deal adequately with the robustness issues [76]. In particular, when the inner loop part of the process is subject to structural and/or parametric variations, the control system does not guarantee an acceptable performance. It is desirable to enhance the performance robustness of the classical cascade control system and make it adaptive to both the plant non-linearity and dynamic change. Furthermore, tuning the PID controllers requires effective process identification and controller design rules. For cascade control, it is difficult to obtain the well-tuned PID parameters for both the outer loop and the inner loop simultaneously. If re-tuning of the system dynamic is needed because of the environment change or aging effect, the situation may be even worse.

To enhance the robustness performance of AHU and surmount the problems for cascade control systems mentioned above, instead of a fixed PI or PID controller, a neural network controller is used in the outer control loop.

In the NN assisted cascade control system studied in this chapter, we use the simultaneous perturbation stochastic approximation based training algorithm proposed in Chapter 4 to train the neural network online. With the SPSA based training algorithm,

the weight convergence of the neural network and stability of the control system is guaranteed. We apply the new cascade control scheme to the air temperature control of the AHU system to deal with the chilled water flow rate fluctuation, which is the main disturbance in a typical chilled water distribution system. Testing results obtained from both single loop and cascade control strategies are presented to demonstrate the performance of the new control scheme. The experiment results show that, with the proposed cascade control scheme, the temperature control performance of AHU is significantly improved for both temperature set point tracking and chilled water flow rate disturbances rejection.

5.2 Description of AHU Control System

The cooling only AHU system is shown in Figure 5.1, it consists of cooling coil, air dampers, fans, chilled water pumps and valves. The fresh air, depending on the outdoor air damper settings, may be mixed with the air passing through the re-circulation air damper. Return air is drawn from the zones by the return fan and is either exhausted or re-circulated, depending on the position of the mixing box dampers. The temperature and flow rate of the outdoor and re-circulation air streams determine the conditions at the exit of the mixed air plenum. Air exiting the mixed air plenum passes through the cooling coils. After being conditioned in the coils, the air is distributed to the zones through the supply air ductwork. The supply air temperature is measured through the downstream airflow of the supply fan. For the off-coil temperature control loop, the manipulated variable is the valve opening position that controls the chilled water supplied to the cooling coil. The measured process output is the off-coil downstream temperature of the supply fan. The objective of the AHU is to maintain the supply air temperature at the set-point value.

Let G_p and G_c denote the dynamic models of the AHU process and the fixed PID temperature controller in the single control loop respectively, the block diagram of the conventional temperature control system is shown in Figure 5.2.

The drawback of the conventional PID controller G_c is that it has a single degree of freedom in the parameter tuning. Considering a central HVAC plant as shown in Figure 5.3, where the main chilled water distribution pipe may supply chilled water to many AHUs, flow rate change in one AHU branch will affect all other loops. When conventional single loop temperature control scheme is used with the output of the temperature controller applied directly to the control valve, no correction will be made until its effect reaches the temperature measuring elements. Therefore, there is a considerable lag in correcting flow rate disturbances.

Figure 5.1: Schematic diagram of conventional AHU control system (single control loop)

Figure 5.2: Block diagram of AHU's supply air temperature control (single control loop)

Figure 5.3: Typical chilled water distribution system

To improve the response of the simple feedback control, with a cascade control technique using a separate flow rate control loop, the flow rate controller will correct any change in the chilled water flow rate. Figure 5.4 shows a schematic diagram of the cascade control system for supply air temperature, while the control block diagram is shown in Figure 5.5 where G_{c1} , G_{c2} , G_{p1} , G_{p2} stand for the temperature controller, chilled water flow rate controller, AHU process and valve process, respectively.

Figure 5.4: Schematic diagram of cascade control for supply air temperature

Figure 5.5: Block diagram of conventional cascade control

5.3 Neural Network Assisted Cascade Control Scheme

To deal with the system nonlinearity and uncertainty (especially the dynamic change of the inner loop), instead of the traditional PI or PID controller, we employ the neural network (NN) controller proposed in Chapter 4 as the outer loop controller of AHU temperature control. As shown in Figure 5.6, the equivalent outer loop process G_{p0} consists of the inner loop P/Pi controller G_{c2} , the inner loop valve process G_{p2} and the AHU process G_{p1} (Refer to Figure 5.5)

Figure 5.6: Block diagram of the outer control loop

Figure 5.7 shows the structure of the neural network assisted cascade control system. It can be seen that, the outer control loop comprises a fixed proportional feedback controller and a neural network controller that is trained to approximate the inverse dynamics of the plant.

The neural network is trained online with the SPSA based training algorithm. As discussed in Chapter 4, the SPSA based training algorithm guarantees the convergence of the weights of the neural network, but also the stability of the closed control loop

Figure 5.7: Structure of the neural network assisted cascade control scheme

5.4 Simulation study

The main purpose of this simulation study is to evaluate the performance of the neural network assisted cascade control system on a nonlinear plant.

The outer loop process (Refer to Figure 5.5) is given as a continuous time transfer functions. $G_{p1}(s) = \frac{0.2s^2 - 7}{s^2}$. To make the plant nonlinear, for the inner loop process $G_{p1}(s)$, we employ a neural network model which is offline trained to modeling a motor dynamics as in [66] and the structure of neural networks is the same as in [72]. To simplify the tuning process, for the inner loop controller, we use a P controller and a PI controller is used for outer loop. Based on Chien-Hrones-Reswick (CHR) tuning rule

[77], the controllers are tuned with results: inner loop P controller $K_p=2$, outer loop PI controller $K_p=0.8$, $K_i=1.9$. We test the performance of the control system in term of the response to step setpoint change and disturbance. The test is repeated twice for each controller at different working points. It should be noted that the NN assisted cascade control system uses the same P and PI controller parameters as its counterpart in the conventional cascade controller.

Simulation results are given in Figure 5.8 –5.11. As shown in Figure 5.8 and 5.9, because of the nonlinearity of the plant, the conventional cascade control system's performance degrade significantly in term of settling time for the step setpoint change and disturbance rejection. However, when the neural network assisted PI controller is employed in the outer loop, the negative affect casued by the nonlinearity to the control system performance is alleviated.

Figure 5.8: Performance of conventional cascade control
(Step setpoint change from 0 to 20, disturbance added at time-step 40)

Figure 5.9: Performance of conventional cascade control
(Step setpoint change from 100 to 120, disturbance added at time-step 40)

Figure 5.10: Performance of NN assisted cascade control
(Step setpoint change from 0 to 20, disturbance added at time-step 40)

Figure 5.11: performance of NN assisted cascade control
(Step setpoint change from 100 to 120, disturbance added at time-step 40)

5.5 Real-time Experiments and Results

5.5.1 Experiment Setup

The test is conducted on the pilot centralized HVAC system as shown in Figure 3.6. The cooling coils for the system are two rows with the dimension of 25cm×25cm×8 cm as shown in Figure 5.12. Here, 1, 2, 3, 4 and 5 indicate the location of cooling coil, off-coil temperature sensor, chilled water control valve, chilled water pump and supply air fan, respectively.

