Optimal Control and Fault Detection in Heating, Ventilating and Air-Conditioning Systems

by

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ABSTRACT

The control of heating, ventilating and air conditioning (HVAC) systems has been improved during recent years. However, the savings associated with these new control strategies can be lost if faults occur in the HVAC and control systems.

This thesis describes a methodology for fault detection based on the optimal control of the HVAC system. In order to demonstrate the process, a representative system is simulated and the optimal control strategy is determined. Bias and random errors are then introduced into the control system. Deviations from optimal performance are sensed and the faults producing non-optimal performance are detected and located.

The optimal control strategy uses outputs from the energy management and control system. A regression equation for the total power in terms of the forcing functions and the control variables is fit through operational (simulated) data collected under different values of the controlled and uncontrolled variables. This equation is quadratic with respect to the control variables. Equating the Jacobian with respect to the control variables to zero yields a set of equations which determine the optimal values for the control variables. The variables are subject to equality and inequality constraints. The equations represent optimal control at all times.

To detect faults, a comparison is made between the measured (simulated) system power during operation and the power predicted from the formula. Various approaches to using this difference in power are described. The statistical significance of individual measurements is examined. Furthermore, sequences of data are inspected. Statistical analyses check for the significant difference between these sequences and sequences without faults. The tradeoff between the level at which faults can be detected and the quickness of detecting faults is discussed.

The evaluations may be carried out for the whole system as well as for individual components. Using the techniques on each component permits the location of the fault to be determined. Quick repair of faults can make a significant contribution to energy savings in a HVAC system.

ACKNOWLEDGEMENTS

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NOMENCLATURE

Roman Symbols

AHU - air handling unit

BEMCS - building energy management and control system

b - regression coefficient

$c_{p,a}$ - specific heat of air

COP - coefficient of performance

E - Error

f - vector of uncontrolled variables

F_o - mass fraction of outdoor air in the supply air stream

g - vector of equality constraints

h - vector of inequality constraints

h - enthalpy

H_0 - null hypothesis

H_1 - alternative hypothesis

J - instantaneous operating cost

$\dot{m}$ - mass flow rate

M	- vector of discrete control variables
n	- number of observations
R^2	- coefficient of determination
T	- dry bulb temperature
u	- vector of continuous control variables
P_{pred}	- power predicted from the formula
P_{meas}	- measured or simulated power
$\dot{Q}$	- load
s	- sample standard deviation
s_p	- pooled variance
t	- tabulated t-value
TWB	- wet bulb temperature
x	- vector of input stream variables
x	- predictor
y	- vector of output stream variables
y	- measured or simulated value
$\hat{y}$	- predicted or fitted value
$\bar{y}$	- sample average
Y	- transformed observation
z	- tabulated z-value

Greek Symbols

α	- significant levels or tail area
$\alpha/2$	- two-sided tail area
β	- regression coefficient

δ - difference in the means of two sets of data

δ_0 - difference in the means of two sets of data assuming the null hypothesis

ε - error term

ω - absolute humidity

ν - degrees of freedom

η - population mean

σ - population standard deviation

Additional Subcripts and Superscripts

a - air

A - treatment A or first sequence

B - treatment B or second sequence

c - coil

chw - chilled water

i - inlet condition

lat - latent

o - outlet condition

o - outdoor air

opt - optimum

sens - sensible

set - set point

T - transposed vector (superscript)

vent - ventilation

w - water

z - zone air

UNIT CONVERSION TABLE

Multiply	by	to obtain
Btu	1.055	kJ
Btu/hr	$2.93*10^{-4}$	kW
°F (32°F = 0 °C)	5/9	°C
ft	0.3048	m
gallon (US)	$3.785*10^{3}$	m^3
HP	0.7457	kW
inch	0.0254	m
lb (mass)	0.454	kg
psi	6.89	kPa
ton, refrigeration	12000	Btu/hr
ton, refrigeration	3.517	kW

Chapter 1

INTRODUCTION

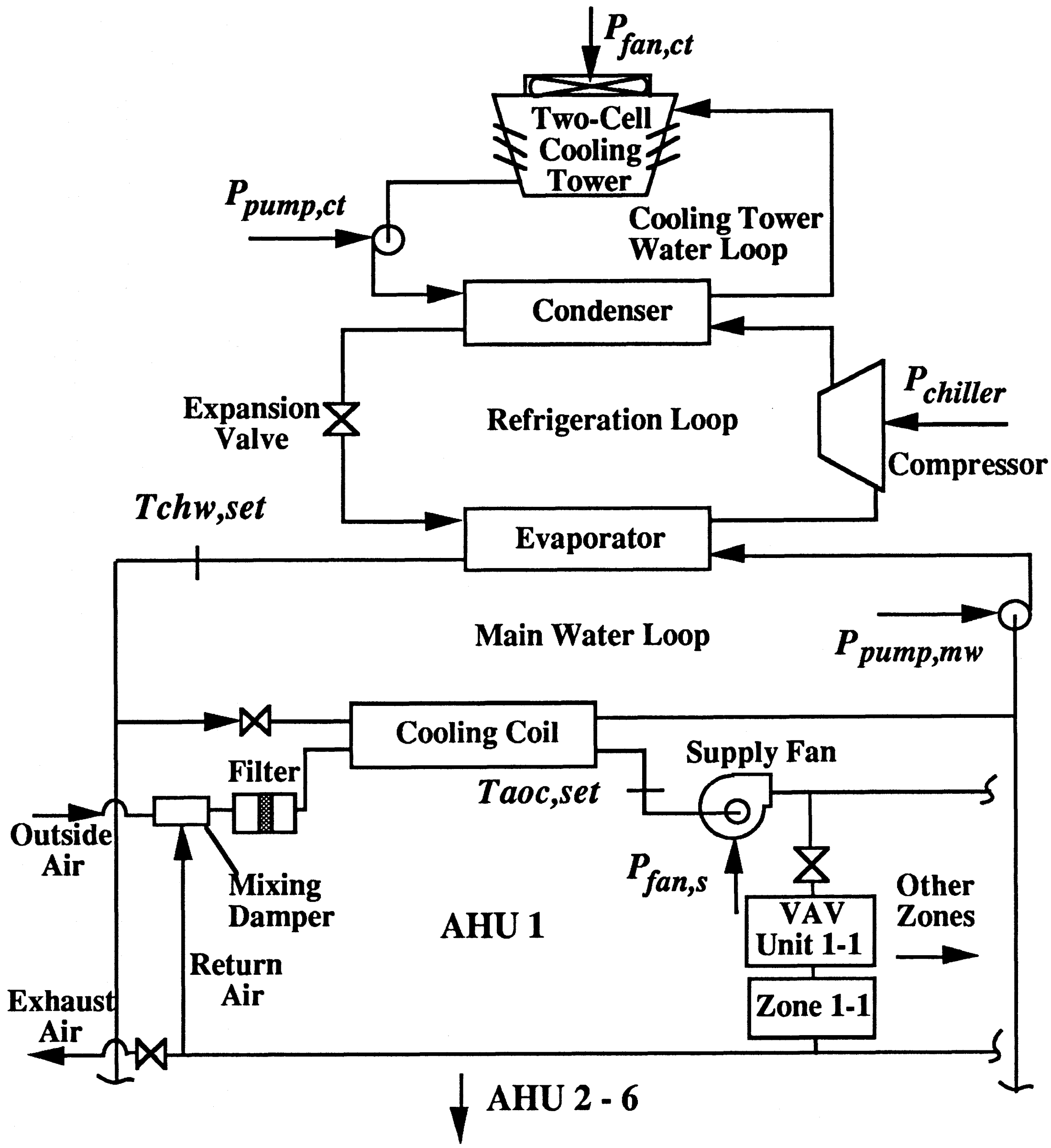
In the first part of the introduction, background information is given on heating, ventilation and air conditioning (HVAC) systems. In section 1.2, the goals and objectives of this thesis are stated. In section 1.3, an air conditioning system which is employed as an example throughout the thesis is described. This system is simulated and the tasks of optimal control and fault detection are illustrated using simulation results from this system. Some examples of faults which can occur in HVAC systems are described in section 1.4. Finally, in section 1.5, previous work related to fault detection in HVAC systems is discussed.

1.1 BACKGROUND

Heating, Ventilation and Air Conditioning systems account for a large percentage of the energy used worldwide. Improvements in design, control, and maintenance of these systems can result in large energy savings. This thesis concentrates on the cooling requirements of buildings.

A conventional air conditioning system without storage consists of one or more cooling towers, pumps, fans, motors, chillers, and air handling units. Figure 1.1 shows a schematic of a conventional variable air volume air conditioning system. The mixing damper mixes outside air and return air from the zones in the desired ratio. After passing through a filter, the mixed air is cooled and dehumidified in the cooling coil. A supply fan provides the ventilation of the air through the different zones. In variable air volume systems the fan supplies the zones with the right amount of air to meet the load. Therefore, often no reheat is necessary. The air is cooled by chilled water which is produced by a chiller. In the *refrigeration cycle,* inside the chiller, the refrigerant is evaporated, superheated, and compressed. Due to the high temperature of the refrigerant in the condenser, heat is transferred to the water in the cooling tower loop, condensing the refrigerant. Finally, the refrigerant expands to the original pressure. Through combined heat and mass transfer in the cooling tower, the heat is rejected to the environment.

Setting of the control variables is performed in a supervisory controller. These control variables may be both continuous, such as temperature settings, or discrete, such as fan speed mode. In the sample air conditioning system only the air temperature out of the cooling coil (Taoc,set) and the water temperature out of the evaporator (Tchw,set) are set by the supervisory controller. The settings of the control variables change the power requirements for the components. They should be set such that the system power consumption is minimized subject to maintaining the building comfort. The control of air conditioning systems is more fully discussed in Chapter 2.



$$P_{tot} = P_{fan,ct} + P_{pump,ct} + P_{chiller} + P_{fan,s} + P_{pump,mw}$$

Figure 1.1 Schematic of a conventional air conditioning system

The control of Heating, Ventilation and Air Conditioning systems has been improved during recent years. It is desirable to control the system in an optimal fashion. Large energy savings can be accomplished if optimal control strategies are employed. However, the savings associated with these optimal control strategies can be lost if faults in the HVAC and control systems are not detected. Significant amounts of energy and money can be saved if the faults are quickly detected. Furthermore, the safety of the equipment and the comfort of the people in the building are important reasons to quickly find and repair faults in the system.

1.2 OBJECTIVES

The main purpose of this thesis is the development of a general methodology for fault detection in HVAC systems. Faults which have a major impact on the system or the total power consumption of the system require detection. For achieving the goal of developing a methodology for fault detection, several steps were required. A representative HVAC system was designed with the performance of cooling towers, fans, pumps, chillers, coils, and motors selected from manufactures' catalogs. Models for each of the system components were employed to simulate the system. For some components, existing models were adjusted or new models were developed. The controller responsible for setting temperatures and simulating the zones needed to be developed. The system with *planted* errors was simulated and compared to a system under optimal control without errors.

A methodology for optimal control is described based upon work of Braun [1988]. Optimal control laws for the sample system are developed. Based on the optimal control of the HVAC system, a methodology for detecting faults is developed. Several ways of recognizing faults are discussed. The methodology is extended so that faults in the system can be located. Finally, suggestions for further research in fault detection are made.

1.3 REPRESENTATIVE SYSTEM

1.3.1 Equipment Sizing

The representative system in Figure 1.1 needs to be designed to allow sufficient cooling to be provided at all times. Therefore, the cooling equipment has to meet the maximum load on the design day. Given the design building load, representing the solar gains and heat gains from people and equipment, and some additional specifications, the system is ready to be designed. The exact procedures for sizing the equipment is discussed in ASHRAE handbooks [1987, 1988] and other publications (e.g. McQuiston and Parker [1982]). The general methodology is to select equipment in the following order:

1. The cooling coil(s) of the air handling unit(s),
2. The fan(s) of the air handling unit(s),
3. The main water loop pump(s),
4. The chiller(s),

5. The cooling towers including their fan(s),
6. The pump(s) of the cooling tower water loop, and
7. The electric motors for the driven devices.

The total load on the cooling coil is the sum of the building load, the ventilation load, and the fan load. The ventilation load is an additional load which represents the additional heat introduced to the system by the outside air. Outside air has often a significantly higher temperature and humidity than the air returning from the zones. Hence, the enthalpy of the outside air is higher than the enthalpy of the return air. The ventilation load can be expressed as

$$\dot{Q}_{vent} = \dot{m}_o (h_o - h_z) \tag{1.1}$$

where,

$\dot{m}_o$ = mass flow rate of outdoor air

h_o = enthalpy of the outdoor air

h_z = enthalpy of the the combined air from the zones.

Due to air quality considerations, a specific air change rate in the zones has to be fulfilled. This requires that a specific amount of outside air has to be added to the return air. Derived from mass and energy balances, the temperature and absolute humidity of the air entering the coil can be calculated from:

$$T_{a,i,c} = T_z (1-F_o) + T_o F_o \tag{1.2}$$

$$\omega_{i,c} = \omega_z \,(1\text{-}F_o) + \omega_o\, F_o \tag{1.3}$$

with,

T_z = temperature of the zone

F_o = mass fraction of outdoor air in the supply air stream

T_o = ambient dry bulb temperature

ω_z = absolute humidity of the combined air from the zones

ω_o = absolute humidity of the outside air

The fan load is an additional load due to the dissipation of electric power which is required to run the fan. The air mass flow rate through the conditioned space is evaluated from

$$\dot{m}_a = \frac{\dot{Q}_{z,\,sens} + \dot{Q}_{fan}}{c_{p,a}\,(T_z - T_{a,o,c})} \tag{1.4}$$

where,

$\dot{Q}_{z,\,sens}$ = sensible zone heat load

$\dot{Q}_{fan}$ = fan load (sensible)

$c_{p,a}$ = specific heat of the air (assumed constant)

$T_{a,o,c}$ = air outlet temperature out of the cooling coil

The sensible heat ratio of the cooling coil, i.e. the ratio of sensible load to total load, can be computed from

$$SHR_c = \frac{\dot{Q}_{z,sens} + \dot{Q}_{vent,sens} + \dot{Q}_{fan}}{\dot{Q}_z + \dot{Q}_{vent} + \dot{Q}_{fan}} \tag{1.5}$$

If the loads were known, the coil selection would be easy. However, the fan load is a function of the selected cooling coil. Therefore, the sizing of the cooling coil requires an iterative procedure. Some additional specifications such as water temperature rise at design conditions are necessary to select an appropriate coil.

The fan can be sized by calculating the pressure loss in the air handling unit. These pressure losses are caused by friction in the ducts, filter, cooling and heating coils, dampers, and the mixing box. Once the pressure losses and the efficiency of the fan at design conditions are determined, the fan motor can be selected. The design fan load can be determined by taking the efficiency of the motor into account.

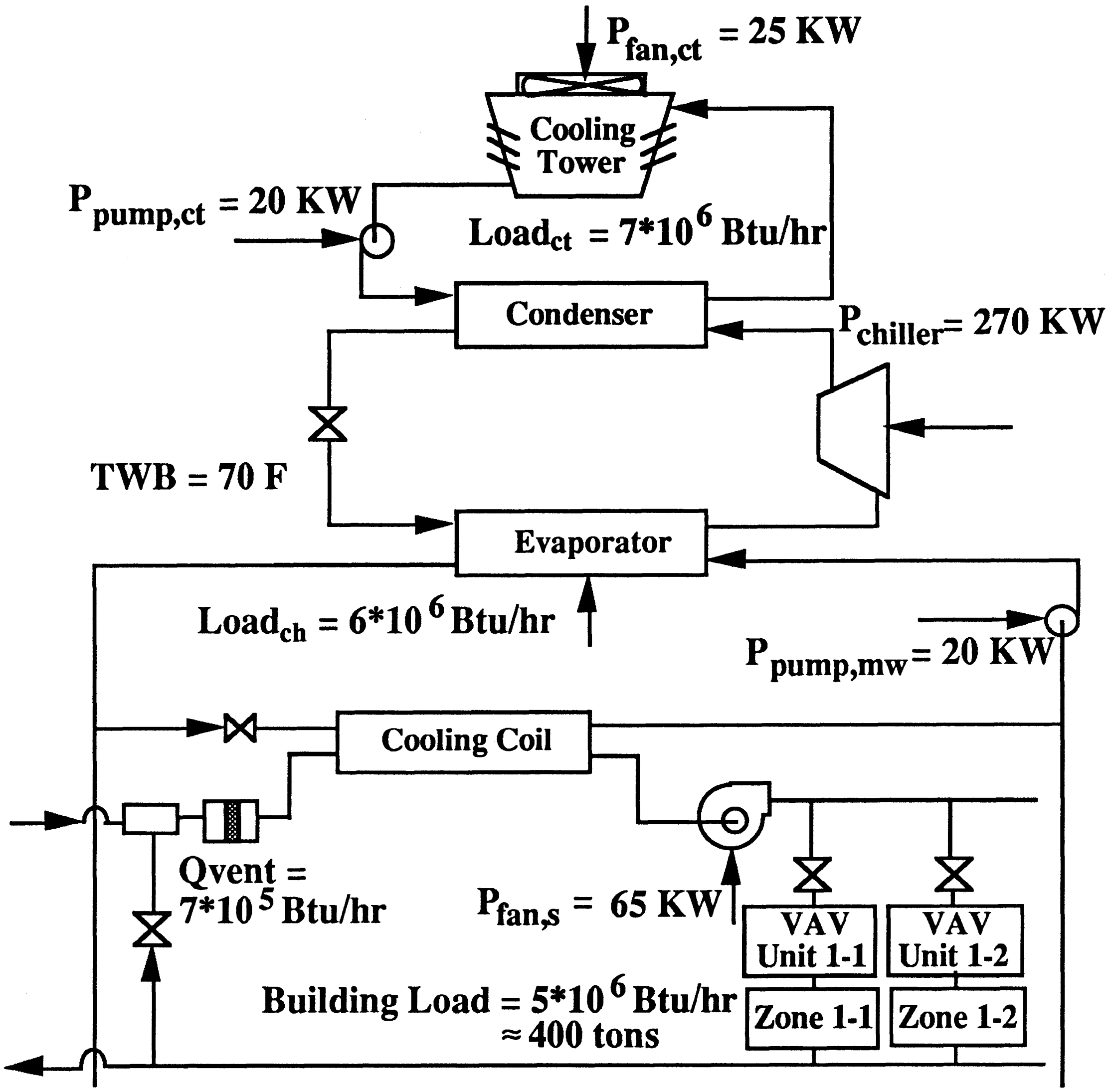
In the next step, the main water loop pump has to be sized. Based on the water flow rate, the pressure drop in the main water loop due to friction in the pipes, the control valves, the cooling coil, and the evaporator has to be computed. The appropriate pump can then be selected from manufacturer's data. With given pump size and motor efficiency at design conditions, the pump load due to dissipation is calculated. The load on the chiller is evaluated as the sum of the load on the cooling coil and the pump load. Usually the pump load is only a very small portion of the total chiller load. A chiller has to be selected based on the chiller load, the chilled water temperature, and the temperature changes across the evaporator and the condenser, all at design conditions.

The pump in the cooling tower loop is selected based on the water flow rate and the total head loss in this loop. These losses are due to losses in pipes, condenser, tower nozzles, valves, and the static head loss representing the difference in height of the hot and cold water basins. The addition of cooling coil load and chiller and pump powers, including motor efficiencies, is the total load which has to be met by the cooling tower. Finally, the cooling tower is chosen based on conditions at the design day: 1) the range (difference between inlet and outlet water temperature), 2) the approach (the difference between the water outlet temperature and the ambient wet bulb temperature), 3) the ambient wet bulb temperature, and 4) the flow rate of the water through the tower.