Figure 5.12: AHU control system

5.5.2 Experiment 1

In this experiment, both off-coil temperature and chilled water flow rate are measured. The actuator is the chilled water control valve controlled by step motor. The chilled water temperature is controlled at around 8°C and supply air pressure is controlled to be constant by keeping the supply fan running at a constant speed. In order to compare the performances of single loop control with cascade control, the overall process model of the AHU system is identified as $G_p(s) = [0.2/(140s + 1)]e^{-49s}$ and a single loop PID controller based on Chien-Hrones-Reswick (CHR) tuning rule [77] is then designed and implemented with minor adjustments to obtain the best response. The PID parameters achieved are $K_p=17.5$, $K_i=0.18$, $K_d=320$. For the cascade control strategy, the classical structure is designed first with fixed PI controller for inner loop and fixed PID controller for outer loop. The existing technique for tuning the classical cascade controllers is in two steps: firstly, the inner loop controller is tuned, subsequently, the inner loop controller is commissioned and the outer loop controller is tuned to complete the tuning

process. Following the CHR tuning rule, with a further trial-and-error method, the optimal parameters for the real-time experiments are obtained. The PI controller of the inner loop: $K_{p2} = 22.21$ $K_{i2} = 0.88$; The PID controller of the outer loop: $K_{p1} = 0.8268$, $K_{i1} = 0.0044$, $K_{d1} = 0.598$ respectively. For a fair comparison, the same PI controller is used in the inner loop for the neural network assisted cascade control scheme. A three-layer neural network is used in the outer control loop with 12 hidden layer neurons, all the initial weight values are chosen to be zero, the gain parameter of the SPSA based neural network is given as $K_p = 0.8$. For the SPSA training algorithm, following the guideline given in [78], let $c_k = c/k^r$, here we choose $c = 5$ and $r = 0.101$ in the experiment.

Figure 5.13 - 5.16 shows the different response of single loop control and cascade control for the case of temperature set point change and chilled water flow rate fluctuation. The test is carried out as follows:

- Stabilize the off-coil temperature at 18°C.
- Reset the off-coil temperature to 19°C while keep the chilled water flow rate stable, at time $t=250s$.
- For the same temperature set point, increase chilled water flow rate by increasing the chilled water pump speed, at $t=1500s$.
- Keep set point unchanged, decrease the chilled water flow rate by decreasing the chilled water pump speed, at $t=2300s$.
- Reset the off-coil temperature to 20°C while keep the chilled water flow rate stable, at time $t=3000s$.

The results are also summarized in Table 5.1. It shows clearly that the proposed neural network assisted cascade control system improves temperature control performance of AHU in term of the set point tracking and disturbance rejection ability. Compared with

the classical cascade control structure, by introducing the neural network to compensate the system non-linearity, the proposed control system maintains a better performance at different operating points.

Figure 5.13: Speed of chilled water pump

Figure 5.14: Supply air temperature control performance of AHU in Experiment 1 (Single loop PID control)

Figure 5.15: Supply air temperature control performance of AHU in Experiment 1 (Cascade control with PI inner loop controller and PID outer loop controller)

Figure 5.16: Supply air temperature control performance of AHU in Experiment 1 (Cascade control with PI inner loop controller and NN outer loop controller)

TESTING (PI plus NNC)	CRITERIA	SINGLE LOOP (PID)	CASCADE (PI plus PID)	CASCADE (PI plus NNC)
set-point change 18°C -- 19°C	Settling Time (s)	670	450	280
disturbance (flowrate increase)	Settling Time (s)	380	280	230
disturbance (flowrate decrease)	Settling Time (s)	350	240	190
set-point change 19°C -- 20°C	Settling Time (s)	800	580	400

Table 5.1: Performance Comparison in Experiment 1

5.5.3 Experiment 2

Because of the aging effect and system components degradation, for an originally well tuned PID controller, the control performance of the controller usually will degrade after certain period of times. In the second Experiment, we continue to compare the performance between the classical cascade control and the neural network assisted cascade control scheme. The integral gain of the well tuned PI controller in the inner control loop is decreased to 0.4 (i.e. $K_{i2} = 0.4$) to simulate the control performance degradation due to the aging effect of long working hours, while other parameters of these two cascade control system and test steps remain the same with the first experiment.

Figure 5.17: Supply air temperature control performance of AHU in Experiment 2
(Cascade control with PI inner loop controller and PID outer loop controller)

Figure 5.18: Supply air temperature control performance of AHU in Experiment 2
(Cascade control with PI inner loop controller and NN outer loop controller)

The experiment results are shown in the Figure 5.17, 5.18 and summarized in Table 5.2. Comparing them with the results in the first experiment, for the neural network assisted cascade control system, the control performance change is little in term of the set-point tracking and disturbance rejection ability. While the performance of the classical cascade controller is degraded a lot because of the inner loop PI controller's parameter change, which means, by integrating with the neural network trained by the SPSA based algorithm, the inner loop PI controller's performance degradation for aging effect can be compensated to certain degree. This experiment also shows that, even the inner loop fixed controller is not tuned to its optimal value, the neural network assisted cascade control system can still give a satisfactory performance because of its adaptiveness.

TESTING (PI plus NNC)	CRITERIA	CASCADE (PI plus PID)	CASCADE (PI plus NNC)
set-point change 18°C-- 19°C	Settling Time (s)	590	320
disturbance (flowrate increase)	Settling Time (s)	300	260
disturbance (flowrate decrease)	Settling Time (s)	270	200
set-point change 19°C-- 20°C	Settling Time (s)	720	450

Table 5.2: Performance Comparison in Experiment 2

5.6 Conclusion

In this chapter, a cascade control strategy for temperature control of AHU is introduced to deal with the chilled water flow rate fluctuation, which is the main disturbance in a typical chilled water distribution system and causes the deterioration of the temperature control performance of AHU. A neural network controller for the outer control loop is employed to enhance the adaptive ability and robustness of the entire control loop. The neural network is trained online with the SPSA based training algorithm with the guaranteed convergence and stability. Real-time experiment results demonstrate the performance of the new cascade control scheme. The temperature control performance of AHU is improved significantly compared to the classical PID control system in term of the set point tracking and chilled water flow rate disturbances rejection.

Chapter 6

Optimization for Condenser Water Loop of HVAC System Using a Hybrid GA/SPSA Strategy

6.1 Introduction

The energy consumed in building HVAC systems accounts for more than 50% of total building energy usage. A small increase in system operating efficiency can result in substantial energy savings. The schematic shown in Figure 6.1 is a typical HVAC system, which comprises two sections: In-building section and Out-building section. It can be further divided into five loops: indoor air loops, chilled water loops, refrigerant loops, condenser water loops and outdoor air loops. The process of a condenser water loop consists of chiller condensers, pumps, cooling towers and fans. Chiller condensers transfer indoor cooling load and the heat generated by compressors into condenser water. Pumps provide the energy to circulate water between chiller condensers and cooling

towers. The heat is rejected to the ambient air through heat transfer and evaporation by cooling towers.

Figure 6.1: Schematic of a typical HVAC system

As one of the five main function loops, the operation of condenser water loop has significant effect on the overall system performance. The key issues for efficient operation of this loop are the performance of cooling towers as well as the interactions between cooling towers, condenser water pumps and chillers. For cooling towers, Cassidy and Stack's work [79] showed that varying the speed of cooling tower fans is a good way to reduce energy consumption. Braun and Doderich [80] proposed near-optimal control of cooling towers based on parameters estimated from design data. This method is further adopted by Cascia [81] to simplify the component model and provide equations for determining the set points of near-optimal control. For interactions between chillers and cooling towers, Shelton and Joyce's work [82] recommended 1.5 gpm/Ton condenser water flow rate as an optimal solution. Later, Kirsner [83] pointed out that high condenser water flow rate (3 gpm/Ton) has good performance at full load condition, while low condenser water flow rate (1.5 gpm/Ton) has advantages at part load conditions. Michael and Emery [84] analyzed the cost-optimal selection of the cooling tower range & approach and provided the design information for hermetic centrifugal and reciprocating chillers. Schwedler [85] studied the variation of condenser water supply

temperature and used several examples to demonstrate his main idea that the lowest possible leaving tower water temperature does not always conserve system energy. However, his research only considered the fans with half-speed and full-speed conditions, which is not conclusive. In spite of the progress made in recent years on individual component modeling, control, optimization and operation rules, because of the nonlinear and coupling nature, there is still lack of a systematic approach that consider the condenser water loop as a whole to optimize its operation performance.

In this chapter, firstly, to identify the energy conservation potential of the process, the mathematical models of major components in the condenser water loop, and the interaction between them are analyzed. The analysis shows that the optimization problem for the condenser water loop process is a high dimensional optimization problem which subjects to both linear and nonlinear constraints, contains both continuous and discrete decision variables. Therefore, the conventional gradient-based optimization methods cannot be applied directly. An exhaustive search method or a combined exhaustive search with conventional gradient-based methods, even though, can be applied to find the optimal solutions, it is impractical for such a complicated problem due to its time consuming nature. As a heuristic algorithm, genetic algorithm (GA) [86] offers another approach to solve the optimization problems in HVAC system. This paradigm, based on biological evolution, seeks to optimize an objective function by evolving a population of solutions. However, as a population based algorithm, GA is not suitable to solve the optimization problem in real-time. In [87], GA is applied to the HVAC as a model-based optimization approach, which means that the system mathematic models are supposed to be predetermined. The modeling is based on the physical laws, and there are large amounts of parameters need to be identified in these mathematical models. With the availability of manufacture catalog data or on-site testing data, the mathematical models can be achieved to realize the model based process optimization. Unfortunately, due to

the complexity of HVAC system, it is very difficult to achieve accurate models. Even though the models obtained are accurate, because of the aging effect and the system components degradation, the established model may not match the real system anymore after long time running. In this point of view, an optimization approach which does not completely rely on the predetermine models will be a better choice. The simultaneous perturbation stochastic approximation (SPSA) algorithm, proposed by Spall [69] [70], is such kind of model free optimization method. As long as the objective function is measurable during the operation of the system, the SPSA can be applied to optimize the decision variables to achieve the minimal objective function. However, a complete model free algorithm is impractical for the HVAC system, because it is hard for the system to maintain a normal working condition when all controlled variable randomly varied in the whole operation range respectively. Especially the discrete variables, such as the number of chillers, fans and pumps, will cause large working condition change, even when their amounts are slightly changed by one.

In this chapter, we proposed a hybrid GA/SPSA optimization strategy. Based on the predetermined system analysis models, first, the genetic algorithm (GA) is employed to obtain the optimization results for both continuous and discrete variables offline. Considering the existents of the mismatch between the identified model and the real system, further optimization for the continuous variables is carried out using the SPSA algorithm in an online fashion. The SPSA, which is a model free optimization method, has the inherent computational efficiency and offers a powerful yet simple to implement paradigm. In SPSA, by perturbing all the decision variables simultaneously, only two objective function measurements are needed to approximate the gradient. The SPSA may be sensitive to the initial value of the variables to be optimized, however, in the hybrid GA/SPSA strategy proposed in this chapter, the variable initialization for SPSA algorithm is based on the result of the he model-based offline GA optimization.

Particularly, the SPSA only deals with the continuous variables, therefore, HVAC system normal working condition will not be seriously affected when the online optimization is in process. Testing on an experimental HVAC system shows that, with the hybrid GA/SPSA optimization strategy, the optimization problem for condenser water loop of HVAC system can be solved in a more effective way and the operating cost of the condenser water loop can be substantially reduced compared with conventional operation strategy.

6.2 Problem Formulation

In condenser water loop, there are three types of devices that consume energy, namely chillers, pumps and fans. Therefore, the objective function is to minimize total energy consumption of these devices

$$\min P = P_{chiller} + P_{pump} + P_{fan} \quad (6.1)$$

The power consumptions of chillers, pumps and fans are given respectively by [88, 89] (See page xii for the nomenclature list of this chapter):

$$P_{chiller} = \sum_i Q_{cap,i} \cdot COP_{nom,i} \cdot (PLR_{adj,i}) \cdot (Temp_{adj,i}) \quad (6.2a)$$

where

$$PLR_{adj,i} = b_0 + b_1 \left(\frac{Q}{\sum_i Q_{cap,i}} \right) + b_2 \left(\frac{Q}{\sum_i Q_{cap,i}} \right)^2 \quad (6.2b)$$

$$Temp_{adj,i} = c_0 + c_1 T_{CHWS} + c_2 T_{CHWS}^2 + c_3 T_{CWS} + c_4 T_{CWS}^2 + c_5 T_{CHWS} T_{CWS} \quad (6.2c)$$

and

$$P_{pump} = \sum_j P_{pump,nom,j} \left(d_0 + d_1 \left(\frac{m_{w,j}}{m_{w,nom,j}} \right) + d_2 \left(\frac{m_{w,j}}{m_{w,nom,j}} \right)^2 + d_3 \left(\frac{m_{w,j}}{m_{w,nom,j}} \right)^3 \right) \quad (6.3)$$

$$P_{fan} = \sum_k P_{fan,nom,k} \left(e_0 + e_1 \left(\frac{m_{a,k}}{m_{a,nom,k}} \right) + e_2 \left(\frac{m_{a,k}}{m_{a,nom,k}} \right)^2 + e_3 \left(\frac{m_{a,k}}{m_{a,nom,k}} \right)^3 \right) \quad (6.4)$$

where, i is the number of operating chillers; j is the number of operating condenser water pumps; and k is the number of operating cooling tower fans. Note that the performance of the condenser water loop is affected by several factors, which are formulated as constraints of the optimization problem, such as physical limitation of individual components, interaction among them and the outdoor environment. The mathematical formulations and physical explanations of these constraints are given below.

Constraint (1):

P_{pump} and P_{fan} are influenced by $m_{w,j}$ and $m_{a,k}$ monotonously, physical limitations for $m_{w,j}$ and $m_{a,k}$ are $m_{w,j,min} \leq m_{w,j} \leq m_{w,j,max}$; $m_{a,k,min} \leq m_{a,k} \leq m_{a,k,max}$.

Constraint (2):

The T_{CWS} is also restricted by boundaries, which are often provided by chiller manufactures for safe operation of chillers

$$T_{CWS,min} \leq T_{CWS} \leq T_{CWS,max}$$

Constraint (3):

The cooling generated by chiller is calculated as

$$Q = m_{CHW} C_{pw} (T_{CHWR} - T_{CHWS})$$

Constraint (4):

For the cooling tower, given in [90], the following constrain holds

$$Q + P_{chiller} = \sum_k \left(\frac{a_1 m_{a,k}^{a_3}}{1 + a_2 \left(\frac{m_{a,k}}{m_{w,k}} \right)^{a_3}} (T_{CWR} - T_{wb}) \right)$$

where $m_{w,k}$ is the water flow rate to each cooling tower. It should be note that there are two factors affecting cooling tower performance in Constraint 4, one is $m_{w,j}$ vs $m_{a,k}$ and the other is T_{CWR} vs T_{wb} . Analysis of the relationship of these variable will help to identify the energy saving potential of the optimization approach.

Without loss of generality, when analyzing the cooling tower performance it is assumed that the condenser water is evenly distributed in each cooling tower

$$m_{w,k} = \frac{1}{K} \sum_j m_{w,j} \quad (6.5)$$

To simplify the analysis, it is assumed that T_{CWR} and T_{wb} are constants in discussing the effect of $m_{w,j}$ vs $m_{a,k}$. Figure 6.2 shows five curves of equal heat rejection rate [91], where the x-axis is percentage of water flow rate and y-axis is percentage of airflow rate. These curves of equal heat rejection rate are divided into three portions.

Figure 6.2: The performance of a cooling tower

Apparently, the energy efficient operating range must lie inside the Portion (3). In this portion, a reduced airflow rate leads to lower fan power consumption, but the water flow rate has to be increased, resulting in increased pump power consumption. Similarly, a reduced water flow rate lowers the pump power consumption but results in increased fan power consumption. Constraint (4) limits the value of $m_{w,j}$ and $m_{a,k}$ due to the cooling tower characteristics.