In Figure 1.2, the approximate powers and loads for the equipment are shown for a building load of about 400 tons. It can be seen that the chiller is the major consumer of power. This means that it is very important to optimize the operation of the chiller even if other components are running less efficiently. The fans in the air handling units (AHU) have the second highest percentage power consumption. The optimal control depends on the tradeoff between the components with variable power input.

1.3.2 Simulation of the Air Conditioning System

The program used to simulate the air conditioning system is the Transient Simulation Program TRNSYS (Klein, et. al. [1988]). This modular program consists of different subroutines which model the performance of particular system components. The subroutines are written in the computer language FORTRAN. TRNSYS was first developed as a simulation program for solar energy systems, but other components for various kinds of energy systems were later included. The user is able to create new models and use or modify old ones. After selecting the components, they have to be linked together to form a complex system model.



$$P_{tot} = P_{fan,ct} + P_{pump,ct} + P_{chiller} + P_{fan,s} + P_{pump,mw}$$

Figure 1.2 Example for powers and loads in a representative air conditioning system

In a *simulation deck,* the information flow between the components is established, i.e. it is defined which component outputs are inputs to other components. It is helpful to draw a block diagram in which the flow of information is indicated. In the deck, the equipment specifications (e.g. number and diameter of tubes in the cooling coil) also have to be fixed as parameters. The simulation deck for the designed system is given in Appendix A.

The simulation has to be provided with forcing functions such as ambient dry bulb temperature and humidity. The timestep as well as the beginning and end of the simulation are specified by the user. For each timestep, the inputs into all components have to converge within a specified tolerance. The method used to obtain convergence for the set of equations describing all components is the successive substitution method.

Most of the components included in TRNSYS are steady state models. These models could be extended with differential equations to include the dynamic behavior of the system. A similar simulation program to TRNSYS, which includes dynamic behavior of the components, is HVACSIM+ which was developed at the National Bureau of Standards. However, Hackner [1985] found that for air conditioning systems without a thermal storage unit, the dynamic behavior of the equipment can be neglected. Therefore, the use of steady state models in TRNSYS is an appropriate choice for simulating these systems.

Many components are available in the TRNSYS library and were used in this work. However, a few subroutines had to be developed or changed. TRNSYS components were developed for a supervisory controller, a local loop controller, an electric motor, and a flow converter. These components are described and listed in Appendix B.

1.4 EXAMPLES OF FAULTS IN HVAC SYSTEMS

Some examples for faults in a HVAC system are given in Table 1.1. Errors in sensor readings can lead to a non-optimal behavior of the system. The sensor error might have a constant value (bias), might increase with time, or might change with time in a random order. Wrong calibration or no calibration are reasons for sensor errors. If stratification in ducts or pipes occurs, the sensed fluid temperature might not be the actual mean temperature. Errors can also be introduced by the controller or by a control transmitter. A failure of a sensor can be caused by a bad connection.

Table 1.1: Examples of faults in a HVAC system

- sensor errors (calibration, sensor, stratification, transmitter, controller, etc.)
- sensor failure
- reduction in water and air flow rates due to valve and damper malfunction
- leakage of air or water
- blockage in pipes
- degradation of equipment performance
- damage of equipment

If valves or dampers are not opening and closing in an appropriate way, the flow rates of the water or the air could be undesirable. If air or water is leaking out of the system, a change in pressures and flow rates can occur. Blocking in ducts or pipes increases the resistance of the air of water flow. Thus, higher fan or pump power is required to achieve the same conditions. The degradation of equipment performance such as the decrease in the coefficient of performance for the chiller can occur. Fouling inside the evaporator can be a cause. Equipment degradation or equipment damage not only increases the system power but may also prevent the achievement of comfort conditions.

The proposed fault detection technique should also be able to detect faults that have not been anticipated and are not in the table. All faults will prevent optimal behavior and should therefore be detected. With the technique proposed in this thesis, all faults which have an influence on the total or any component power consumption can be detected.

1.5 PREVIOUS WORK IN FAULT DETECTION

Much work has been done in the development and improvement of building energy management and control systems (BEMCS). However, their full capabilities have not been reached because they have not been able to detect faults in the HVAC system. At present, this process is limited to the check of upper and lower limits of sensor values and the experience and understanding of building operators to recognize degradation of performance. Recently, the interest in this matter has increased because studies have shown large energy losses due to faults. The studies found in the area are briefly summarized at this point.

Kao and Pierce [1983] and Kao [1985] examined the influence of sensor errors in the air handling unit of a HVAC system. Computer calculations using the BLAST program (Hittle [1979]) were used to simulate the yearly air handling system energy consumption of a hypothetical office building. The system was operated with an enthalpy economy cycle. Constant volume systems with reheat coils or variable air volume units were employed. The effects of location and magnitude of errors (errors were held at a constant value between negative and positive 10 F) were examined. It was found that errors can increase the annual energy requirements for that system up to 50%. Errors in the mixed air temperature sensor and the coil air outlet temperature were most critical from the standpoint of energy consumption.

Liu and Kelly [1989] developed a prototype computerized diagnostic method for the detection of faults in an air handling unit (AHU) using sensor data from the BEMCS. They propose that besides running an actual system, a computer model of the AHU should be used to determine a set of optimum performance parameter. Deviations between system and computer model are indicated. The modelling of the system is computational very intensive. Faults are located using a rule-based system which is written in the symbolic language Prolog.

Haberl et. al. [1989] suggest the use of rule-based fault detection systems. The programs written for that task consist of many "if-then" commands. Knowledge from operators has to be collected over years. Building data are used to compare data with predicted values from steady state models. Faults, such as delayed shut off of fans and lights, and incorrect settings of shut off times, were examined. The faults could be detected in a study of three buildings if the energy required was about 25 % higher than the predicted energy.

Usoro and Schick [1985] present a methodology for fault detection in a AHU using a nonlinear mathematical model and an extended Kalman filter. The dynamics of the system is examined. The method is computational intensive.

Anderson et. al. [1989] employed a quasi-real-time expert system. A statistical analysis preprocessor estimates operating parameters. The actual and the estimated energy consumption are compared. A rule-based expert system analyzes the collected data and reports problems in the system.

The mentioned methods are only able to detect a specific type of fault or are only able to detect faults in one part of the air conditioning system. Furthermore, the rule based systems used to detect faults have to be developed over a long period of time and require much knowledge from the building personal. Also, most of the procedures are computationally very intensive. Therefore, it is desirable to develop a methodology which can be used for any system without prior knowledge of the system. All faults which have an impact on the power consumption of the whole system or of one or more components should be detected using the proposed methodology. The additional computational effort by the BEMCS should be small.

Chapter 2

CONTROL OF HVAC SYSTEMS

During the last two decades the control of HVAC systems has changed dramatically. These changes had two main reasons: the increase of energy prices and the availability of digital computers. The increase of energy prices forced the air conditioning industry to develop control strategies which reduce the power consumption of HVAC systems. The availability and improvement of low cost computers made these tools available to the HVAC industry. The development of Building Energy Management and Control Systems (BEMCS) was only possible by using computers. Recently, the control of HVAC systems is changing again because the aspect of air quality is becoming a major concern. Contaminants and odor have to be removed from the zones.

This chapter starts with an introduction to the control of HVAC systems. In section 2.2, control strategies which are employed in air conditioning systems are discussed. These conventional control strategies will be used as a comparison to optimal control, discussed in section 2.3, and near optimal control, introduced in section 2.4. These comparisons are demonstrated in section 2.5. The chapter will be summarized in section 2.6.

2.1 INTRODUCTION TO THE CONTROL OF HVAC SYSTEMS

In this section, the fundamental terms in the control of HVAC systems are explained. In section 2.1.1, the terms of closed loop and open loop control are explained. The types of controls found in BEMCS can be divided into local loop control and supervisory control. These two types of control are discussed in sections 2.1.2 and 2.1.3. The improvements in digital computers had a big impact in the increased use of direct digital control (DDC) which is explained in section 2.1.4. An example of how the system of Figure 1.1 is controlled is outlined in section 2.1.5.

2.1.1 Closed Loop and Open Loop Control Systems

A control system is composed of two parts: 1) a controller that has the ability to sense a variable, determine whether it meets the design specifications, and take corrective action if necessary and 2) a controlled device that receives information from the controller and takes action with respect to this information.

A thermostat in a home would be a simple example for a controller. The thermostat senses the room temperature; if the room temperature is too low, it sends a signal to a gas valve in a warm air furnace for it to open. An increase in the room temperature will at some point cause the thermostat to send a signal to the gas valve to close. This type of control system, in which the controller senses the result of its action is called a *closed loop or feedback control system.*

An *open loop system* is one that does not incorporate feedback, i.e. the controller does not sense the result of its action. An outdoor temperature sensor could be an example for an open loop system. If the outdoor temperature drops, sensed by the thermostat, eventually hot water is provided to the buildings heating system. The thermostat, however, never senses the hot water. It does not receive any feedback from the action it took. It only senses the outdoor temperature.

2.1.2 Local Loop Control

In local loop control, pieces of equipment respond to changes in settings and come to new operating conditions. These control functions operate independently of each other and control only specific pieces of equipment. The controller receives an information from one sensor in the local system and controls another variable in the local system with respect to this information. The two control points for local loop control are often located close together. Prior to complete management systems, the whole air conditioning system was controlled with local control loops. Usually, local control loops are relatively simple and robust and can be quickly installed. However, they need to be maintained. Local loop controllers work in either of the following ways: (1) pneumatic, (2) electric, (3) electronic, or (4) direct digital (section 2.1.2). The development of direct digital control is taking over fields which were traditionally performed by the other control variants. Today, local loop control is still used because of the many controls in the system. Safety is another reason for the use of local loop control. Even if the supervisory controller breaks down, the HVAC system has to remain in a safe status for people and equipment.

Figure 2.1 gives an example for local loop control in a variable air volume system of an air handling unit. The fan is expected to supply as much air as is needed to the different zones. The control assures a specifically set constant static pressure in the duct behind the fan. If one zone suddenly requests more air by opening a valve, the static pressure will decrease for a moment. At this moment, the local loop feedback control causes the fan to increase its speed until the set pressure is reached again.

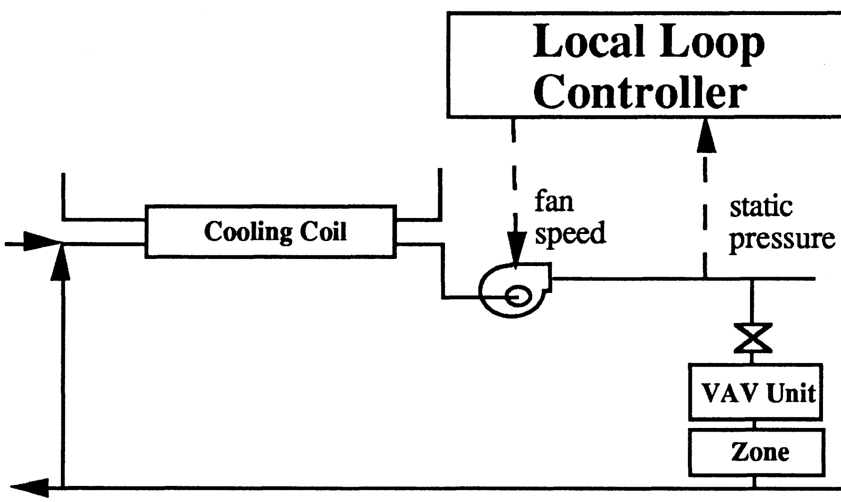


Figure 2.1 Constant static pressure local loop control in a VAV air handling unit

2.1.3 Supervisory Control

Measurements from the whole system are connected to a main computer, the supervisory controller. From here, supervisory control is performed. In a supervisory control system, many variables have to be measured, monitored, and stored. These measurements are input to functions which represent the control strategy. Independent control variables are evaluated and set based on the control strategy. The control strategies can reduce the running time of the equipment and the loads at peak power periods, provide comfort based on outside conditions, use the right amount of outside air for cooling, and spot malfunctions in the system. Furthermore, the output performance of the system can be monitored and stored by the supervisory computer.

Supervisory controllers offer the opportunity of diversity in control decisions and have the potential for an optimized control of HVAC systems in a simple or very complex fashion. Often, lighting, security alarms, and fire alarms are built into the same computer. The software in the supervisory controller can be changed easily and quickly. If a supervisory controller is installed, usually less manpower is required than for a system with only local loop control [Schneider (1981)]. While all local controls have to be checked at their locations, supervisory control allows the check of many control functions at the same place by one operator.

In supervisory control systems accurate measurements are essential. Especially, if open loop readings are needed, accurate and thus expensive measurement devices are required because no feedback is given to check if, for example, a temperature is really reached. Only the sensor measurement is available. Therefore, these devices can have a large impact on the whole system performance.

The installation of a supervisory controller can be expensive, especially if it is included after the building was constructed and if many points in the system are connected to the computer. However, energy savings, safety, and flexibility associated with the supervisory control make these controls necessary in modern buildings. For the task of fault detection, supervisory controllers are needed.

In Figure 2.2, an example for supervisory control in a variable air volume system of a air handling unit is shown. The supervisory controller is provided with sensor data of the system and ambient conditions. Depending on these measurements, the supervisory controller sets the air temperature leaving the cooling coil. After setting a new temperature, a valve opens or closes which changes the water flow rate through the coil so that the new set temperature will be met. The supervisory controller also sets damper positions of outside, exhaust, and return air.

In modern air conditioning systems, local loop and supervisory control are employed simultaneously. These combined control systems try to combine the advantageous of local and supervisory control.

2.1.4 Direct Digital Control

In a revolutionary change in the control of air conditioning systems, the application of microprocessors has increased drastically. The microprocessors are programmed to duplicate the control functions of analog electronic, electric, or pneumatic local loop controllers. A change in one measurement is directly used to change a different variable. The control acts at discrete time steps and not continuously. If the controller in a closed loop is a digital computer, as shown in Figure 2.3, it is called direct digital control (DDC).

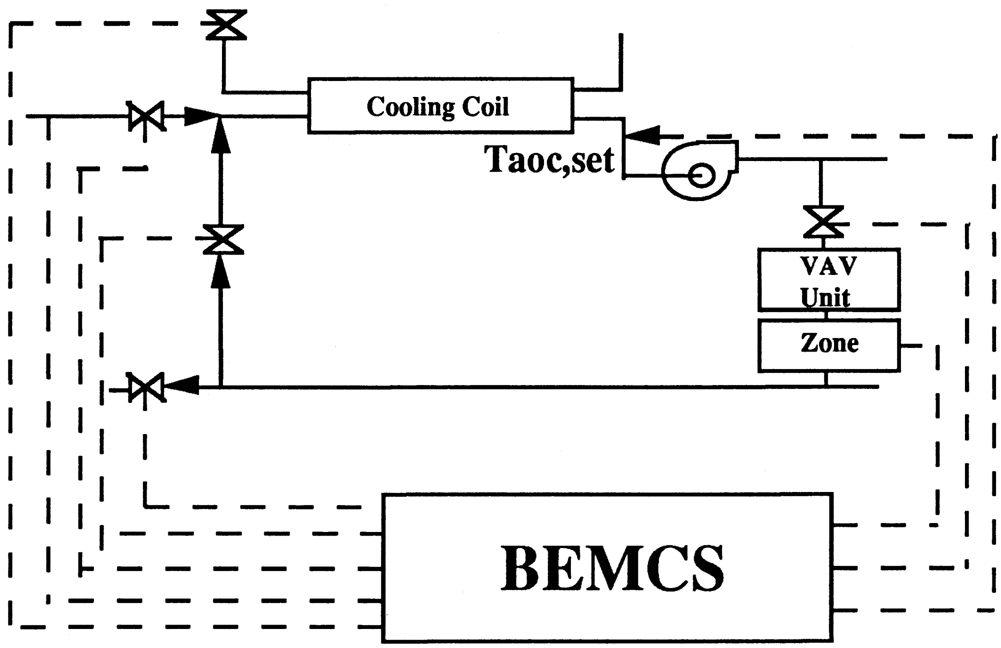


Figure 2.2 Supervisory control of coil air outlet temperature in an air handling unit

Until recently, computers were only used for the supervisory controller. This, however, has limitations because even sophisticated supervisory controllers can not make up for deficiencies in local loop controllers. Furthermore, the combination of computer and mechanical or electro-mechanical devices is often expensive. These are reasons that today computers are sometimes used to completely control air conditioning systems.

If the DDC is installed, alternative control techniques can be quickly tried without further costs. The control can be upgraded if wanted. As the cost for computer hardware decreases, the costs for DDC might sometimes be lower than the costs for conventional controls.

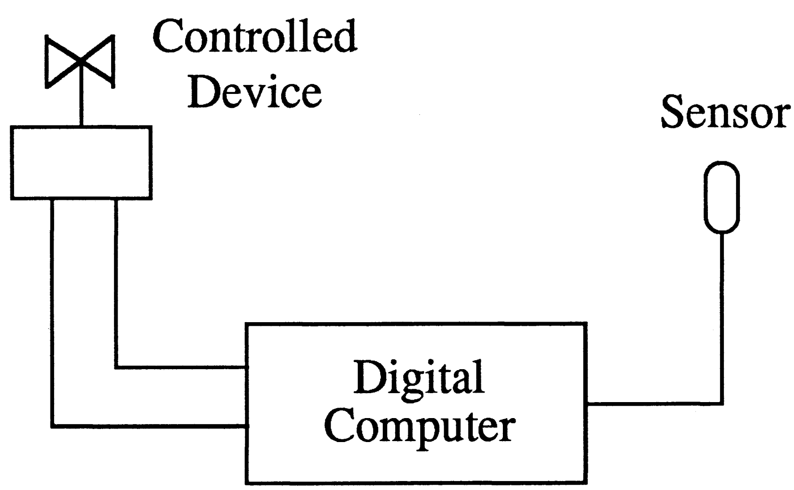


Figure 2.3 A direct digital control loop

Due to the increasing use of open loop DDC, more accurate sensors have to be utilized. A one degree change in some temperature, such as chilled water, can effect energy consumption by a couple percent, so that a control system with even one degree of error is not fully controllable in terms of energy usage (Computer Controls Corporation). This is one reason that fault detection becomes more important with the developments in the control of HVAC systems.

2.1.5 Control of the Example System

A possible control of the example system is presented in Figure 2.4 and discussed below. Some of the sensor data are used for determination of the optimal control of the system.

Temperature and humidity of the outside air are sensed. The ratio of mixing outside and return air is set by the supervisory controller depending on the control strategy. The air temperature out of the cooling coil is set by the supervisory controller as a function of the uncontrolled variables (load, sensible heat ratio (SHR), and ambient dry and wet bulb temperature). Measurements of air flow rate, humidity, and static pressure are taken. Temperature and humidity are measured in the zone. The chilled water temperature out of the evaporator is another temperature set by the supervisory system.

In the main water loop the water flow rate and return water temperature out of the coil are measured. The status of the cooling tower fan and the status of the cooling tower loop pump are set by the supervisory system. In the chosen system these two devices have constant speed. Studies show that allowing variable speed devices would not decrease the total power consumption significantly (Cummings [1989]). If the cooling tower fan has a variable speed drive, another set point temperature in the cooling tower loop has to be chosen. The cooling tower sump temperature and the water temperature entering the tower are measured.

The controlled variables in the designed system are

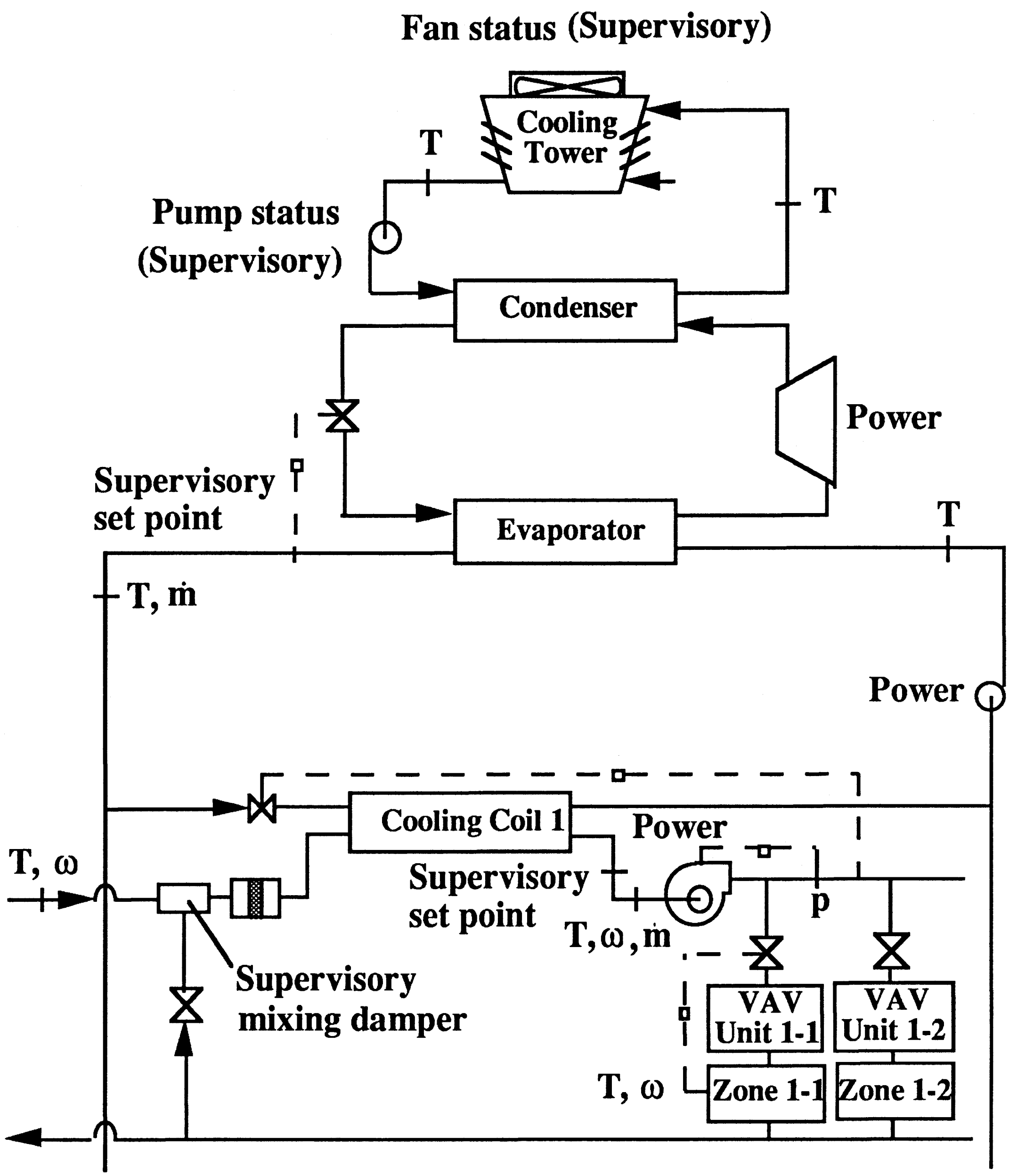


Figure 2.4 Possible control of the example system

1. The supply air temperature,
2. The chilled water temperature, and
3. The zone temperature.

The manipulated variables that have to be changed to maintain these set point temperatures are

1. The chilled water mass flow rate,
2. The refrigerant mass flow rate, and
3. The supply air mass flow rate,

respectively.

In the following discussion of set point temperatures, only supply air and chilled water temperature will be mentioned because the zone temperature is held constant during the simulations. A constant zone temperature was chosen because all of the zones were modeled as zones with the same cooling requirements. In reality, these zones would have different temperatures due to different thermostat settings. In this thesis, it was desirable to study a simple air conditioning system which includes all main components. With these simplifications, the system can be easily surveyed and the task of fault detection can be demonstrated in a clear fashion.

The following assumptions and simplifications are made:

(1) constant cooling tower fan speed

(2) constant pump speed in cooling tower loop

(3) constant fraction of outdoor air

(4) equal load for all six air handling units

(5) steady state operation

(6) perfect local loop controllers, i.e. small time constant and no offset, and

(7) constant zone temperature.

2.2 MODELING OF SIMULATION COMPONENTS

The example system simulation includes the main controler and all components shown in Figure 1.1. The supervisory controller, local loop controller, electric motor, and flow converter component are discussed in this section. The FORTRAN codes for the components are listed in Appendix B.

2.2.1 The Supervisory Controller

The simulation model of a conventional air conditioning system is controlled in a fashion similar to a real system. The system is controlled in order to meet the latent and sensible loads. Therefore, manipulated variables have to be changed if a change in forcing functions occurs. The forcing functions for an air conditioning system are:

1. Ambient dry bulb temperature,
2. Ambient wet bulb temperature,
3. Sensible building load, and
4. Latent building load.

Braun [1988] and others found that the ambient dry bulb temperature has almost no impact on the total power consumption of an air conditioning system.

The manipulated variables are changed in order to maintain the set points of all controlled variables set by the supervisory controller. The supervisory controller gives the orders to different parts of the system. In Figure 2.5, the system control and the information flow in the simulation is demonstrated in a block diagram. The controller uses either open-loop or feedback control to obtain the correct values for the manipulated variables. In the simulation, the supervisory controller sends a control signal to the equipment (e.g. a control signal γ for fan speed) in an open control loop, based on the actual forcing functions. The cooling coil requires a feedback control to provide the supply air temperature set by the supervisory system. The control signal for the water flow rate is updated until the control variable, Taoc,set, reaches the set point designated by the supervisory controller. This procedure is discussed in the following section.

The control strategy is built into the supervisory controller. The values for the control variables are computed from simple functions in terms of the forcing functions which are input to the supervisory controller. The computed supply air and chilled water temperature are then input to other components. In this thesis, no explicit zone model which simulates the conditioned space was employed. Instead, simple evaluations of zone conditions are included in the supervisory controller.

The air flow rate which is necessary to meet the sensible load is calculated for a given set of forcing functions. If the room humidity is higher than a specified comfort limit, a message is printed out, and the set point temperatures have to be decreased to allow sufficient dehumidification. Usually, the fraction of outdoor air in the air stream is held constant. However, for air quality considerations, the outdoor air flow rate has a lower limit which is set with respect to the number of people expected to be in the building.

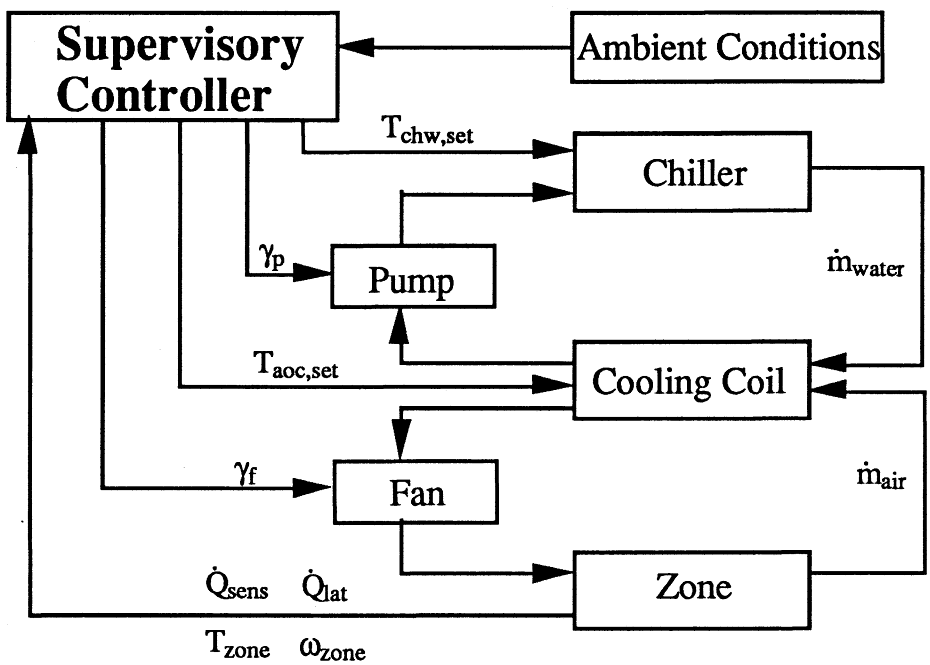


Figure 2.5 Block diagram of information flow in the simulation

The supervisory controller also receives the power requirements from all components as an input. The sum of all component powers is the total system power. The component and the total system powers are then stored in a file and can be examined whenever needed. For the task of fault detection, the measured (simulated) power is compared with a predicted power inside the supervisory controller. If a fault is observed by the controller, it will be indicated.

2.2.2 The Local Loop Controller

In the simulations, an effectiveness model of the cooling coil (Braun [1988]) is employed. The model requires all stream variables at the inlet as input. The stream variables at the exit are output from the component. However, in this study the air temperature out of the coil is set by the supervisory controller. Therefore, a feedback local loop control has to be used.

In Figure 2.6, a block diagram demonstrates the decision process and information flow for the cooling coil simulation problem. The air mass flow rate can be evaluated using the room and supply air set point temperatures and the sensible load. Using a first guess of the coil inlet humidity, the coil air outlet temperature and humidity can be evaluated. At this point, the evaluated air outlet temperature and the air outlet set point temperature are compared. If these temperatures are not the same, the water mass flow rate has to be changed. The secant method is used to reach a quick convergence between these temperatures.

After convergence is reached, a new room humidity can be evaluated. In the simulation, the room humidity was allowed to fluctuate between comfort limits given by ASHRAE [1988]. Employing the new room humidity, a new coil air inlet humidity can be evaluated which is then input to the cooling coil component. TRNSYS iterates until the inputs to all components are converged so that the correct humidities will be computed. Therefore, the process includes iterating in an inner loop to reach the supply air temperature and an outer loop to reach the right coil air inlet humidity.

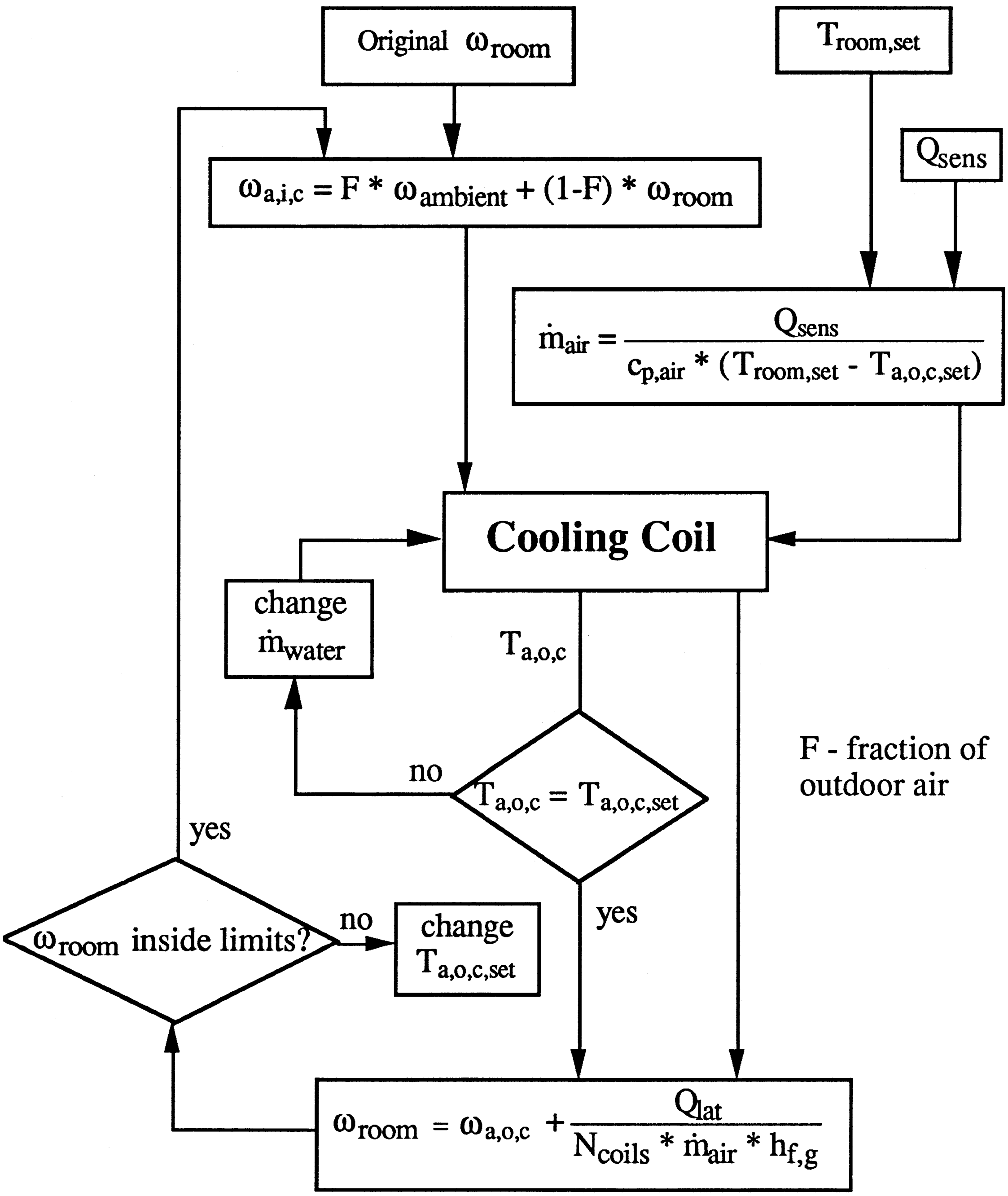


Figure 2.6 Block diagram illustrating the decision process and information flow around the cooling coil in the simulation

2.2.3 The Electric Motor

The behavior of the motors which are selected during the design process has to be represented in simulation components. The component for an electric motor describes the part load performance of the particular motor. Either constant speed or variable speed motors can be simulated. Manufactures' data are curve fitted to obtain a quadratic expression. Mode (variable or constant speed drive), shaft power (power required from the motor at full load), service factor (indicates the permissible continuous overload of the motor), and the coefficients of the regression equation are parameter inputs into the component.

2.2.4 The Flow Converter

Because several air handling units are employed in the simulation, the sum of the water flow rates through all coils has to be taken to obtain the water flow through the evaporator of the chiller. Also, the water flow from the chiller has to be divided into flows for the air handling units. In the final system, six air handling units are employed. For simplicity, it is assumed that the mass flow rates through all coils are equal. The mode (specifies if flow rate has to be split or added) and the number of air handling units are parameters to this component.

2.3 CONVENTIONAL CONTROL

Control strategies employed in air conditioning systems today often are quite simple. For many years it was thought that air conditioning systems were too complicated to introduce optimal control strategies. Therefore, no effort is made in these control strategies to achieve optimal control. Often, no BEMCS is employed. A simple control strategy will be used as a comparison to the near optimal control strategy proposed in section 2.5. A control strategy in this study is understood as the way in which the controlled variables (supply air temperature and chilled water temperature) are set.

Recently many theoretical attempts for optimizing the overall control strategy were made. Different ones are used in practice. However, most of the optimization procedures are computational very intensive and require a great understanding by building operators so that they often are not realized.

A simple way to control the system would be to keep the mass flow rates of the refrigerant and the water constant and only change the air mass flow rate in a way that the load is always met. This approach, however, is far away from the optimum control which minimizes the power consumption. Another way would be to set all controlled variables to a constant value. In this case, a sensor measurement of the chilled water temperature that is lower than the set temperature results in moving the vanes of the compressor towards a closed position so that the set point temperature is reached again. Although this strategy is also far off the optimum, constant set points are used quite often in air conditioning systems. The set points chosen are usually the design set points. However, if the system is oversized and during operation when the loads are less than the design loads, the set points can also be chosen differently.

Sometimes so called reset schedules are utilized. Here, the supply water temperature is reset upwards if the cooling demand is reduced. Different techniques have been proposed to raise the chilled water temperature at low loads. A simple one would be to sense the water temperature of the water returning to the chiller. If this temperature decreases the load is also decreasing. Therefore, the supply water temperature can be increased so that the efficiency of the chiller increases. Sometimes, similar changes in set points are made by experienced building operators. This might happen several times a day, daily, or even less often.

Due to the reset of chilled water temperature, undesirable high space temperatures and humidities in certain zones may occur if the VAV systems are not working properly. Furthermore, with increased supply water temperature and constant water flow rate, the supply air temperature increases which results in a higher power consumption for the fans in the air handling units.

Due to the simplicity of the conventional control strategies and the experience with these strategies, they are still widely used. However, because the conventional control strategies operate far off the optimum, optimal control strategies should be developed.

2.4 OPTIMAL CONTROL

As discussed above, a tradeoff between the power consumption of different system components exists as control variables are changed. For a given set of forcing functions, an optimal set of controlled variables exists which minimizes the cost of operation. This is the cost of the total energy to operate the chillers, cooling tower fans, cooling tower water pumps, chilled water pumps, and the air handling unit fans.

2.4.1 Illustration of Optimal Control

In Figure 2.7, the total system power, air handling unit fan power, the chiller power, and the main water loop pump power are presented as a function of the set point temperatures for the example system. The power consumptions of the cooling tower pump and fans are constant for all conditions and are therefore not shown. The figure is valid for a fixed set of forcing functions (TWB = 65 F, Load = 300 tons, SHR = 0.8). The figure shows the tradeoff between the component powers as the set points change. There is an optimal combination of set points which minimizes the total power consumption. At this point, none of the component powers is minimized. Figures 2.8 - 2.11 provide the total and component powers separately and with different scales for the power.