The term $T_{CWR} - T_{wb}$ in Constraint (4) reflects the effect of T_{wb} on the cooling tower performance. Assuming cooling tower heat rejection rate and condenser water supply temperature are kept to be constants, the optimal operating point of cooling towers changes if T_{wb} changes. Figure 6.3 gives an example where the cooling tower heat rejection rate is assumed to be a fixed value for different wet-bulb temperatures of ambient air, 20 °C and 25 °C, respectively. The optimal operating points are labeled as pentagons to indicate the corresponding power consumption of fans and pumps. While the curves of fan power consumption are the same for different wet-bulb temperatures, the condenser water flow rate changes with changing airflow and outdoor environment for a constant cooling tower heat rejection rate.

The optimal airflow rate is 85% of the full load at 25 °C and 50% at 20 °C. For an optimal operating point, the power consumption is 12% of the full load at 20 °C wet-bulb temperature. If the airflow rate is kept at 85% of the full load at 20 °C instead of 50%, the combined power consumption of fan and pump is 19% of the full load. Compared with 12% of the full load at the optimal point, almost 7% energy of the full load savings could be achieved with the varying mass flow rate of water and air.

Figure 6.3: Optimal operating points at different Wet-Bulb temperatures

Constraint 5:

The variable T_{CWS} influences both the chiller power consumption and the cooling tower performance

$$Q + P_{chiller} = \left(\sum_j m_{w,j} \right) C_{pw} (T_{CWR} - T_{CWS})$$

These constrain reveals that there exists trade-offs between chiller power and fan power.

It has been generally acknowledged [80,82,83,92,93,94,95,96] that a decreasing T_{CWS} results in an increasing COP and lower energy consumption of chillers. However, a lower T_{CWS} leads to a smaller T_{CWR} and then higher $m_{a,k}$ and $m_{w,k}$ for fixed Q and T_{wb} . As $m_{a,k}$ and $m_{w,k}$ increase, the fan power and condenser water pump power increase cubically. Figure 6.4 illustrates the trade-off between the chiller and cooling tower fan power associated with an increasing tower airflow [80]. Here, a fixed condenser water flow rate is assumed. As the airflow increases, the fan power increases. At the same time, there is a

reduction in condenser water supply temperature, resulting in lower chiller power consumption.

On the other hand, T_{CWR} in turn affects the heat exchange efficiencies in cooling towers. When the condenser water supply temperature decreases, the condenser water return temperature also decreases for the same cooling load. This results in the lower efficiencies of the cooling tower under the same ambient wet-bulb temperature as the enthalpy difference between ambient air and condenser water becomes smaller. The optimal operating point occurs at a point where the rate of power increment in fans and pumps is equal to the rate of power reduction in chillers.

Figure 6.4: Trade-offs between chiller power and fan power

6.3 Model Based Offline Optimization with GA

Based on the mathematical models discussed in section 6.2, the model-based optimization can be implemented offline. With the manufacture catalog data and on-site testing data, the component model parameters, which are constants in Equation (6.1)-

(6.4) can be determined. From the system model analysis in section 6.2, we can see that the optimization problem for the condenser water loop is a high dimensional, including both continuous and discrete variables, with both linear and nonlinear constraints. Therefore, the conventional gradient-based optimization methods cannot be applied directly. In this study, as the offline stage of the proposed hybrid optimization method, we employ the GA to achieve the optimal results. The genetic algorithm is more attractive than other optimization algorithms in several aspects:

- It can handle problem constraints by simply embedding them into the chromosome encoding procedure.
- It is feasible to solve multi-model, non-differentiable, non-continuous problems, *etc*, since it is independent of the function gradient.
- It is very easy-to-understand and involves very little mathematics.
- It has implicit parallel computation features, which make it more efficient than the exhaustive search methods.

In the condenser water loop optimization problem, $i, j, k, m_{a,k}$, and $m_{w,j}$ are independent variables, T_{wb} , T_{CHWS} , T_{CHWR} , and m_{CHW} are variables that can be measured, Q , T_{CWS} , and T_{CWR} are variables to be determined by constraints. The implementation of a modified genetic algorithm for this particular problem can be divided into four phases: encoding, construction of fitness function, evolution, and termination.

(a) Encoding

The first step for genetic algorithm is encoding. It is a process of transforming a series of problem inputs into a serial of codes that can be easily interpreted and used in evaluating information it represents by the fitness function. In this application, both discrete variables (i, j, k) and continuous variables ($m_{a,k}, m_{w,j}$) are converted into binary strings and are connected together to form a chromosome.

For the discrete variables, each bit represents the status of each component. For example, “1” stands for either a chiller, a pump or a fan is staging on, while “0” for off.

For the continuous variables such as the mass flow rates of air and water, the upper and lower bounds of their binary strings stand for minimum and maximum values in Constraint (1). The lengths of binary strings are determined by the control precision of the corresponding variables: The more precise set point control, the longer binary string.

(b) Construction of fitness function

In order to fulfill Constraints, penalty functions are commonly used to penalize an infeasible solution. In this step, a penalty function is added if any constraint cannot be fulfilled. The fitness function is expressed in the following equation.

$$fitness = \frac{1}{P_{f1} + P_{f2} + P_{f3} + P_{total}} \quad (6.6a)$$

with

$$P_{f1} = v_1 \cdot \left(Q + P_{chiller} - \sum_k \left(\frac{a_1 m_{a,k}^{a_3}}{1 + a_2 \left(\frac{m_{a,k}}{m_{w,k}} \right)^{a_3}} (T_{CWR} - T_{wb}) \right) \right)^2 \quad (6.6b)$$

$$P_{f2} = v_2 \cdot \left(Q + P_{chiller} - \left(\sum_j m_{w,j} \right) C_{pw} (T_{CWR} - T_{CWS}) \right)^2 \quad (6.6c)$$

$$P_{f3} = \begin{cases} 0 & \text{if } T_{CWS,min} \leq T_{CWS} \leq T_{CWS,max} \\ v_3 (T_{CWS} - T_{CWS,min})^2 & \text{if } T_{CWS,min} \geq T_{CWS} \\ v_3 (T_{CWS} - T_{CWS,max})^2 & \text{if } T_{CWS} \geq T_{CWS,max} \end{cases} \quad (6.6d)$$

where v_1 , v_2 , and v_3 are the penalty multipliers, which should be large positive numbers. With this fitness function, the minimal system power consumption without violating any constraints has the maximum fitness value. The fitness values will be used as guides for evolution.

(c) Evolution

The evolution consists of three major functions: selection, crossover, and mutation [97]. These functions are performed for each generation to produce the next generation with improved fitness values.

- Selection is the process of determining the number of times that a particular individual is chosen for reproduction. The “roulette wheel” selection method [97] is adopted in the application based on linear-scaled fitness values.
- Crossover is a basic function to produce new individuals, which have some parts of both parents genetic material. A single-point crossover method is adopted here and shown by the following example.

Parent 1: 1 1 1 1 1 1 “crossover at the 2nd bit” New individual 1: 1 1 0 0 0 0

Parent 2: 0 0 0 0 0 0 $\Rightarrow$ New individual 2: 0 0 1 1 1 1

- Mutation is a random process where one bit of binary string is flipped to produce a new individual. Single-bit mutation is used in the example below.

Original individual: 1 1 1 1 1 1 “mutation at the 5th bit”

New individual: 1 1 1 1 0 1

The crossover and mutation points are all selected randomly in each generation. The probability of crossover and mutation are selected according to the recommendations in [98,99,100].

(d) Termination

The computation of the genetic algorithm is terminated when the following criteria are reached.

- The maximum number of generations is reached;
- The fitness value of the best individual converges to certain asymptote.

The implementation of the model based offline optimization using GA is shown in Figure 6.5.