As seen in Figure 2.8, the curves of total power consumption for a fixed chilled water temperature and changing supply air temperature exhibit a clear minimum. If the air outlet temperature is changed from the optimum to lower values, i.e. the difference

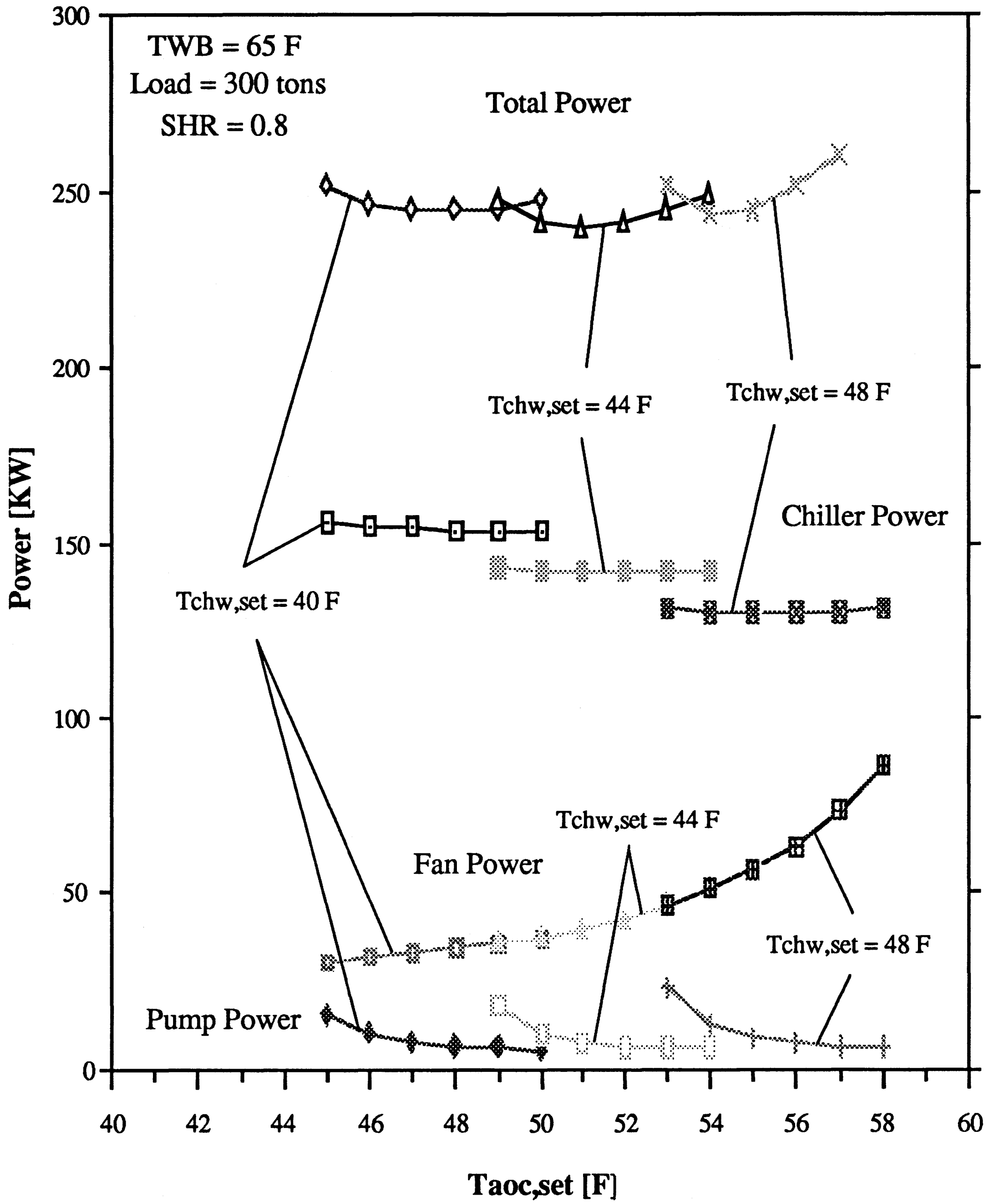


Figure 2.7 Component and total system powers as a function of the set point temperatures

between set point temperatures decreases, a steep increase in power occurs. On the other hand, if the air outlet temperature is changed to higher values, i.e. the difference between set point temperatures increases, the increase in power is smaller. The same effect can be seen if the chilled water temperature is changed at constant supply air temperature. Thus, it is better to operate the system such that the difference in set point temperatures is too high rather than too low. However, at high chilled water temperatures, a small increase or decrease of the optimal temperature difference result in a similar significant power increase.

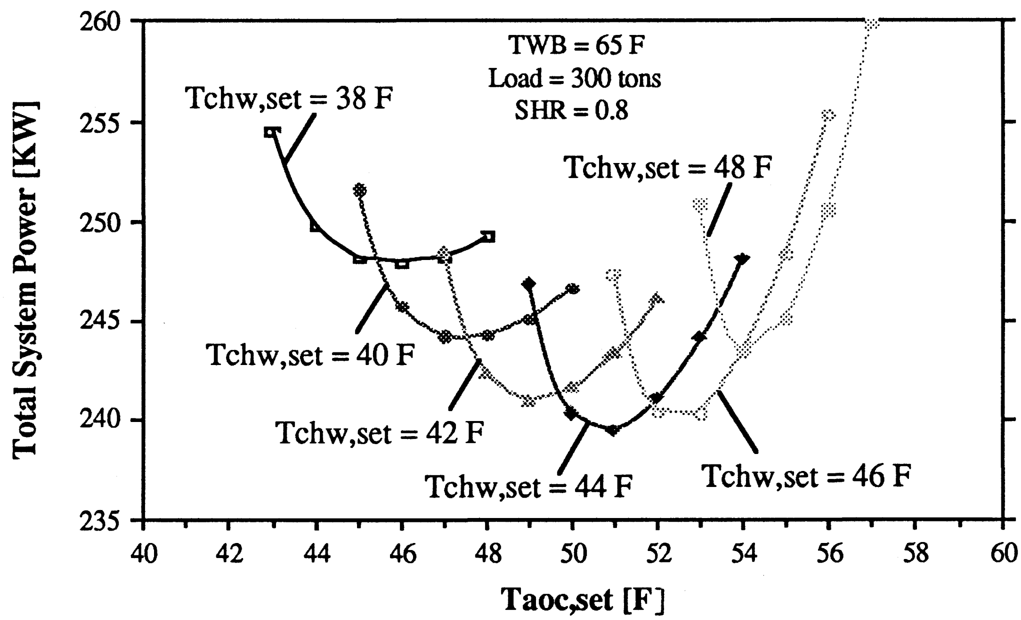


Figure 2.8 Total system power as a function of the set point temperatures

The supply fan power, shown in Figure 2.9, increases with the supply air temperature because the flow rate has to be increased to meet the cooling load. The fan power does not depend on the chilled water supply temperature for a constant supply air temperature. Therefore, points with different supply water temperatures but the same supply air temperatures consume the same amount of fan power.

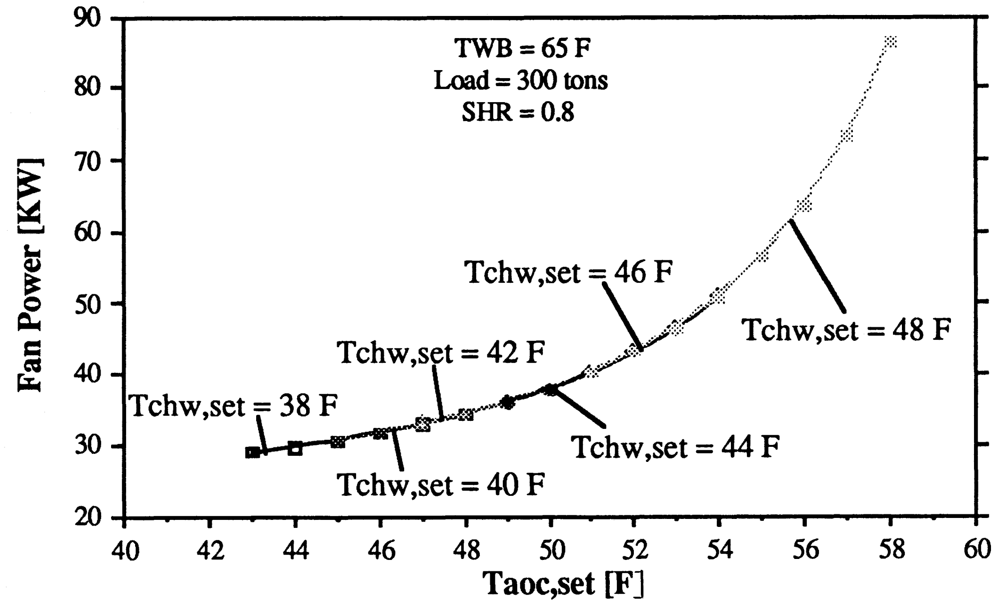


Figure 2.9 Fan power as a function of the set point temperatures

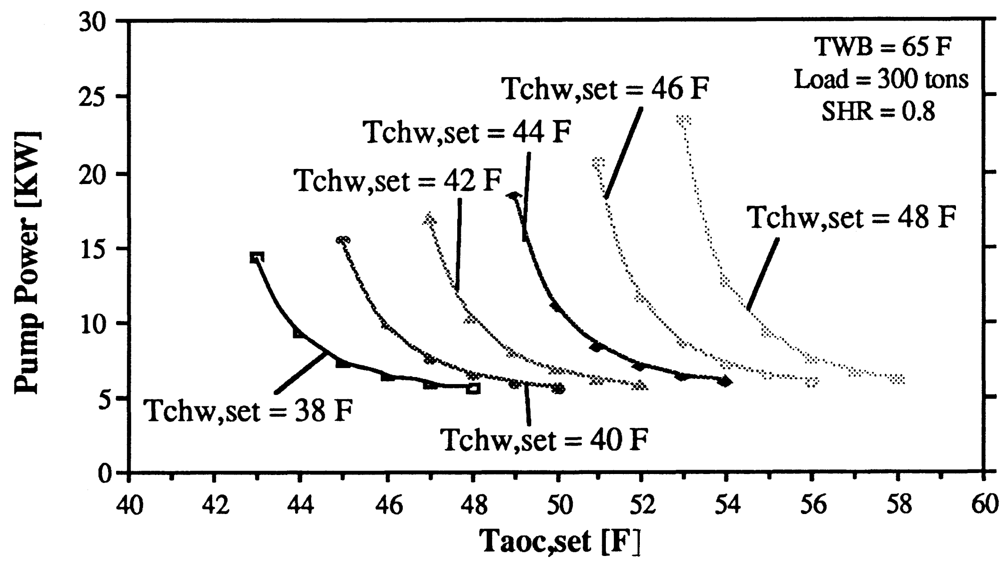


Figure 2.10 Pump power as a function of the set point temperatures

The main water loop pump power decreases with increasing air outlet temperature, as shown in Figure 2.10, because less water has to be provided for a fixed chilled water temperature. The curves, however, become flatter and eventually include a minimum for higher air outlet temperatures because the mass flow rate of the air increases. The pump power curves become steeper for higher chilled water temperatures.

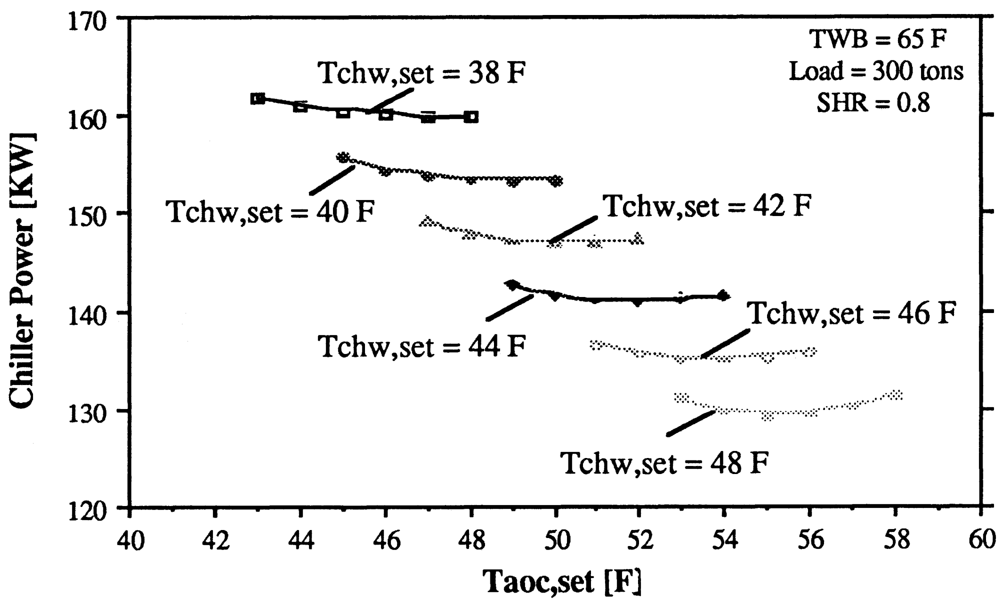


Figure 2.11 Chiller power as a function of the set point temperatures

The chiller power, illustrated in Figure 2.11, increases if a lower chilled water temperature has to be provided. The expansion valve area is decreased with decreased chilled water temperature. Thus, the pressure drops across the expansion valve and the compressor increase. For constant chilled water temperature, the chiller power shows a slight dependence on the air outlet temperatures. The load on the chiller is the sum of the building load, the ventilation load, the fan load, and the pump load. If the building load is constant, only changes in ventilation, fan, and pump load have an influence on the chiller load. At low supply air temperatures, the pump load is high while the fan and ventilation loads are low. The ventilation load changes because the system is operated with a constant fraction of outdoor air. (However, there is a lower limit on the amount of fresh air flow.) At high supply air temperatures, the pump load is low while the ventilation and fan loads are high. Therefore, a minimum in chiller power for constant chilled water temperature can be observed because a tradeoff in the pump load and the fan and ventilation load as additional loads to the building load exists.

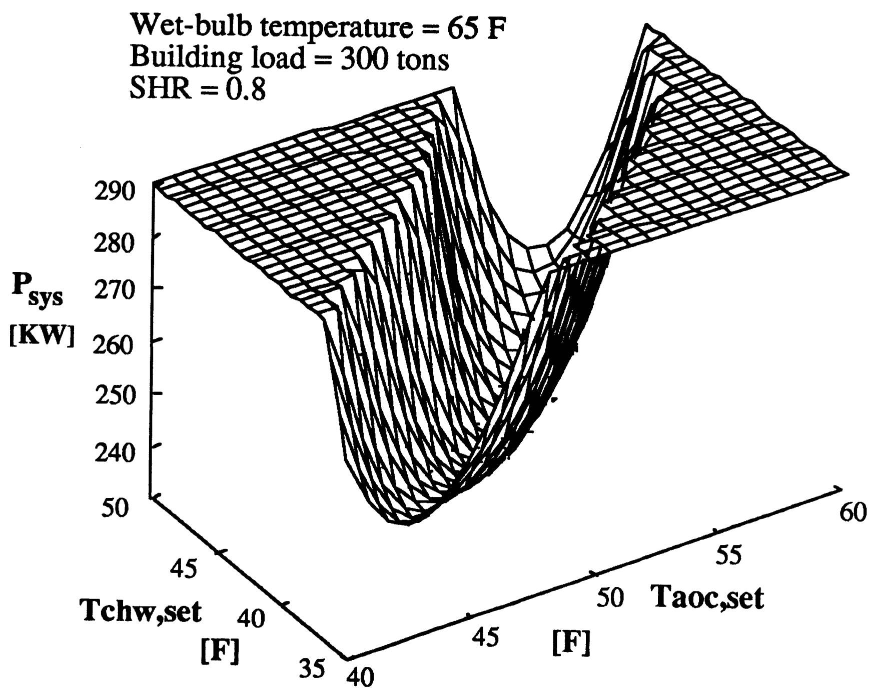


Figure 2.12 System performance map for a medium cooling load

In Figure 2.12, a three-dimensional performance map is presented for the same set of forcing functions as above. The surface creates a trough which stretches diagonally across the plane of set point temperatures. The bottom of the trough is the line on which the optimal set of controlled variables is located. To both sides of the trough, the surface moves up steeply. This is mainly due to the cubic dependance of fan and pump power on the flow rates of air and water. Therefore, small changes in set point temperatures can produce a large increase in total power. If the air outlet temperature is changed from a point on the trough to higher values, the air flow rate has to be increased which results in higher fan power. Low supply air temperatures require a high water flow rate and result in an increase in main water loop pump power. If the chilled water temperature is changed from a point on the trough to higher values, the water flow rate needs to be increased. At lower values the chiller requires more power input.

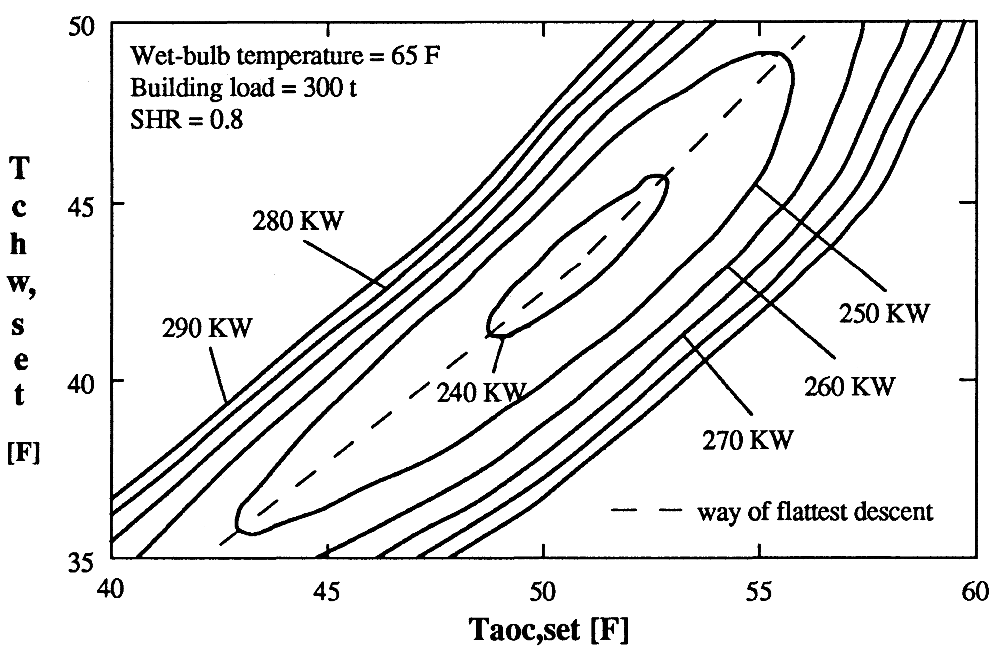


Figure 2.13 Total system power contours for a medium cooling load

For the same set of forcing functions, a two dimensional performance map is presented in Figure 2.13. Lines of constant system power are drawn. In two-dimensional performance maps the optimal control of the system can be identified for a set of forcing functions. The same trough as in Figure 2.12 can be recognized. The trough, which characterizes the way of flattest descent in the three dimensional plot in Figure 2.12, represents almost a straight line for the given forcing functions (medium load). Later, it will be seen that the trough can be very well approximated with a straight line for all loads (see Figures 2.15 and 2.16).

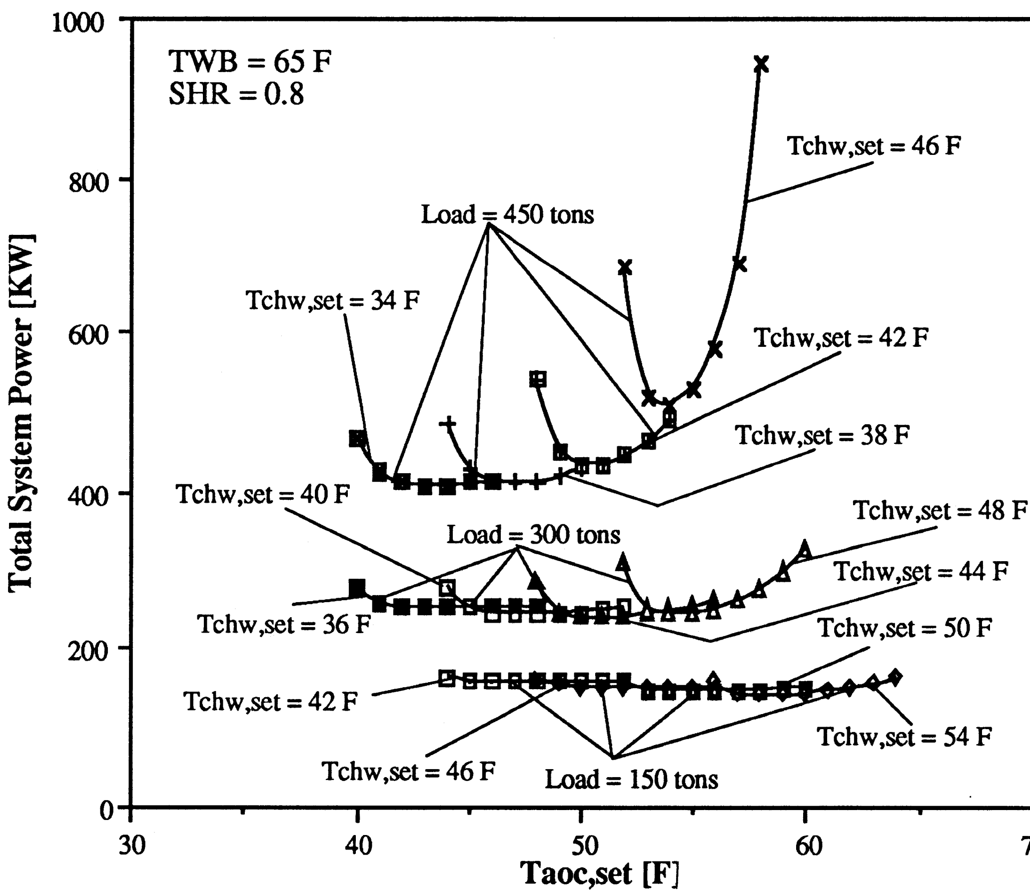


Figure 2.14 Total system power for different loads and set point temperatures

The trough has steeper walls at high loads than at low loads. This effect is shown in Figure 2.14. The total system power is shown as a function of the set point temperatures for high, medium, and low loads. The dependence of the system power on the set points at high loads is much larger than at low loads. The curves at high load include a well established minimum while the power curves at low load are almost flat. Thus, it is more important to chose the right set point temperatures for high loads.

2.4.2 Analysis of Optimal Control

An optimization procedure finds the minimum of the sum of the operating costs of each component J_i as a function of the uncontrolled variables or forcing functions f with respect to the discrete control variables M and the continuous control variables u. Discrete control variables are the relative speed of a multi-speed fan, the number of operating chillers, and the number of operating fans or pumps. Independent continuous control variables could be, for example, the chilled water temperature and the supply air temperature. Braun [1988] represented the total system cost as

$$J(f, M, u) = \sum_{i=1}^{n} J_i(x_i, y_i, f_i, M_i, u_i) \tag{2.1}$$

where, for any component i,

J_i = operating cost

x_i = vector of input stream variables

y_i = vector of output stream variables

f_i = vector of uncontrolled variables

M_i = vector of discrete control variables

u_i = vector of continuous control variables

The total system cost has to be minimized with respect to the control variables M and u and is subject to equality and inequality constraints. An equality constraint might occur, for example, if two or more chillers are in operation. The sum of their loads must equal the system load. Inequality constraints might include bounds on controlled variables. For example, the chilled water temperature has lower and upper bounds to avoid freezing in the evaporator and to allow sufficient dehumidification of the supply air to keep the zone conditions within acceptable bounds. These examples of inequality constraints are demonstrated in Figures 2.15 and Figure 2.16. Figure 2.15 represents a high cooling load (450 tons). The optimal chilled water temperature has a value of about 34 F. However, the lowest limit for the supply water temperature is set to 38 F. For this reason, the chilled water temperature has to be set to 38 F. To determine the optimal supply air temperature for the constrained chilled water temperature, the way of flattest descent has to be taken in the contour plot. The optimal air outlet temperature occurs where the way of flattest descent crosses the chilled water temperature of 38 F.

Figure 2.16 represents a low load (150 tons). To assure enough dehumidification, the upper limit of the chilled water temperature is set to 55 F. If the optimal chilled water temperature were above this specified value, it would have to be reduced to 55 F. The optimal air outlet temperature could again be determined by taking the way of flattest descent. However, in this case, the optimum chilled water temperature occurs to be inside the bounds and can therefore be employed. The upper bound of chilled water temperature is reached only at very low loads and wet bulb temperatures (section 2.4).

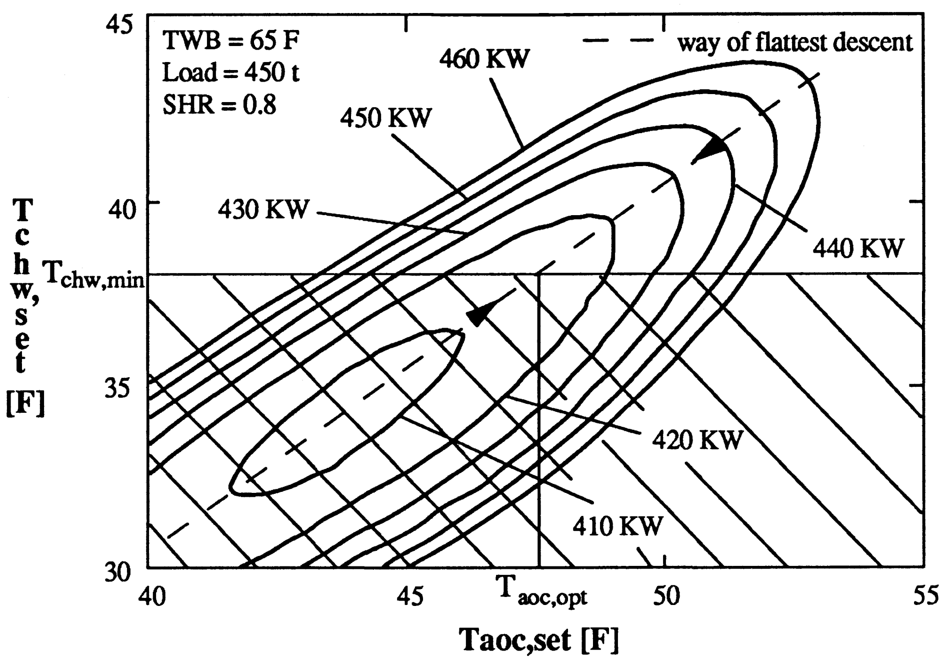


Figure 2.15 Total system power contours for a high cooling load

The equality and inequality constraints can formally be represented as

$$g\ (f, M, u) = \begin{bmatrix} g_1\ (f_1, M_1, u_1, x_1, y_1) \\ \dots \\ g_n\ (f_n, M_n, u_n, x_n, y_n) \end{bmatrix} = 0 \tag{2.2}$$

and

$$h\ (f, M, u) = \begin{bmatrix} h_1\ (f_1, M_1, u_1, x_1, y_1) \\ \dots \\ h_n\ (f_n, M_n, u_n, x_n, y_n) \end{bmatrix} \geq 0 \tag{2.3}$$

respectively, where , for any component i,

g_i = vector of equality constraints

h_i = vector of inequality constraints

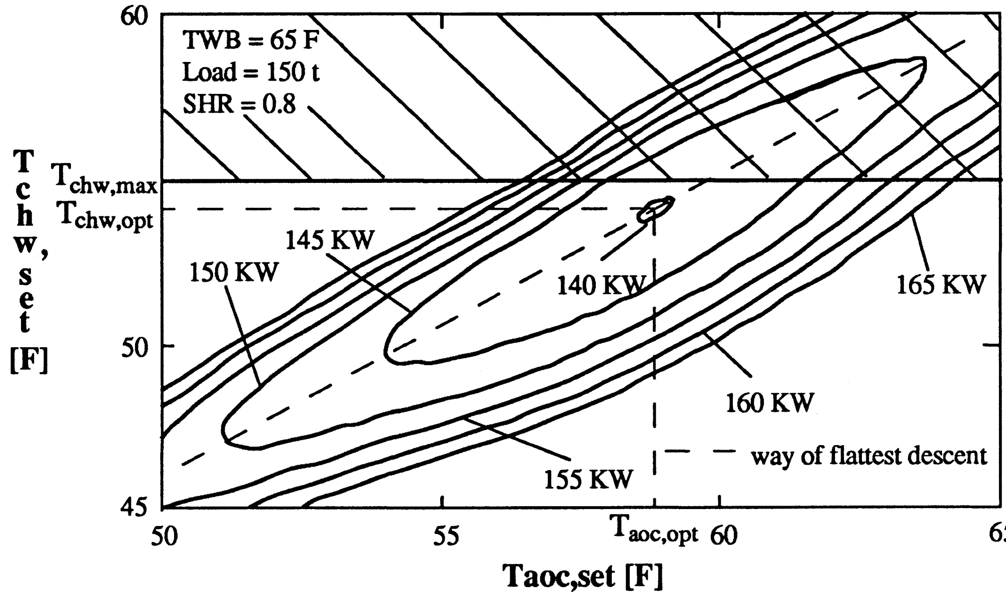


Figure 2.16 Total system power contours for a low cooling load

While the total cost and constraints are independent of the input and output stream variables (temperatures and flow rates), component operating costs and constraints are a function of these variables.

Sometimes the cost which has to be minimized includes items such as equipment wear, maintenance, or others. In this study it is assumed that the costs for these items do not change with different control strategies and are therefore not included in the cost which has to be minimized. Furthermore, equations (2.1) - (2.3) can be simplified because no discrete controlled variables are employed in the designed system. Thus, no equality constraints are needed.

If the system is operated in a way that at every instant the total power consumption is minimized, optimal control is achieved. For solving the optimization problem, models for the component costs or powers J_i have to be developed. No model, however, can present the reality exactly. Most of the available optimization procedures for complicated models are computationally very intensive. Therefore, the goal is to develop simple models and a methodology leading to a control strategy which is as close as possible to the optimal control.

2.5 NEAR OPTIMAL CONTROL

In this section, a methodology for controlling HVAC systems is developed which determines the independent control variables that minimize the instantaneous cost of operating chilled water systems. Because the determined values do not represent the absolute minimum but values very close to the optimum, this control is called near optimal control. An overall empirical cost function for the total power consumption of the cooling plant is developed. The work is based on work done by Braun [1988].

2.5.1 Quadratic Power Formula

A simple function for which a minimum exists and for which this minimum may be determined analytically is a quadratic function. Braun [1988] showed that the power consumption of a chiller may adequately be represented as a quadratic function of the load and the temperature difference between leaving condenser and evaporator water temperatures. He also demonstrated that the power of the continuously adjustable pumps and fans may be accurately represented with a quadratic function of its control variables through either a second-order Taylor series approximation or a single quadratic correlating function. A similar concept can be utilized for the whole system. In the developed methodology, the total system power is represented as a quadratic function of the control variables, while it can be any real value function of the uncontrolled variables. However, it is shown that a quadratic function also represents the power consumption in terms of the uncontrolled variables (wet bulb temperature, cooling load, and sensible heat ratio) accurately. Therefore, the following function may be used to represent the total system costs:

$$J(f, M, u) = u^T\hat{A}u + \hat{b}^T u + f^T\hat{C}f + \hat{d}^T f + f^T\hat{E}u + \hat{g} \tag{2.4}$$

where $\hat{A}$, $\hat{C}$, and $\hat{E}$ are coefficient matrices, $\hat{b}$ and $\hat{d}$ are coefficient vectors, and $\hat{g}$ is a scalar. All the coefficients have to be determined empirically. Once again, although the system power in this formula is quadratic with the uncontrolled variables, a cubic or higher order function could have been chosen.

The empirical coefficients depend upon the operating modes, i.e. the discrete control variables. Therefore, a formula has to be developed for every feasible combinations of discrete variables.

Applying the first order condition for a minimum to the quadratic equations allows to analytically solve for the optimal control. The Jacobian of the quadratic function for power with respect to the control variables is equated to zero:

$$\frac{\partial J(f,M,u)}{\partial u} = 0 \tag{2.5}$$

Solving for the optimal values of continuous control variables yields

$$u^* = k + Kf \tag{2.6}$$

where,

$$k = -\frac{1}{2}\hat{A}^{-1}\hat{b}$$

$$K = -\frac{1}{2}\hat{A}^{-1}\hat{E}$$

If no constraints apply at this set of controlled variables, the system cost can be computed as

$$J^* = f^T\theta f + \sigma^T f + \tau \tag{2.7}$$

with,

$$\theta = K^T\hat{A}K + \hat{E}K + \hat{C}$$

$$\sigma = 2K\hat{A}k + K\hat{b} + \hat{E}k + \hat{d}$$

$$\tau = k^T\hat{A}k + \hat{b}^T k + g$$

The control using equation (2.5) results in a minimum cost if and only if the Hessian of the cost function is a positive-definite matrix. For equation (2.4) $\widehat{A}$ has to be positive definite. It can be seen in Figure 2.12 that a global minimum but no global maximum exists.

If the system involves discrete variables, the optimal control for each feasible combination of discrete variables has to be compared. The combination which yields the lowest system power has to be picked as operating mode. In the case of the designed system, only one set of discrete control variables exists. Therefore, only one formula was developed. Furthermore, bounds on the continuous control variables have to be included in the selection of the control variables.

2.5.2 Near Optimal Control Laws for the Example System

Once the empirical coefficients in equation (2.4) are known, taking the derivatives with respect to the controlled variables yields linear control laws. In the considered case, derivatives have to be taken with respect to the chilled water temperature and the air outlet temperature. The following two equations must be solved analytically for the optimal set point temperatures:

$$\frac{\partial P_{formula}}{\partial T_{chw,set}} = \dots = 0 \tag{2.8}$$

$$\frac{\partial P_{formula}}{\partial T_{aoc,set}} = \dots = 0 \tag{2.9}$$

After rearranging, the equations for the set point temperatures can be written as:

$$T_{aoc,set,opt} = g_1(TWB, Load, SHR) \text{ and}$$

$$T_{chw,set,opt} = g_2(TWB, Load, SHR, T_{aoc,set,opt})$$

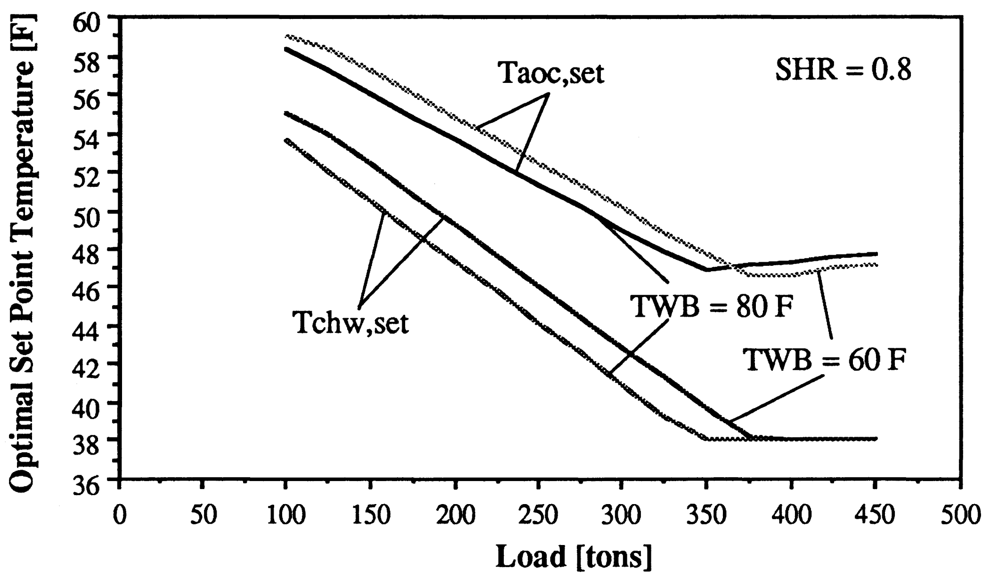


Figure 2.17 Near optimal set point temperatures as a function of the load

The unbounded set point temperatures are linear functions of the forcing functions due to the assumption of quadratic dependance of power to these variables. The linear control laws are shown in Figure 2.17 - 2.19. The near optimal set points are presented as a function of the load for high and low ambient wet bulb temperature, as a function of the wet bulb temperature for two different loads, and as a function of the sensible heat ratio for two different loads, respectively.

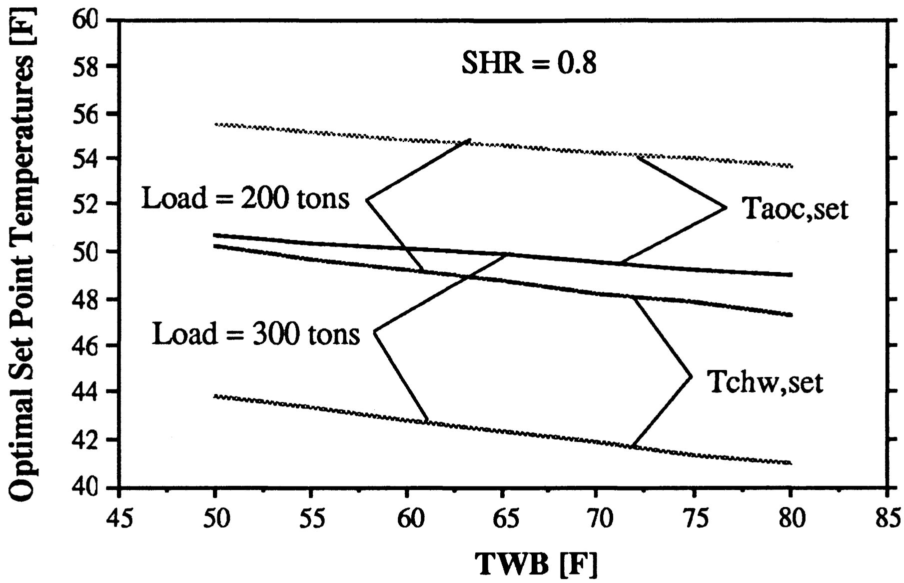


Figure 2.18 Near optimal set point temperatures as a function of the wet bulb temperature

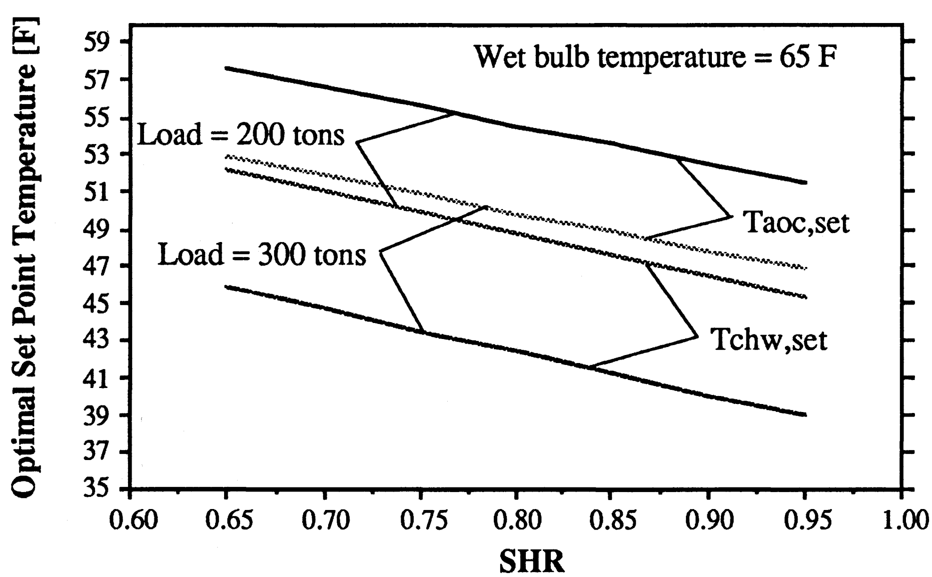


Figure 2.19 Near optimal set point temperatures as a function of the sensible heat ratio

The optimal temperature difference between the two set point temperatures increases with load and ambient wet bulb temperature (Figure 2.17 - 2.18) while the sensible heat ratio has almost no effect on it (Figure 2.19). The optimal set point temperatures decrease with increasing load, ambient wet bulb temperature, and sensible heat ratio. As shown in Figure 2.18, the influence of the ambient wet bulb temperature on the optimal set point temperatures is small because it only influences the small amount of ventilation load and the operation of the cooling tower. The influence of the sensible heat ratio shown in Figure 2.19, however, is relatively high. If the sensible heat ratio increases and the supply air temperature is held constant, the supply fan requires much more power, whereas a high latent load usually does not have an influence on the fan power because the room humidity is allowed to float.