Figure 6.5: Implementation of the model based offline optimization using GA

6.4 Online Optimization with SPSA

The GA optimization is based on the predetermined mathematical model of system components. However, in practice, for a complex system like HVAC, the accurate model is impossible to obtain. The optimal results achieved offline by GA usually are not exactly the optimal set point values for each local control loop according to current environment condition. On the other hand, naturally, the GA cannot guarantee to find the global optimum. This is the main motivation for the hybrid optimization strategy proposed in the chapter. To improve the optimization result, using the SPSA, further online optimization is carried out. SPSA algorithm is model free in nature. It should be noted that the optimization results achieved during the offline stage by GA contribute to the online SPSA optimization in two folds: first, the offline optimization result offers an optimal variable initialization of the SPSA algorithm. Furthermore, the online SPSA based optimization only deals with the continuous variable, while the discrete variables take the value as the GA's optimization result directly.

The SPSA algorithm proposed by Spall [69] [70] is a numerically efficient stochastic optimization algorithm. Unlike the conventional gradient-based optimization methods that evaluate the gradient of the objective function by perturbing each decision variable separately (as in the standard two-sided finite difference approximation), the SPSA formalism approximates the gradient by perturbing all the variables simultaneously. Irrespective of the number of decision variables to be optimized, only two objective function measurements are sufficient for the gradient approximation. Implementation of SPSA may be easier than other stochastic optimization methods, since there are fewer algorithm coefficients that need to be specified, and there are some published guidelines providing insight into how to pick the coefficients in practical applications [102].

The optimization objective underlying the SPSA-based optimization is defined as: find the N-dimensional optimal decision variable vector, $\theta^* = [\theta_1^*, \theta_2^*, \dots, \theta_N^*]^T$, such that it

simultaneously minimize the objective function. For the online stage of the condenser water loop optimization problem, we only optimize the continuous decision variables to achieve a further minimized objective function. In this case, the decision variable vector is $\theta = [\theta_1, \theta_2, \dots, \theta_N]^T = [m_{a1}, m_{a2}, \dots, m_{ak}, m_{w1}, m_{w2}, \dots, m_{wj}]^T$, and the objective function is $P(\theta)$ as in equation (6.1). The SPSA implementation is iterative. Different from the original algorithm, which begins the iterations with a randomly initialized solution vector $\theta_0 = [\theta_{1_0}, \theta_{2_0}, \dots, \theta_{N_0}]^T$, in this case, the vector θ_0 is the model-based GA optimization results achieved at the offline optimization stage. For the minimum point θ^* , the gradient of the objective function, $P(\theta)$, attains zero magnitude. That is

$$G(\theta^*) = \left| \frac{\partial P(\theta)}{\partial \theta} \right|_{\theta=\theta^*} = 0 \quad (6.7)$$

The estimate of the decision variable vector θ is updated iteratively as given by [69]

$$\theta_{t+1} = \theta_t - a_t \hat{G}_t(\theta_t) \quad (6.8)$$

where a_k is the learning rate and $\hat{G}_t(\theta_t)$ is the approximation of the gradient function with

$$\hat{G}_t(\theta_t) = \frac{P(\theta_t^+) - P(\theta_t^-)}{2c_t} r_t \quad (6.9)$$

where

$$\theta_t^+ = \theta_t + c_t \Delta_t \quad (6.10)$$

$$\theta_t^- = \hat{\theta}_t + c_t \Delta_t \quad (6.11)$$

In the above equation, $\Delta_t \in R^N$ is a random directional vector that is used to stimulate the decision variable vector θ_t simultaneously, $c_t > 0$ is a sequence of positive number satisfying certain regularity conditions [78, 70]. The random vector Δ_t is generated via Monte Carlo according to conditions specified in [78, 70]. If the i th element of Δ_t is denoted as Δ_{ti} , then the sequence of $r_t \in R^N$ is defined as

$$r_t = \left[\frac{1}{\Delta_{t_1}} \dots \frac{1}{\Delta_{t_p}} \right], \quad (6.12)$$

where c_t is a positive scalar, and $\Delta_t = [\Delta_{t_1}, \Delta_{t_2}, \dots, \Delta_{t_N}]^T$ is a vector of random variables drawn from the symmetric Bernoulli distribution. Figure 6.6 shows the flowchart of SPSA online optimization.

It should be noted that both the discrete and continuous variables are obtained when retrieving the set points from the optimal set point database according to the current environment condition, the set points vector θ_t are the offline optimization result achieved by GA as shown in section 6.3, while within the SPSA, the vector θ_t only contains the continuous variables, i.e. $m_{a1}, m_{a2}, \dots, m_{ak}, m_{w1}, m_{w2}, \dots, m_{wj}$ as we already discussed. The SPSA termination criteria can be set as the difference between $P(\theta_t)$ and $P(\theta_{t-1})$ is small enough or after certain iteration there is not much improvement compare with the minim $P(\theta_t)$ achieved in history.

Figure 6.6: Implementation of the online optimization using SPSA

6.5 Experimental Studies

The test is conducted on the same pilot centralized HVAC system as in previous chapters,

The specifications of the experimental HVAC pilot plant are given as below:

- Totally there are 12 rooms, 3 chillers, 3 chilled water pumps, 3 condenser water pumps and 3 cooling towers in the HVAC system.
- Three chillers have the same nominal cooling load capacity of 1.20 kW with 7 °C chilled water supply temperature and 30 °C condenser water supply temperature.
- The nominal energy consumption of each chiller is 0.87 kW at the full load condition.
- The rated water flow rate of each condenser water pump is 0.5 kg/s and the pump consumes 0.33 kW power under the full load condition.
- Each cooling tower is equipped with a 0.17 kW fan at the full load condition, which can provide a 0.2 kg/s airflow rate.

The conventionally used increment/decrement chiller staging method with fixed condenser water flow rate and airflow rate control strategy is used to compare with the optimal set points control method. Its operating condition setting is as following:

- The condenser water flow rate is fixed at 0.5 kg/s per condenser water pump and the pump is staging on with the corresponding chiller.
- The airflow rate in cooling tower is fixed at 0.2 kg/s when the cooling tower fan operating under the rated speed.

Since it is difficult to simulate exactly a typical profile of one-day's cooling load in the laboratory environment, in this experimental study, only certain operating points are used on the pilot plant to validate the proposed optimal method. On the scale of the system's

full cooling load ability, 10 working point are chosen to carry on the testing. The different cooling loads are realized by changing the chilled water flow rate and the temperature difference between the chilled water supply and return. The ambient wet-bulb temperature is calculated by the measured data from temperature and humidity sensors.

Figure 6.7: Power consumption of chillers

Figure 6.8: Power consumption of pumps

Figure 6.9: Power consumption of fans

Figure 6.10: Total power consumption

Experiment results are shown in Figures 6.7-6.10, although only 10 steady state operating points are tested, as shown in Figures 6.7-6.10, the experiment results are sufficient to validate the proposed optimization method. It should be noted that, after the optimization being applied, for the total power consumption (Figure 6.11) nearly 50% of energy can be saved compared with the traditional methods under very low part load condition. Even under the full load condition, the optimal method consumes nearly 10% less energy. It can also be seen that, in most operating conditions, the online SPSA optimization achieved better optimization results compared with the model-based offline GA optimization. From Figures 6.8-6.10, it can be seen that the energy saving is mainly from the condenser water pumps and the cooling tower fans operating at a lower speed. A lower condenser water flow rate results in an increased condenser water supply temperature which in turn increases the temperature difference between the condenser water inlet and ambient environment to meet the required heat rejection rate. Although it makes the chiller consume slightly more energy, the advantages of increased heat

exchange efficiency of cooling tower and decreased pump and fan power make the whole system operate more efficiently.