As mentioned in section 2.4, the chilled water temperature is constrained to allow sufficient dehumidification and to prevent freezing in the evaporator tubes. The lower limit of 38 F for the chilled water temperature is often reached at high loads. At the moment when the chilled water temperature is restricted and becomes a horizontal line, the optimal supply air temperature also will not keep its linear course because the optimal difference between the set point temperatures increases with load. The upper limit of 55 F for chilled water is only reached at very low loads and wet bulb temperatures, as can be seen in Figure 2.17.

Due to the quadratic nature of the power formula, the lines representing the two different wet bulb temperatures in Figure 2.17 or loads in Figures 2.18 and 2.19 are parallel. Lines for other wet bulb temperatures or loads could be drawn into the figures relative to the two parallel lines. For example, a line for a wet bulb temperature of 70 F would be located in the middle between the lines for TWB = 60 F and TWB = 80 F in Figure 2.17.

Although a quadratic relationship between forcing functions and system power was assumed, more complicated relationships could have been assumed. In that case, the control laws would not be linear which, however, could be easily handled by the supervisory controller. However, as will be shown, the quadratic relationship is satisfactory in determining optimal control laws.

2.5.3 Methodology to Obtain Quadratic Power Formula

In the previous section it was explained how the optimal control could be obtained from a given quadratic function. This section provides information on how to obtain a *good* quadratic power formula.

The total system power is not exactly a quadratic function of the controlled and uncontrolled variables. However, near the optimum, the behavior of the system power can be very well approximated with a quadratic function. Therefore, to obtain an accurate equation, data near the optimum is needed. Thus, it is important that the region in which the data is taken includes the optimal conditions. After collecting enough data, a regression can be performed to obtain the quadratic correlation for the power. In this study the MINITAB regression package was used to obtain the coefficients of the quadratic equation.

The steps which have to be accomplished if simulations are employed (as in this project) are discussed in this section. In the next section, recommendations for applying the methodology to a real building are given.

Collecting the data At the beginning, the optimal control variables are not known. Hence, the controlled (chilled water temperature and supply air temperature) and uncontrolled variables (wet bulb temperature, building load, and sensible heat ratio of the building load) have to be utilized over a broad range of conditions as input to the simulation. The forcing functions or uncontrolled variables should include the whole range of possible conditions. After obtaining results for the system power from the simulation, the region in which the optimum might be located is narrowed. In the next step, the employed control variables are adjusted to be in the vicinity of the expected optimum. These steps are repeated until the region excludes all the control variables that cause large non-optimal power consumptions. Only the data close to the optimum should be utilized when the final regression is applied. In this study, a program was written to create the input variables to the simulation.

Regressing the data After collecting the data, a regression formula is fit through the set of data points. The number of possible coefficients in terms of the controlled and uncontrolled variables quadratic equation for each feasible set of modes is

$$N_{coef} = N_u^2 - \frac{N_u(N_u-1)}{2} + N_u + N_f^2 - \frac{N_f(N_f-1)}{2} + N_f + N_f N_u + 1 \tag{2.10}$$

where N_u is the number of continuous control variables and N_f is the number of uncontrolled variables. Thus, in the case of two continuous control variables

(Tchw,set and Taoc,set) and three forcing functions (TWB, Load, SHR), 21 coefficients have to be determined by the regression.

Linear regression techniques are used to fit a model of the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_{n+1} x_1^2 + ... + \beta_{2n+1} x_1 x_2 + ... + \varepsilon \tag{2.8}$$

where y is the response, x_i are the predictors, β_i are the regression coefficients, n is the number of variables in the equation (in the considered case n = 5), and ε is an error term with a normal distribution with a mean of zero and a standard deviation σ. Linear regression means linear in the model parameter β_i, i.e. parameter in such form as e^{β_i} are not possible. The regression estimates β_i by b_i and σ by s. The fitted equation is then

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + ... + b_{n+1} x_1^2 + ... + b_{2n+1} x_1 x_2 + ... \tag{2.9}$$

where $\hat{y}$ is the fitted or predicted value. The regression software uses least squares to fit the model to the predictors. Fitted values (the result obtained from the regression formula for each set of input variables) and residuals (difference between observed and fitted value) can be stored and used for further analysis.

Two outputs from the regression can be used to judge the quality of fit between predicted and observed values. The earlier mentioned estimated standard deviation s and the coefficient of determination R^2. R^2 is the fraction of the variation in y that is explained by the fitted equation. These two parameters have to be improved as far as possible to obtain a good fit.

Usually a regression formula as simple as possible is wanted, i.e. the fewer coefficients that are included in the regression formula the better. If no interactions between variables are included, the influence of every variable can be explained in a simple fashion. In this study, however, interactions between the variables occur. The interactions are necessary to obtain a good fit of the equation with the data. Therefore, the influence of a single variable is not immediately evident from the formula.

The regression software includes variables in the regression equation which have a large impact on the formula. Variables which have almost no impact on the fitted value will be removed from the equation. A predictor is also removed from the equation if it is highly correlated with other variables, or when one predictor column is nearly constant. This, however, might produce complications. Some variables which include the control variables should stay in the equation. For example, it is clear in the example system that an interaction between optimal chilled water temperature and optimal air outlet temperature exists. However, it might happen that the interaction term between these two variables is not included in the regression equation. If no interaction term is present, two uncoupled equations are obtained if the first derivatives are taken with respect to the control variables. Two uncoupled equations are critical if a constraint on one of the variables is reached. In this case, it is important that the unbounded control variable changes its value depending on the bounded control variable. In such cases, the critical variable has to be forced to stay in the equation using special commands available in regression packages. Another way to include this and other variables in the regression equation would be to decrease the limit of influence on the equation at which coefficients are included in the formula. In MINITAB, the *tolerance* command can be used for this task.

In Appendix D, an example of a MINITAB command file as well as an example of an output from the regression package is presented. Unusual observations are part of the output from the regression package. The unusual observations are normally far off the optimum. Often these values have a big impact on the whole formula. Hence, they should be taken out of the data set to improve the fit. The residual plots for the regression, including approximately 4000 data points, are presented and discussed in Appendix E.

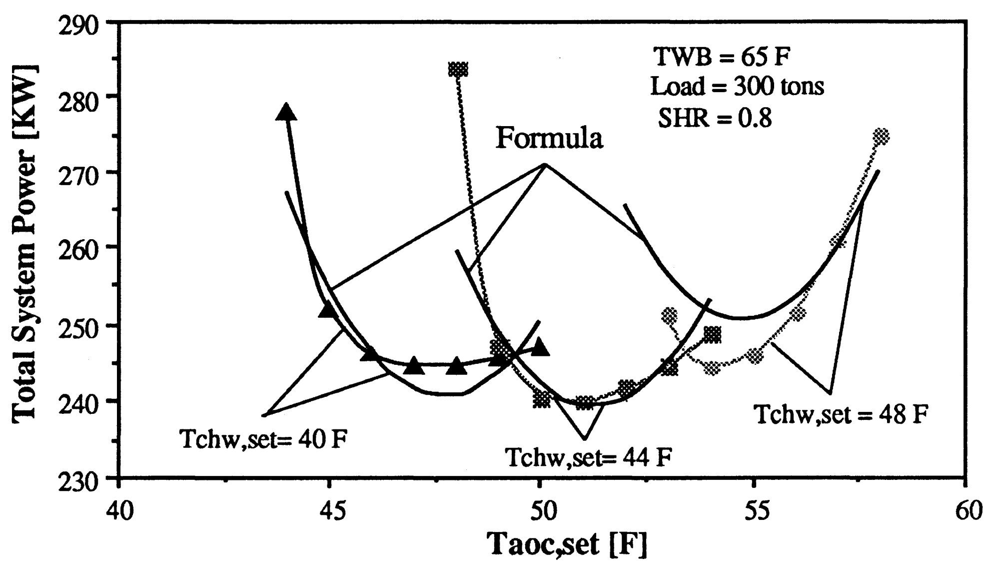


Figure 2.20 Power from simulation and formula for a medium cooling load

At this point, the quality of the biquadratic equation should be examined. In Figure 2.20 - 2.22, the system power consumption of the simulation and the equivalent power from the formula are presented in an expanded power scale for a wet bulb temperature of TWB = 65 F, a sensible heat ratio of SHR = 0.8, and a medium load (300 tons), low load (150 tons), and high load (450 tons), respectively. The agreement between simulation and formula for the medium load is good but, more important, the location of the minimum power consumption is almost the same.

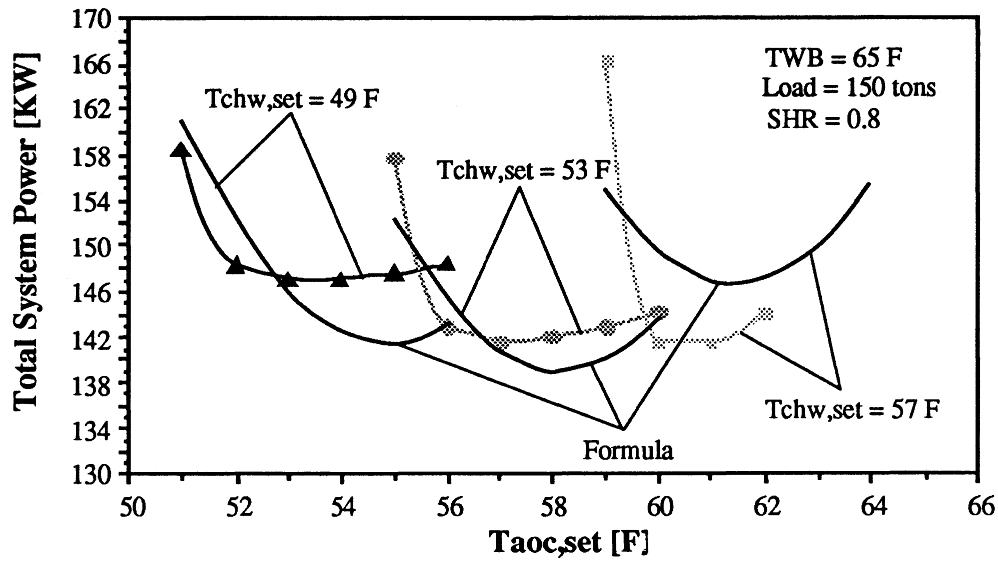


Figure 2.21 Power from simulation and formula for a low cooling load

In all three figures, the near optimal supply air temperature obtained from the formula is sometimes slightly higher than the real optimum. Also, the near optimal chilled water temperature is sometimes shifted to slightly lower than the optimal temperature. Thus, a larger difference in the set point temperatures results from near optimal control than from actual optimal control. However, an increase in the difference of the set point temperatures causes only a slight increase in the total system power. This effect can be seen in Figure 2.21 where the power from simulation and formula is compared at a low load (150 tons). The optimal set point temperatures and the near optimal set point temperatures obtained from the formula do not always agree exactly, but the difference in power for optimal and near optimal control is negligible. However, the difference in power predicted by the formula and the power obtained from the simulation can be significant. The difference in predicted and simulated power can also be high at a high cooling load (450 tons), as shown in Figure 2.22. However, due to the large change in power consumption for changing set points, the formula predicts almost the same optimal control variables as the ones given by the simulation results.

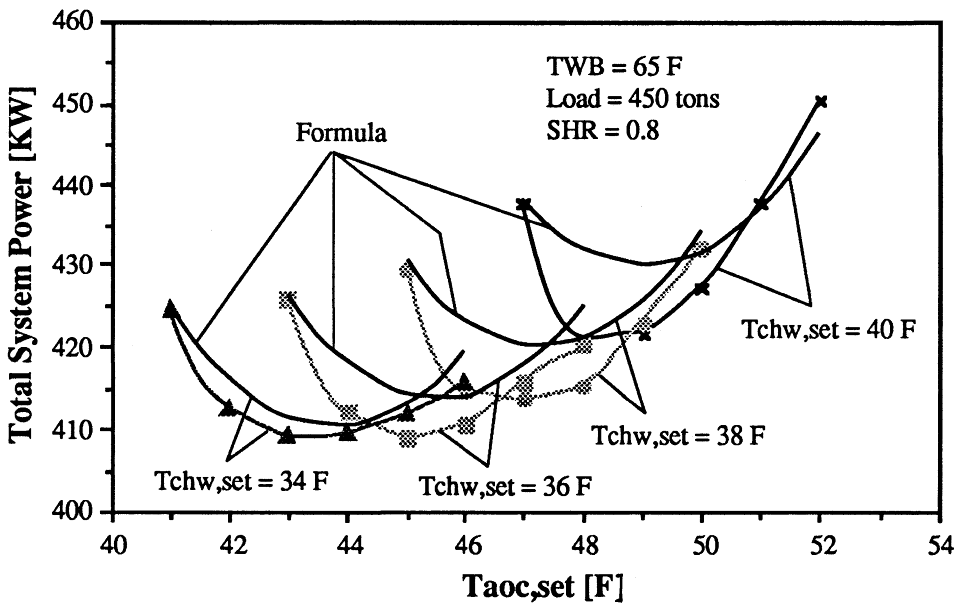


Figure 2.22 Power from simulation and formula for a high cooling load

2.5.4 Suggestions for Near Optimal Control in a Real Building

The procedures discussed in the previous sections were accomplished for data which were collected from a simulation. Now, some suggestions are made for how to use the same methodology in a real building.

Set point temperatures are specified for the design conditions. Often these set point temperatures are close to the optimal control at high loads. (In fact, if the system is not oversized, they are the only feasible set of control variables at design conditions). Therefore, the set point temperatures should be changed around the design set points for different values of the forcing functions. If a low load is expected, the set points should be higher. The system power consumption and the corresponding forcing functions as well as the controlled variables should be stored. Data should be collected over a broad range of conditions and, if possible, equally distributed over the range of forcing functions. If the number of data points representing one region of forcing functions would be much larger than others, some of the collected data could be left out. Then, the first regression equation could be calculated.

Although it is preferable to regress data which is very close to the optimum, good results can also be obtained if data is included which is not very close to the optimum. In Figure 2.23 the near optimal set point temperatures are shown for two different sets of simulation data (one is regressed with a standard deviation of s = 6.6 KW (R^2 = 99.7%), the other with s = 38.3 KW (R^2 = 95%). Although one data set has a much better fit than the other, the optima are almost the same. For the *bad* fit, the difference in set point temperatures is slightly larger than for the *good* fit which does not have a major impact on the total system power consumption, as mentioned earlier. This is the reason that data can be taken over a broad range of controlled variables, can then be regressed, and, finally, the near optimal control can be calculated. In both cases, however, the optimal control conditions were included in the region of data collection. In further operation, the controlled variables can be slightly changed around the calculated optimal control variables. This new operational data could be input to another improved regression formula and therefore leads to improved near optimal control. This process of improving the optimal control is repeated until for different formulas, changes in the set points no longer occur. If system changes which effect the optimal control conditions are made, the same process is used to update the formula.

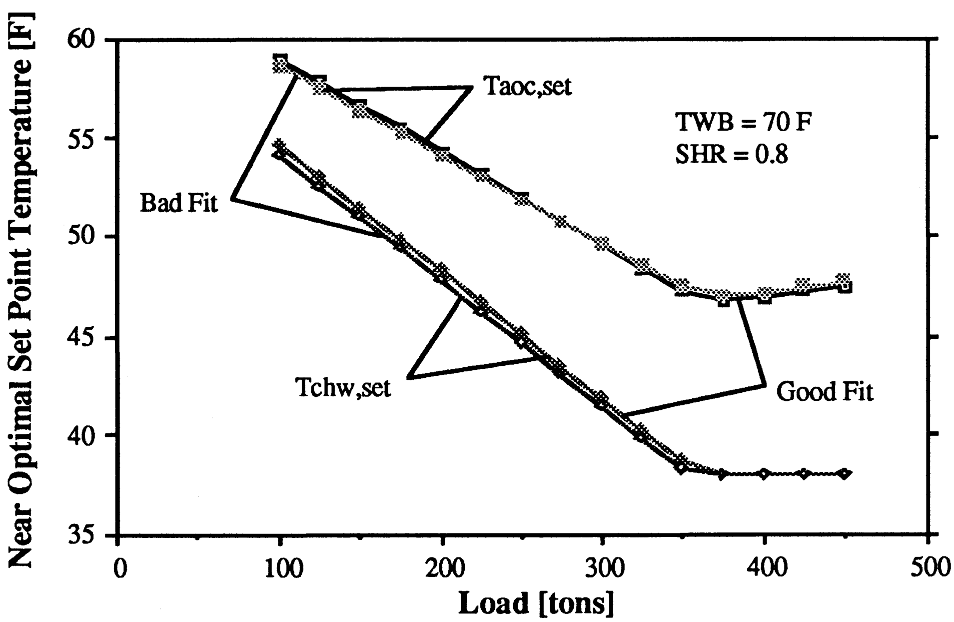


Figure 2.23 Near optimal set point temperatures for good (s = 6.6 KW) and bad regression fit (s = 38.3 KW)

2.5.5 Methodology Summary

The steps associated with achieving near optimal control are summarized below.

1) Run system under a broad range of conditions with different values of control variables. (Use experience in first runs, i.e. at high loads, set point tempera-

tures should be lower and differences in set point temperatures should be higher than at low loads.)

2) Look at data to narrow the region where optimal control is assumed.
3) Take new data closer to the optimum, but be sure that optimum is included in region where data is collected.
4) Regress the collected data to obtain a quadratic power function.
5) Set the Jacobian of the function with respect to the control variables to zero.
6) Solve analytically for the continuous control variables and build the equations into the supervisory controller.
7) If optimal control is not reached or changes in system occurred, run system with set points near the computed near optimal control from 6).
8) Employ only the data close to the optimum and go to 4).
9) If no changes in power to earlier control occur, no more updating is required unless changes in system are made. If more than one formula is employed, the fit might improve (e.g. one formula for the winter, one formula for the summer).

2.6 COMPARISON OF CONTROLS

In this section, different control strategies are compared. Particularly, the near optimal control is compared to a reference control strategy which employs constant set point temperatures. The design set point temperatures for the system are chosen as being constant at all times (Tchw,set = 45 F, Taoc,set = 55 F). However, because the system is slightly oversized, the design set point temperatures do not represent optimal control at design conditions. Therefore, another way to control the system is to keep the set points constant at those values which represent near optimal control at design conditions (Tchw,set = 38 F, Taoc,set = 48 F).