6.6 Conclusion

In this chapter, an energy saving strategy for condenser water loop through system optimization is proposed. In order to clearly identify optimization opportunities, detailed characteristic analysis of system components are provided with emphasis on the interactions of control variables inside the cooling tower and between the cooling towers and the chillers. A hybrid GA/SPSA optimization strategy is proposed to find the optimal set points of the system under different cooling load. The experiments based on a real experimental HVAC system show that the proposed method has great potential to reduce energy consumption in condenser water loop.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

In this thesis, a robust neural network control scheme is proposed and applied to control the supply air pressure of the variable airflow volume system. The neural network in the closed control loop is employed to estimate the nonlinear dynamics of the system, and generate the desired control signal to the plant by summing up with a traditional Proportion-Integral or Proportion controller's output. The neural networks are trained in an online fashion with two new training algorithms proposed, i.e. adaptive dead zone training algorithm and SPSA based training algorithm. Both of these two training algorithms can ensure the convergence of the weights, and enhance the controller's robustness and adaptive capability. The stability of the new control schemes is proved based on the conic sector theory. The validity and effectiveness of the proposed control systems are demonstrated with a number of real time experiments on an experimental VAV system.

For the optimization strategy of HVAC system, a hybrid GA/SPSA algorithm with its application for the condense water loop is presented. Based on the predetermined system

analysis models, first, the genetic algorithm (GA) is employed to obtain the optimization results for both continuous and discrete variables offline. Considering the existents of mismatch between the analysis model and the real system, further optimization for the continuous variables is carried out using the SPSA algorithm in an online fashion. The SPSA, which is a model free optimization method, has the inherent computational efficiency and offers a powerful yet simple to implement paradigm. By perturbing all the decision variables simultaneously, only two objective function measurements are needed to approximate the gradient. The SPSA may be sensitive to the initial value of the variables to be optimized, however, in the hybrid GA/SPSA strategy proposed in this thesis, the variable initialization for SPSA algorithm comes from the model-based offline GA optimization. Particularly, the SPSA only deals with the continuous variables, therefore, HVAC system normal working condition is not seriously affected when the online optimization is in process. Testing on an experimental HVAC system shows that, with the hybrid GA/SPSA optimization strategy, the optimization problem for condenser water loop of HVAC system can be solved in a more effective way and the operating cost of the condenser water loop can be substantially reduced compared with conventional operation strategy.

7.2 Recommendations for Future work

Although the neural control controllers proposed in this thesis are shown to work effectively, future research can continue in many different directions:

- On the selection of the neural network parameters, further research needs to be done to find an optimal set of parameters, like the number of hidden layers, the numbers of hidden layer neurons and the optimal initialization of the neural network's weights.

- Certain problems, such as complexity of the neural network structure, increase of training time, and other possible adverse conditions for on-line training, may be encountered when this controller apply to a more complicated systems.
- Conic sector theory has been successfully employed to design the neural network controller in this work. Based on the current progress, further study on the neural network training algorithm and application of sector theory in the related area might be carried out.

For optimization of building HVAC systems, there are still some efforts to be made to fine-tune the whole procedure.

- Genetic algorithms for optimization have great advantages to deal with mixed-integer optimization problems. However, the long computation time and uncertainties caused by less evolution time are still the main obstacles.
- Although there are some guidelines for the parameters selection of SPSA algorithm, its impact of the online optimization still needs to be further investigated.

Author's publications

- [1]. Chengyi Guo, Qing Song, Wenjian Cai, "A Neural Network Assisted Cascade Control System for Air Handling Unit", in press, *IEEE transactions on industrial electronic*, 2005.
- [2]. Chengyi Guo, Qing Song, Wenjian Cai, "Real-time Control of Variable Air Volume System Using a SPSA Based Neural Controller", *Proceeding of 2005 International Joint Conference on Neural Networks*, Montreal, Quebec, Canada, July 31-August 4, 2005.
- [3]. Chengyi Guo, Qing Song, Wenjian Cai, "Supply Air Temperature Control of AHU with a Cascade Control Strategy and a SPSA Based Neural Controller", *Proceeding of 2005 International Joint Conference on Neural Networks*, Montreal, Quebec, Canada, July 31-August 4, 2005.
- [4]. Chengyi Guo, Qing Song, Wenjian Cai, "Real-time Control of Variable Air Volume System Based on a Robust Neural Network Assisted PI controller", *Proceeding of 2004 International Joint Conference on Neural Networks*, Budapest, Hungary, July 2004.
- [5]. Chengyi Guo, Qing Song, Wenjian Cai, "Real-time Control of AHU Based on a Neural Network Assisted Cascade Control System", *Proceeding of IEEE Conference on Cybernetics and Intelligent Systems (CIS) Robotics, Automation and Mechatronics (RAM)*, Singapore, December 2004.

- [6]. Xulei Yang, Qing Song, Aize Cao, Sheng Liu and Chengyi Guo, "Robust C-Shells Based Deterministic Annealing Clustering Algorithm", *Proceeding of 2004 International Joint Conference on Neural Networks*, Budapest, Hungary, July 2004.
- [7]. Aize Cao, Qing Song, Xulei Yang, Sheng Liu and Chengyi Guo, "Mammographic Mass Detection by Vicinal Support Vector Machine", *Proceeding of 2004 International Joint Conference on Neural Networks*, Budapest, Hungary, July 2004.
- [8]. Chengyi Guo, Qing Song, Wenjian Cai, "a Robust Neural Network Assisted PI Controller for Real-time Control of Variable Air Volume System" Submitted to IEE Proc. Control Theory & Applications, 2003.

Reference

- [1] M. S. Imbabi, "Computer validation of scale model tests for building energy simulation," *Int. J. Energy Res.*, vol.14, pp. 727-736,1990
- [2] R. Shoureshi," Intelligent control systems: Are they for real," *J. Dynamic Syst., Measurement, Contr.*, vol. 115, June 1993
- [3] ASHRAE, *ASHRAE Handbook-Fundamentals*, American Society of Heating, Refrigerating and Air-Conditioning Engineers Inc., 1997.
- [4] A.B. Corripio, " Tuning of Industrial Control Systems", *Instrument Society of America*, 1990
- [5] P.W. Murrill, "Fundamentals of Process Control Theory", *Instrument Society of America*, 1981
- [6] Q Bi, WJ Cai," Advanced controller auto-tuning and its application in HVAC systems", *Control Engineering Practice* 8(2000), pp. 633-644, 2000.
- [7] Pinella M., Hittle, D.C., Wechselberger, E., and Pedersen, C., "Self-tuning Digital Integral Control", *ASHRAE Transactions*, vol.92, pt 2B, 1986.
- [8] Brandt, S., "Adaptive control implementation issues", *ASHRAE Transactions*, vol. 92, pt 2B,pp.211- 219, 1986.

-
- [9] O.Mhmed, J.W.Michell and S.A.Klein, 'Feed forward-feedback controller using general regression neural network for laboratory HVAC system: part 1 –present control", *ASHRAE Transactions*, vol 104(2), pp 613-625,1998.
 - [10] M. Heiss, "Error-minimizing dead zone for basis function networks," *IEEE Trans. Neural Networks*, vol. 7, pp. 39-50, 1996
 - [11] F.C. Chen and H.K. Khalil, "Adaptive control of a class of nonlinear discrete-time sytems using neural networks," *IEEE Trans. Automat. Contr.*, vol. 40, pp. 791-801,1995.
 - [12] S. Jagannathan and F.L. Lewis, "Discrete-time neural net controller for a class of nonlinear dynamic systems," *IEEE Trans. Automat. Contr.*, vol. 41, pp. 1693-1699, 1996.
 - [13] Q. Song, J. Xiao, and Y. C. Soh, "Robust Back-propagation Training Algorithm for Multi-layered Neural Tracking Controller", *IEEE Trans. On Neural Networks*, Vol.10, No.5, pp.1133-1141, 1999.
 - [14] Q. Song, R. Katebi and M.J. Grimble, "Robust multivariable implicit adaptive control," *IMA Journal of Mathematical Control & Information*, Vol.10, pp. 49-70, 1993.
 - [15] Simon Haykin, *Neural Networks, A Comprehensive Foundation*, Second Edition,1999
 - [16] F. Rosenblatt, *Principles of Neuron dynamics*, Spartan Books, Washington D.C., 1962
 - [17] B. Widrow, "Generalisation and information storage in networks of adaline neurons", *Self-Organizing Systems*, (M.C. Yovitz, GF.T.Jacobi, and G.D.Goldstein, eds.), Sparta, Washington, D.C, USA, 1962.