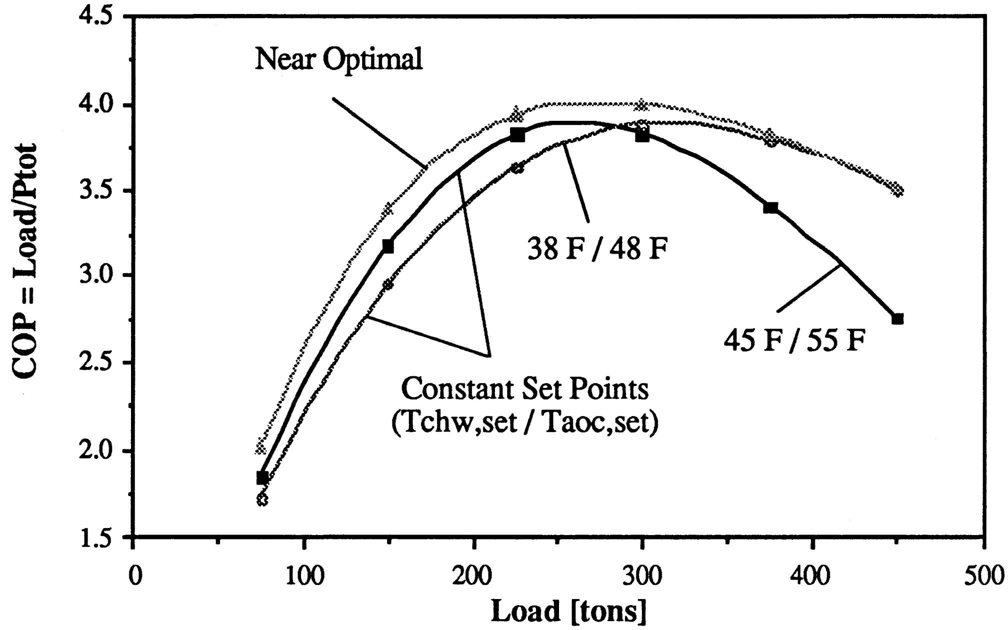


Figure 2.24 System COP for constant set point temperatures and near optimal control

In Figure 2.24 the coefficient of performance (COP) for the system is presented for the three different control strategies. The near optimal control, which is almost equivalent to the optimal control, shows the highest COP for all conditions. The COP for the control strategy 45/55 is relatively far apart from the optimal control strategy for high loads because the supply air temperatures is so high that the fan power increases significantly. At lower loads, this control strategy becomes superior to the control strategy 38/48. The chiller efficiency decreases significantly if the chilled water temperature is low at low loads.

The COP for near optimal control at low loads would be significantly higher if a variable speed chiller had been employed (see Braun [1988]). Even higher savings than the savings calculated here would have been achieved.

A comparison is made for ten hours of changing forcing functions during the design day. The total operational costs for the control 45/55 are approximately 12 % higher than for near optimal control, while the costs employing the control 38/48 are approximately 7 % higher. However, the exact values depend on the location of the building, i.e. the ambient conditions, and the time of operation. The given values are calculated using wether data from Fort Worth, Texas.

2.7 CHAPTER SUMMARY

In this chapter the control of HVAC systems was discussed. Different control strategies were analyzed. The control strategies determine the values of the independent control variables. Continuous and discrete control variables have to be set by the supervisory controller. In an example system, the chilled water supply temperature and the supply air temperature out of the coil were the independent control variables.

Optimal control should be achieved to minimize the overall operational costs of the system. Because calculating the optimal control is not realistic, a near optimal control strategy was developed. This control strategy uses outputs from the energy management and control system. A regression equation for the total power in terms of the forcing functions and the control variables is fit through operational (simulated) data, collected under different values of controlled and uncontrolled variables. This equation is quadratic with respect to the control variables. Equating the Jacobian of the power function with respect to the control variables to zero yields a set of equations which determine the optimal values for the continuous control variables. These equations represent near optimal control at all times.

The near optimal control can be improved during further operation by taking data under near optimal conditions. This data again can be regressed to obtain a control which is closer to the optimal control. Through this process, a sufficient near optimal control is quickly reached. The increase in power consumption for the improved near optimal control is negligible compared to optimal control.

Near optimal control and control under constant set points were compared. Savings of about 10 % can be realized if near optimal control is employed. Much larger savings can be achieved under specific conditions.

Chapter 3

FAULT DETECTION IN HVAC SYSTEMS

As discussed by Kao [1985], sensor errors in the air handling unit of a HVAC system can increase the annual energy requirements up to 50 %. Although errors can have a large impact on the operation of HVAC systems, not much work has been done in the area of fault detection. In this study a methodology for fault detection is proposed. The methodology allows those faults in the system which cause an increase in the power consumption to be detected. Also, the location of the fault can usually be determined by the proposed techniques. The most important tool in the techniques are the differences between the measured power and the expected power.

A description of the introduction of faults in the computer simulation is given in section 3.1. In order to establish a methodology for fault detection, three different aspects are discussed: 1) the influence on the total power consumption, 2) the influence on the residual, i.e. the difference between the measured (simulated) and predicted power, and 3) the influence on the individual component powers. The influence of different faults on the power consumption is examined in section 3.2. Statistical analysis on the residuals is utilized to sense errors in the air conditioning system. In section 3.3, different ways of performing fault detection are presented. Refinements and assumptions to the described methodology are discussed in section 3.4. Section 3.5 presents a methodology to locate errors in the HVAC system by examining the individual component powers.

In the course of this chapter, the terms *fault* and *error* are used under the following circumstances: The term fault is a qualitative expression used for everything which causes non-optimal behavior of the system. An error is the quantitative value of the fault. For example, a fault could occur in the chilled water temperature sensor. The fault could be quantitatively described by saying that the error in the chilled water temperature is 5 F. Errors in the chilled water temperature sensor and the air outlet temperature sensor are used as examples for errors throughout this chapter. If not otherwise declared, only one fault is present at a time while the rest of the system operates normally.

3.1 INTRODUCTION TO FAULT DETECTION

3.1.1 Simulating Faults

The representative HVAC system, shown in Figure 1.1, was simulated using TRNSYS. The fault detection is based on the optimal behavior of the system, i.e. if the operation is not optimal in every way, a fault should be able to be detected. Figure 3.1

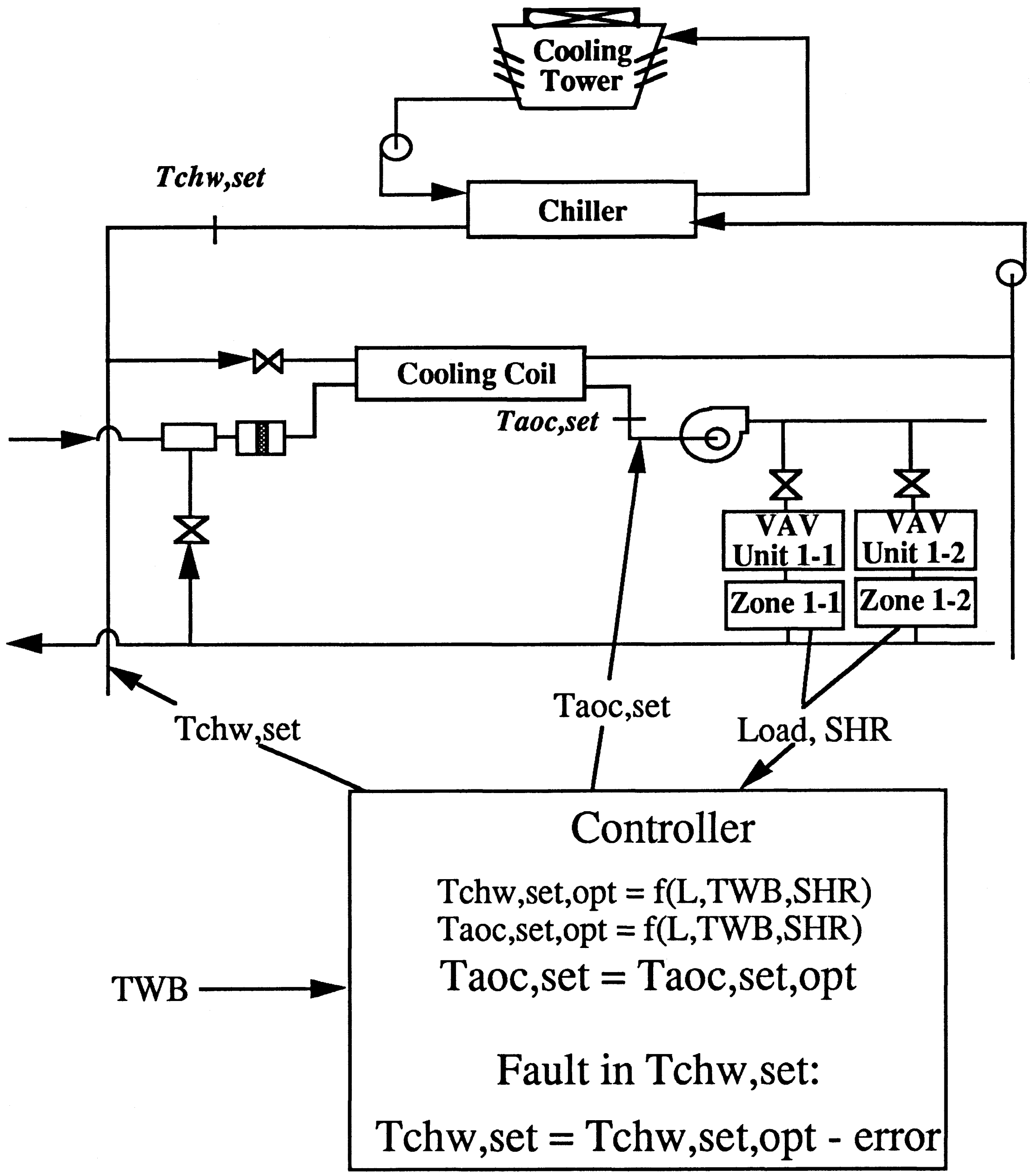


Figure 3.1 Introduction of a fault in the simulation of the system

demonstrates how faults are introduced into the simulation model. The supervisory controller bases its settings of the control variables on measures of the load, the ambient wet bulb temperature, and the sensible heat ratio. The near optimal control set points for chilled water temperature and supply air temperature are determined, set by the supervisory controller, and then met by corresponding lower level controllers.

As an example for studying fault detection, an error in the chilled water temperature is introduced, i.e. the temperature sensor is not operating properly. The temperature indicated by a sensor deviates from the real temperature by the amount of the error. For example, if the indicated temperature is 45 F and the actual temperature is 50 F, the error will be E = -5 F (error = indicated value - real value). The supervisory controller sets the indicated temperature using the optimal control strategy, which then produces the non-optimal actual temperature. The simulation then runs with this new non-optimal value of the chilled water temperature and the originally computed optimal value for the supply air temperature. Due to the non-optimal set points, more power will be required.

3.1.2 Comparison of Measured and Predicted Power

The biquadratic formula for the power, described in Chapter 2, predicts power for a set of forcing functions and controlled variables. A value for power from the formula will therefore be called the predicted value. The powers which are output from the simulation are called measured values. The comparison between the measured and the predicted power is an important tool for the task of fault detection.

Regression methods develop a formula which best fits the set of data. However, the predicted and the measured power data will not be identical for the same set of forcing functions. Thus, even if no error is present, residuals (differences between measured and predicted values) will appear. In Figure 3.2, the residuals for 50 randomly selected sets of forcing functions are presented. The residuals have values near zero, but rarely have the exact value of zero. Negative and positive residuals exist but the mean value is approximately zero. If the residuals from all values which were employed to obtain the regression equation were evaluated, the mean of the residuals would be exactly zero since the regression automatically fits the equation through the data such that the sum of the residuals is equal to zero. For other randomly selected data sets without error, different from the original data set, the mean of the residuals should be close to zero.

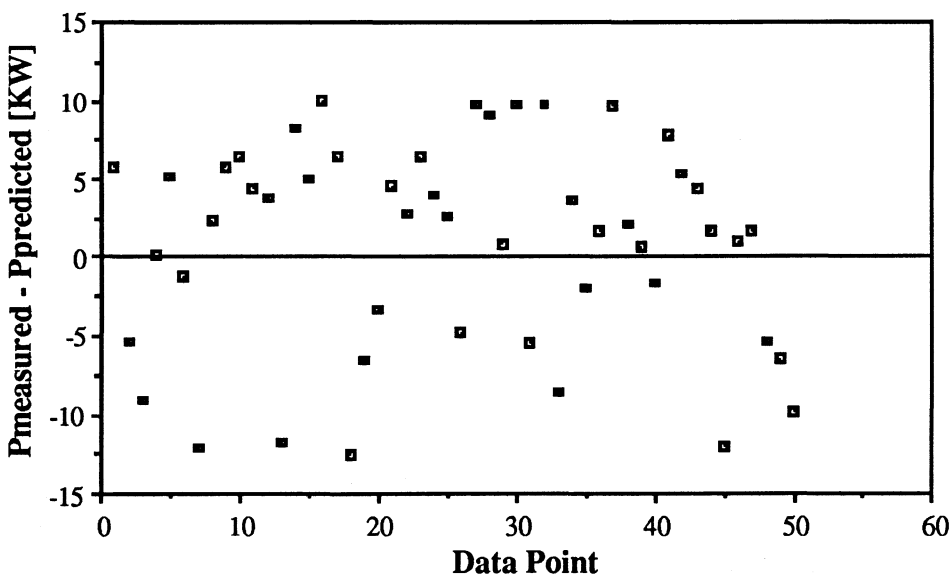


Figure 3.2 Residuals for 50 randomly selected points

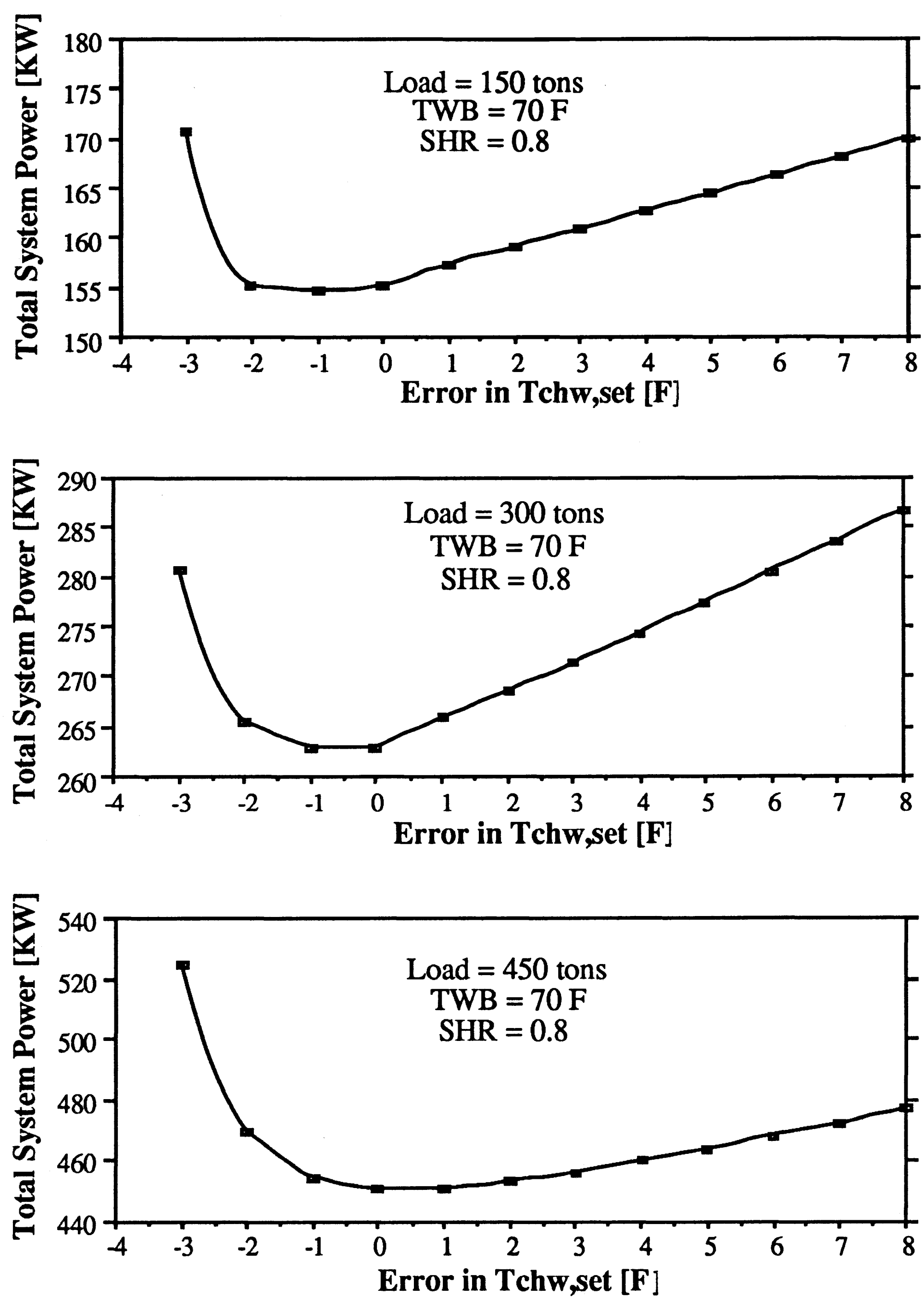


Figure 3.3 Total system power as a function of the error in Tchw,set for low, medium, and high load

3.2 INFLUENCE OF FAULTS ON THE SYSTEM POWER

In Figure 3.3, the total system power is presented in different scales as a function of the error in Tchw,set for low, medium, and high loads, representing forcing functions of TWB = 70 F and SHR = 0.8. The figure is similar to Figure 2.8 where the system power is shown as a function of the chilled water and the supply air temperature. At positive values for the error in Tchw,set, the power increases in a nearly linear fashion with the error. The increase in power is due to the decrease in the efficiency of the chiller for decreasing chilled water temperature. If negative errors are present, the system power increases rapidly because the chilled water and supply air temperatures approach each other, and the water flow rate increases rapidly.

Figure 3.4 illustrates the system power for different errors in Tchw,set for a high and a low load. It can be seen that for the same error, the sensitivity at higher loads is larger than at low loads. Hence, it is more important to operate without error at high loads. It is also difficult to detect errors at low loads.

The system power required for operation with an error in the supply air temperature is shown in Figure 3.5 for the same forcing functions as before in different scales. If a negative error increases, the system power increases. However, the increase in power is not linear. Especially at high loads and high errors, a more rapid increase than linear occurs. The additional power required by the fan at high supply air temperatures is mostly responsible for the increase in system power. Furthermore, the high ventilation and fan loads are additional loads on the chiller. If a positive error occurs, i.e. the difference between the set point temperatures decreases, the increase in power is larger than for negative errors.

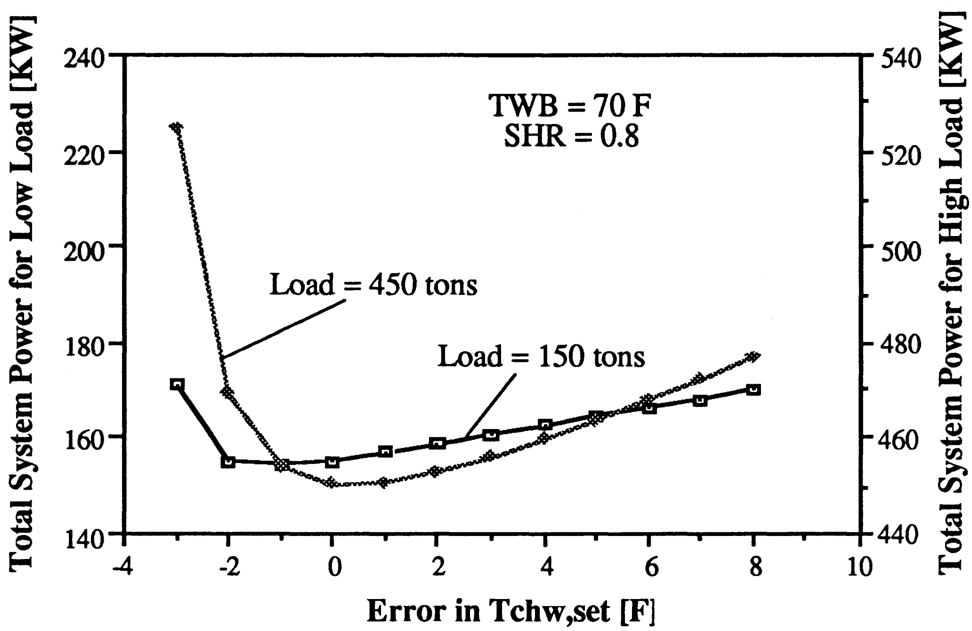


Figure 3.4 Total system power as a function of the error in Tchw,set

In Figure 3.6, the total system power is presented as a function of the error in Taoc,set for a high and a low cooling load. As expected, the increase in system power at high loads is much larger than at low loads. Increases in power at high load of more than 100 KW can occur.