-
- [18] P.J. Werbos, Beyond regression: new tools for prediction and analysis in the behavioural sciences, 1986
 - [19] D.E.Rumelhart, G. E. Hinton, and R.J. Williams, "Learning internal representation by error propagation", *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, D.E.Rumelhart and J.L.McClelland Eds., Cambridge, MA, USA, 1986
 - [20] D. B. Parker, "Learning-logic: casting the cortex of the human brain in Silicon", *Technical Report TR-47*, Centre for Computational Research in Economics and Management Science, MIT, 1985
 - [21] S. Haykin, Neural Networks, A comprehensive Foundation, IEEE Press, New York, 1994.
 - [22] R. Hecht-Nielsen, "Kolgomorov's mapping neural networks existence theorem", *First IEEE International Conference on Neural Network*, vol. 3, pp 11-14, San Diego, CA, 1987.
 - [23] G. Cybenko, "Approximation by superposition of a sigmoidal function", *Technical Report*, University of Illinois, Urbana, 1988.
 - [24] G. Cybenko, "Approximation by superposition of a sigmoidal function ", *Mathematics of Control, Signals, and Systems*, vol.2, pp 303-314,1989.
 - [25] M.M Gupta and D. N. Rao, Editors, Neuro-Control Systems, Theory and Applications, IEEE press, USA, New York, 1994..
 - [26] L. Tillack and J.B. Rishel, "Proper control of HVAC variable speed pumps," *ASHRAE Journal*, Vol. 40, No. 11, pp 41-47, 1998.
 - [27] O. Ahmed, "DDC applications in variable-water-volume systems," *ASHRAE Transactions*, Vol. 97, No. 1, pp 751-758, 1991.

-
- [28] H. Bynum and E. Merwin, "Variable flow—A control engineer's perspective," *ASHRAE Journal*, Vol. 41, No. 1, pp 26-30, 1999.
- [29] J.E. Braun, S.A. Klein, J.W. Mitchell and W.A. Beckman, "Application of optimal control to chilled water system without storage," *ASHRAE Transactions*, Vol. 95, No. 1, pp 663-675, 1989.
- [30] M.A. Cascia, "Implementation of a near-optimal global set point control method in a DDC controller," *ASHRAE Transactions*, Vol. 106, No. 1, pp 249-263, 2000.
- [31] J.M. House and T.F. Smith, "A system approach to optimal control for HVAC and building systems," *ASHRAE Transactions*, Vol. 101, No. 2, pp 647-660, 1995.
- [32] W.J. Wepfer and S.V. Shelton, "Chilled-water loop optimization," *ASHRAE Transactions*, Vol. 96, No. 2, pp 656-661, 1990.
- [33] J.E. Braun, S.A. Klein, J.W. Mitchell and W.A. Beckman, "Application of optimal control to chilled water system without storage," *ASHRAE Transactions*, Vol. 95, No. 1, pp 663-675, 1989.
- [34] B.C. Ahn and J.W. Mitchell, "Optimal control development for chilled water plants using a quadratic representation," *Energy and Buildings*, Vol. 33, No. 4, pp 371-378, 2001.
- [35] S.B. Austin, Chilled water system optimization, *ASHRAE Journal*, Vol. 35, No. 7, pp 50-56, 1993.
- [36] W. Kirsner, "Designing for 42°F chilled water supply temperature—does it save energy?," *ASHRAE Journal*, Vol. 40, No. 1, pp 37-42, 1998.
- [37] T.B. Hartman, "Global optimization strategies for high-performance controls," *ASHRAE Transactions*, Vol. 101, No. 2, pp 679-687, 1995.

-
- [38] T. Hartman, "Packaging DDC networks with variable speed drives," *Heating/Piping/Air Conditioning*, Vol. 70, No. 11, pp 80-84, 1998.
 - [39] G. Avery, Controlling chillers in variable flow systems, *ASHRAE Journal*, Vol. 40, No. 2, pp 42-45, 1998.
 - [40] R.H. Green, "An air-conditioning control system using variable-speed water pumps," *ASHRAE Transactions*, Vol. 100, No. 1, pp 463-470, 1994.
 - [41] T. Hartman, "Design issues of variable chilled-water flow through chillers," *ASHRAE Transactions*, Vol. 102, No. 2, pp 679-683, 1996.
 - [42] T. Salsbury and R. Diamond, "Performance validation and energy analysis of HVAC systems using simulation," *Energy and Buildings*, Vol. 32, No. 1, pp 5-17, 2000.
 - [43] B.A. Flake, Parameter Estimation and Optimal Supervisory Control of Chilled Water Plants, Ph.D. Thesis, University of Wisconsin-Madison, Ann Arbor, Mich, UMI, 1998.
 - [44] E.J. Lee, Modeling and Simulation of a Campus Central Chilled Water System, Ph.D. Thesis, Oklahoma State University, Ann Arbor, Mich, UMI, 1987.
 - [45] J.E. Braun, Methodologies for Design and Control of Central Cooling Plants, Ph.D. Thesis, University of Wisconsin-Madison, Ann Arbor, Mich, UMI, 1988.
 - [46] N. Nocedal and S.J. Wright, *Numerical Optimization*, Springer-Verlag: New York, 1999
 - [47] W. Huang and H.N. Lam, "Using genetic algorithms to optimize controller parameters for HVAC systems," *Energy and Buildings*, Vol. 26, pp 277-282, 1997.

-
- [48] Y. Asiedu, R.W. Besant and P. Gu, "HVAC duct system design using genetic algorithms," *HVAC&R Research*, Vol. 6, No. 2, pp 149-173, 2000.
- [49] T.T. Chow, Q.G. Zhang, Z. Lin and C.L. Song, "Global optimization of absorption chiller system by genetic algorithm and neural network," *Energy and Buildings*, Vol. 34, pp 103-109, 2002.
- [50] P.H. Chen and H.C. Chang, "Genetic aided scheduling of hydraulically coupled plants in hydro-thermal coordination," *IEEE Transactions on Power Systems*, Vol. 11, No. 2, pp 975-981, 1996.
- [51] M.G. Na, "Design of a genetic fuzzy controller for nuclear steam generator water level control," *IEEE Transactions on Nuclear Science*, Vol. 45, No. 4, pp 2261-2271, 1998.
- [52] S.O. Orcro and M.R. Irving, "A genetic algorithm modeling framework and solution technique for short term optimal hydrothermal scheduling," *IEEE Transactions on Power Systems*, Vol. 13, No. 2, pp501-518, 1998.
- [53] Y.Zhang, P. Sen, G.E.Hearn, "An on-line trained adaptive neural controller," *IEEE Control systems Magazine* 15 (5) (1995) 67-75.
- [54] J. Tamomara, S. Omatu, Process control by on-line trained neural controller, *IEEE Trans. Industrial Electronic* 39, 511-521, 1992.
- [55] D.Nguyen, B.Widrow, "Neural networks for self-tuning control systems," *IEEE Control Systems Magazine* 10(3),18-23, 1990.
- [56] M. Heiss, "Error-minimizing dead zone for basis function networks," *IEEE Trans. Neural Networks*, vol. 7, pp. 39-50, 1996.
- [57] F.C. Chen and H.K. Khalil, "Adaptive control of a class of nonlinear discrete-time systems using neural networks," *IEEE Trans. Automat. Contr.*, vol. 40, pp. 791-801,1995.

-
- [58] S. Jagannathan and F.L. Lewis, "Discrete-time neural net controller for a class of nonlinear dynamic systems," *IEEE Trans. Automat. Contr.*, vol. 41, pp. 1693-1699, 1996.
 - [59] S. Jagannathan and F.L. Lewis, "Multiayer discrete-time neural-net controller with guaranteed performance," *IEEE Trans. Neural Networks.*, vol. 7, pp. 107-130, 1996.
 - [60] M.M. Polycarpou and P.A. Ioannou, "Learning and convergence analysis of neural-type structured networks," *IEEE Trans. Neural Networks*, vol. 3, pp. 39-50, 1992.
 - [61] R. Ortega, L. Praly and I.D. Landau, "Robustness of discrete-time direct adaptive controllers," *IEEE Trans. Automatic Control*, Vol.30, No.12, pp. 1179-1187, 1985.
 - [62] Q. Song, R. Katebi, M.J. Grimble, "Robust multivariable implicit adaptive control," *IMA Journal of Mathematical Control & Information*, Vol.10, pp. 49-70, 1993.
 - [63] V.R. Cluett, L. Shah, G. Fisher, "Robustness Analysis of Discrete-Time Adaptive Control Systems Using Input-Output Stability Theory: a Tutorial," *IEE Proc-D Control Theory Appl.*, 135, (2), pp.1179-1187, 1988.
 - [64] Q. Song, R. Katebi, M.J. Grimble, "Robust multivariable implicit adaptive control," *IMA Journal of Mathematical Control & Information*, Vol.10, pp. 49-70, 1993.
 - [65] Matsuba, M.Kasahara, "Stablity limit of room air temperature of a VAV system", *ASHRAE Trans.*, Vol. 104, No.2, pp. 257-265, 1998

-
- [66] M. Zaheer-uddin and G.R. Zheng, "A Dynamic Model of A multi-zone VAV System for the Control Analysis," *ASHRAE Trans.*, Vol. 94. Part 2, pp.219-228, 1994.
- [67] Betzaida A. S. and Miguel V. R., "Nonlinear Control of a Heating, Load Estimation," *IEEE Trans. Control System Technology*, Vol. 7, No. 1, 1999
- [68] S.J. Hepworth and A.L. Dexter, "Neural control of nonlinear HVAC plant," *Proceedings of the IEEE conference on Control Applications*, Vol.3, pt. 3, 1994.
- [69] J.C. Spall, "Multivariate stochastic approximation using a simultaneous perturbation gradient approximation", *IEEE Trans. On Automatic Control*, Vol. 37, pp. 332-341, 1992.
- [70] J.C. Spall and J.A. Cristion, "Model Free Control of Nonlinear Stochastic Systems with Discrete-Time Measurements", *IEEE Trans. On Automatic Control*, Vol. 43, No.9, pp. 1198-1210, 1998.
- [71] M.G. Safanov, "Stability and robustness of multivariable feedback systems", MIT Press, 1980.
- [72] Q. Song, W.J. Hu and T.N. Zhao, "Robust neural controller for variable airflow volume system", *IEE Proc.-Control Theory Appl.*, Vol. 150, No. 2, pp. 112-118, 2003.
- [73] J.E. Seem, "A New Pattern Recognition Adaptive Controller with Application to HVAC Systems," *Automatica*, 34(8), pp. 969-982, 1998
- [74] G. Stephanopoulos, *Chemical Process Control: An Introduction to the Theory and Practice*. New Jersey: Prentice Hall, 1984.
- [75] P.W. Murrill, *Application Concepts Process Control*. RTP, North Carolina, ISA, 1988

-
- [76] C. Maffezzoni, N. Schiavoni and G. Ferretti, "Robust Design of Cascade Control," *IEEE Control Systems Magazine*, JAN, pp.21-25, 1990
 - [77] G.H. Cohen & G. A. Coon, "Theoretical consideration of retarded control", *ASME Trans.*, 75, pp. 827-834, 1953
 - [78] J.C. Spall, "An Overview of the Simultaneous Perturbation Method for Efficient Optimization," *Johns Hopkins APL Technical Digest*, vol. 19, pp. 482–492.1998.
 - [79] M.P. Cassidy and J.F. Stack, Applying adjustable speed AC drives to cooling tower fans. *Annual Petroleum and Chemical Industry Conference*, IEEE, 1988
 - [80] J.E. Braun and G.T. Doderich, "Near-optimal control of cooling towers for chilled-water systems," *ASHRAE Transactions*, Vol. 96, No. 2, pp 806-813, 1990
 - [81] M.A. Cascia, "Digital controller for a cooling and heating plant having near-optimal global set point control strategy," *US Patents 5963458*, 1999.
 - [82] S.V. Shelton and C.T. Joyce, "Cooling tower optimization for centrifugal chillers," *ASHRAE Journal*, Vol. 33, No. 6, pp 28-36, 1991.
 - [83] W. Kirsner, 3 GPM/Ton condenser water flow rate: Does it waste energy? *ASHRAE Journal*, Vol. 38, No. 2, pp 63-69, 1996.
 - [84] K. M. Michael and A. F. Emery. "Cost-optimal analysis of cooling towers," *ASHRAE Transactions*, 100(2):92-101, 1994.
 - [85] M. Schwedler, "Take it to the limit...or just halfway?", *ASHRAE Journal*, 40(7):32-39, 1998.
 - [86] J.H. Holland "Adaptation in Natural and Artificial Systems", Cambridge: The MIT Press. 1994:211
 - [87] Lu Lu, Wenjian Cai, Lihua Xie, Shujiang Li, Yeng Chai Soh, "HVAC system optimization—in-building section", *Energy and Buildings*, 2004

-
- [88] W. F. Stoecker, "Procedures for simulating the performance of components and systems for energy calculations", New York, ASHRAE, 1975.
- [89] J. F. Kreider and A. Rabl, "Heating and Cooling of Buildings—Design and Efficiency," McGraw-Hill, Inc., 1994.
- [90] Lu L, Cai W. "A universal engineering model for cooling towers," *The International Compressor Engineering Conference and Refrigeration and Air Conditioning Conference*, Purdue University, USA, July 2002.
- [91] J. E. Braun, S. A. Klein and J. W. Mitchell, "Effectiveness models for cooling towers and cooling coils," *ASHRAE Transactions*, 95(2):164-174, 1989
- [92] R. Burger, "Energy Conservation strategy, the ignored cooling tower", *Proceedings of the Intersociety Energy Conversion Engineering Conference*, 1852-1856, 1996.
- [93] M. M. Castro, T. W. Song and J. M. Pinto, "Minimization of operational costs in cooling water systems," *Chemical Engineering Research and Design, Transactions of the Institute of Chemical Engineers*, 78(2): 192-201, 2000.
- [94] M. A. Bernier, "Cooling tower performance: theory and experiments," *ASHRAE Transactions*, 100(2): 114-121, 1994.
- [95] M. A. Bernier, "Thermal performance of cooling towers," *ASHRAE Journal*, 37(4):56-61, 1995.
- [96] F. Bosnjakovic and K. F. Knoche, "Pinch analysis for cooling towers," *Energy Conversion and Management*, 39(16-18):1745-1752, 1998
- [97] D.E. Goldberg, "Genetic Algorithms in Search-Optimization and Machine Learning," Massachusetts: Addison-Wesley, 1989.

- [98] W. Huang and H. N. Lam,"Using genetic algorithms to optimize controller parameters for HVAC systems", *Energy and Buildings*, 26: 277-282, 1997.
- [99] Y. Asiedu, R. W. Besant and P. Gu," HVAC duct system design using genetic algorithms", *HVAC&R Research*, 6(2): 149-173, 2000.
- [100] T. T. Chow, Q. G. Zhang, Z. Lin and C. L. Song," Global optimization of absorption chiller system by genetic algorithm and neural network", *Energy and Buildings*, 34: 103-109, 2002.