In Figure 3.7, the effects of the errors in both set point temperatures are compared for a medium load. It can be seen that an error in the air outlet temperature has a bigger effect on the total system power than an error in the chilled water temperature. Similar effects are valid for other forcing functions. Hence, an error in Tchw,set will be more difficult to detect than an error in Taoc,set. Most of the following analyses use an error

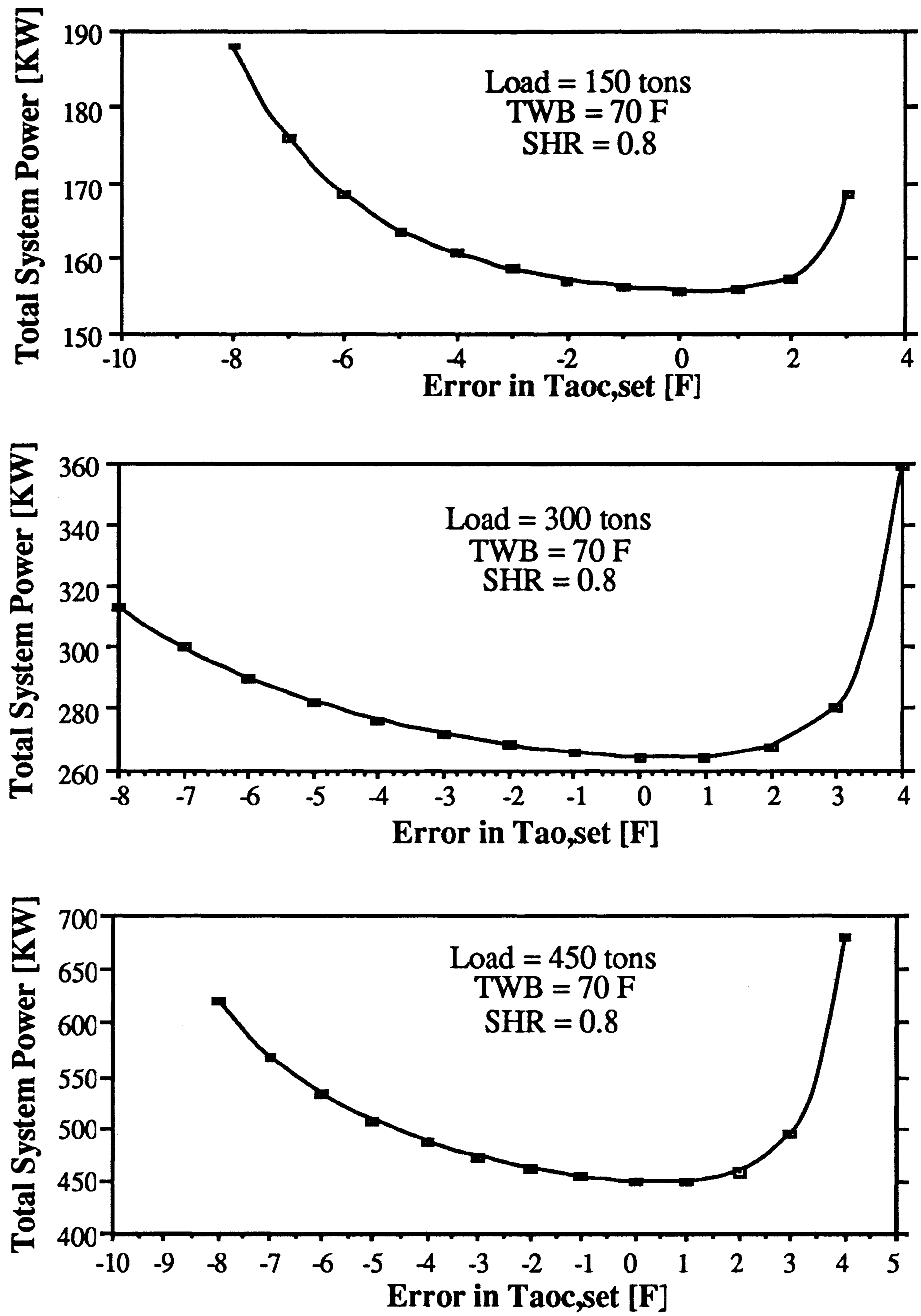


Figure 3.5 Total System Power as a function of the error in Taoc,set for low, medium, and high load

in Tchw,set as an example. If a technique is able to detect errors in Tchw,set, it will probably also be able to detect errors in Taoc,set.

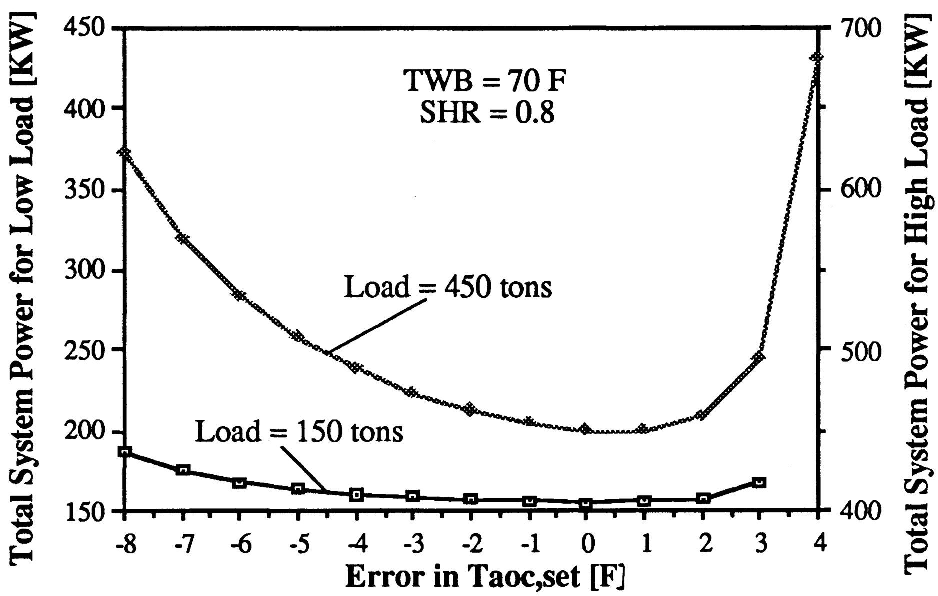


Figure 3.6 Total system power as a function of the error in Taoc,set

For the method of fault detection investigated in this thesis, the residuals are more important than the absolute powers. In Figure 3.8, the residuals are presented for an increasing positive bias error in Tchw,set. The first 50 random data points are equivalent to the data points shown in Figure 3.2. The first data point with a bias error of 1 F, 2 F, 3 F, or 4 F (data points 51, 101, 151, and 201) are obtained by employing the same forcing functions as for the first data point without error (data point 1), data points 52, 102, 152, and 202 are obtained by employing the same forcing functions as for data point 2, etc.. The interval in which the residuals are located is shifted to higher residuals for higher bias errors. At a high bias error of 4 F, only a few negative residuals occur. At low errors, however, the residual plot does not look very different from the residual plot for no error. Thus, it will be difficult to detect small errors.

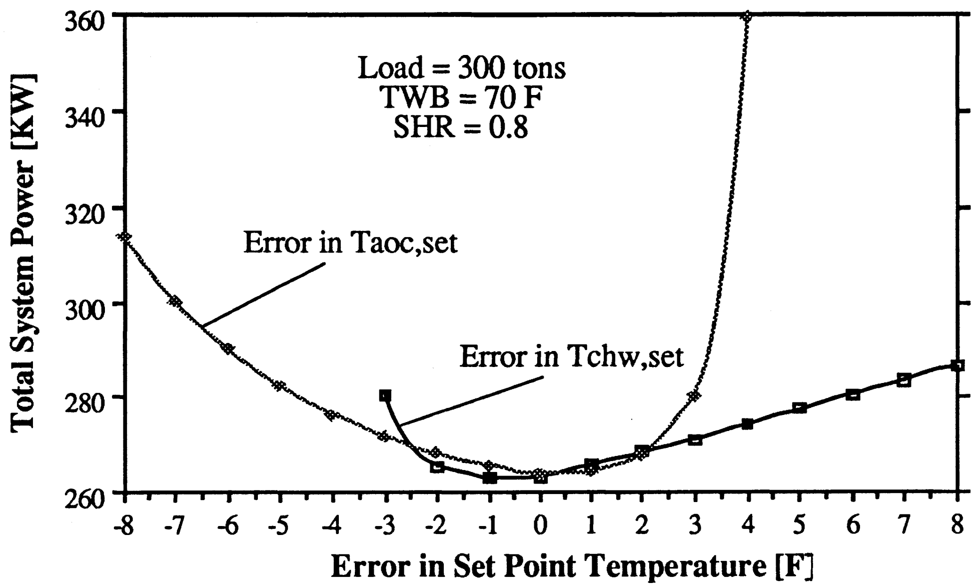


Figure 3.7 Comparison of the effect of errors in Tchw,set and Taoc,set

Figure 3.9 shows a residual plot for increasing random error in Tchw,set obtained in the same manner as Figure 3.8. While the upper limit of the interval in which the residuals are located moves toward higher values for increasing error, the lower part stays on the same level. Because errors were introduced by a random generator, some of the errors are very small.

Random errors are more difficult to detect than bias errors because the magnitude and the mean of the residuals are similar to the ones when no error is present. However, even small random errors can be detected if effective techniques are employed. These techniques are discussed in the next section.

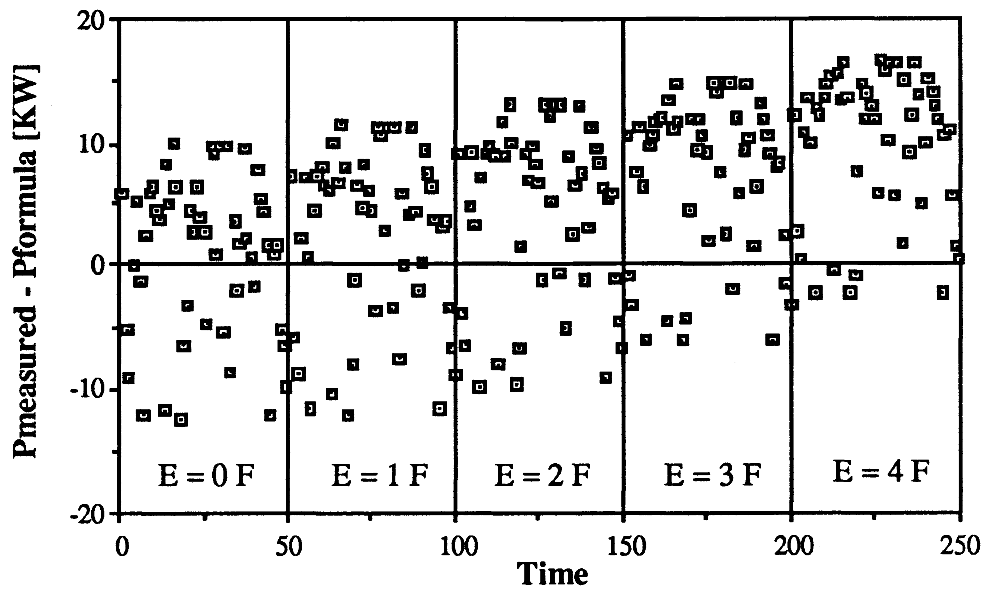


Figure 3.8 Differences in total power for increasing bias error in Tchw,set

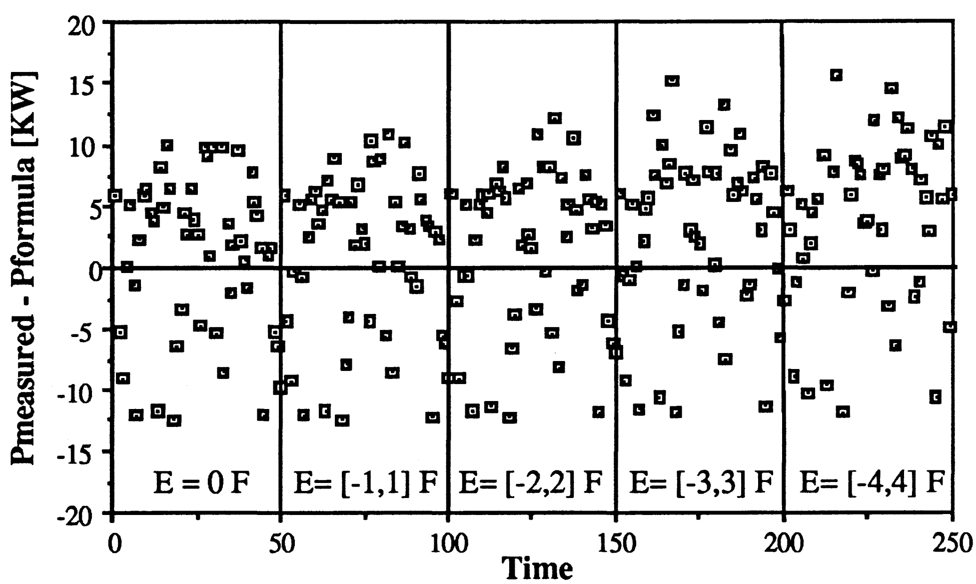


Figure 3.9 Differences in total power for increasing random error in Tchw,set

3.3 EVALUATION OF SYSTEM PERFORMANCE

3.3.1 Statistical Background

Before different methods for fault detection are discussed, some statistical concepts will be introduced. Basic terms such as average, mean, variance, standard deviation, normal distribution, and treatment are not discussed. They are described in various text books, such as Box, et al. [1978].

A *significance test* checks for a difference between two treatments. It checks if a *null hypothesis* H_0 is valid. The null hypothesis assumes that two treatments are the same and the true mean difference δ is zero. The null hypothesis can be stated as H_0: $\delta = \delta_0$. If the null hypothesis is discredited, a *statistically significant difference* between the treatments exists. In this case, the alternative hypothesis H_1 is credited which assumes that δ is not equal to zero. A test in which the alternative hypothesis is stated as H_1: $\delta > \delta_0 = 0$ is called a *one sided significance test.* If either of the treatments can yield higher observations, a *two sided test* is employed. In this case, the alternative hypothesis can be stated as H_1: $\delta \neq \delta_0 = 0$. (Because the t-distribution is symmetric, probabilities for a two-sided test are twice as big as the probabilities for a one-sided test (see Box et al.[1979]).)

A *random drawing* is one where each member of the population has an equal chance of being chosen. If random drawing is assured, the observations are *statistically independent.* If the probability distribution of one observation is affected by the level of another, the observations are *statistically dependent.*

A *population* includes all possible observations and has therefore often an infinite size. A population is described by a population mean η and a population standard deviation σ. A sample taken from the population of observations has a sample average $\bar{y}$ and a sample standard deviation s. Residuals which are the differences between actual and predicted value are said to have n -1 *degrees of freedom*, where n is the number of observations taken. The degrees of freedom represent therefore the size of the sample. Big sample sizes have a large number of degrees of freedom. One degree of freedom is lost because the unknown population mean η has to be estimated with the sample average $\bar{y}$.

The *t-distribution* or Student's distribution approximates the normal distribution and is used if the population standard deviation is not known. The t-distribution changes with the uncertainty in the variance and therefore with the degrees of freedom. When the degrees of freedom approach infinity, the t-distribution approaches the normal distribution (also called z-distribution).

An interval in which observations from the same treatment almost certainly lie is called a *confidence interval.* Confidence intervals are based on *significance levels* α. These levels correspond to probabilities representing varying degrees of scepticism. Several conventional significant levels are in common use. When the probability that a difference between two values as large as that observed is smaller than one of the probability levels, the difference is said to be *significant* at that level. Therefore, if an observation is significant, one can be, for example 95 % or 99 %, confident that the observation does not represent the original reference system. The values 95 % and 99 % correspond to two-sided significant levels of α = 0.05 / 2 = 0.025 and

$\alpha = 0.01 / 2 = 0.005$, respectively. Unless stated differently, a 99 % confidence interval is chosen in the course of this chapter.

3.3.2 Overview

In this section, an overview of the general concepts of fault detection is given. Two methods which are not utilized in the thesis are also discussed briefly and it is recommended that they are tested in future work. To detect all faults in an actual HVAC system, several of the described methods should be applied simultaneously. All methods for fault detection compare the difference in two system parameters, where normally one is calculated from the measured values and one is evaluated from the predicted values. A fault is indicated if following inequality is satisfied:

$$|\text{Measured Parameter - Predicted Parameter}| > \text{Fault Parameter} \quad (3.1)$$

If the difference between the measured and the predicted parameter is greater than a specified fault parameter, a fault will be detected. Five different methods for fault detection are listed in Table 3.1.

In method A, the measured (simulated) system power and the predicted system power are compared instantaneously. If the difference is bigger than a threshold value, a fault will be detected. The threshold value has to be determined such that real errors are predicted, but that in operation without error, no error is indicated.

Table 3.1 Suggested methods for fault detection

Method A: Comparison between the system power P_{meas} and the power predicted from the formula P_{pred}, at every time measurements are taken

Test: $|P_{meas} - P_{pred}| > \Delta P_{fault}$

Method B: Comparison of trends in performance of the system under current operating conditions and the system operating without fault (Comparison of cumulative sum of residuals)

$$\text{Test: } \left| \left(\frac{\Delta P_{diff,cum}}{\Delta time}\right)_{meas} - \left(\frac{\Delta P_{diff,cum}}{\Delta time}\right)_{pred} \right| > \left(\frac{\Delta P_{diff,cum}}{\Delta time}\right)_{fault}$$

$\left(\frac{\Delta P_{diff,cum}}{\Delta time}\right)_{pred}$ is usually equal to zero.

Method C: Comparison of a sequence of consecutive operating data with a sequence of data obtained under operation without fault (comparison of used energy E_{meas} and predicted energy use E_{pred})

Test: $|\Sigma P_{meas} - \Sigma P_{pred}| > \Delta P_{fault,seq}$ or
$|E_{meas} - E_{pred}| > \Delta E_{fault}$

Also: Comparison of the residual distribution for the sequences

Method D: Comparison of energy in and out of components or set of components (energy balance)

Test: $|\Delta E| = |E_{in} - E_{out}| > \Delta E_{fault}$

Method E: Comparison of sequences of predicted powers from different formulas

Test: $|\Sigma P_{pred,2} - \Sigma P_{pred,1}| > \Delta P_{fault,pred}$

In method B, trends in the performance are examined by graphical procedures. Again, examination of the residuals can show more detail than the examination of absolute powers. The cumulative sum of power differences can be inspected. As mentioned earlier, the cumulative sum of residuals should be close to zero if no error is present. Hence, the slope of a line representing cumulative power differences should be close to zero. If the slope of the curve is high, a fault will be detected.

In method C, a sequence of data is examined, instead of observing the power difference at every time step. Sets of residuals are tested for errors. The sequence of data may include two or more points. Employing the residuals from operation under optimal and fault conditions, frequency histograms can be created to demonstrate the distribution of the residuals. Approximate mean values and variances of the residuals can be immediately observed. Large changes in the form of the histograms over time indicate faults. The sooner a fault is detected, the earlier the fault can be corrected. Therefore, the quickness of fault detection for different methods is examined.

For the mentioned methods, significant negative values of the difference between measured and predicted parameter also have to be examined. If the measurements of the forcing functions include errors, significant negative values for the differences might occur. If, for example, the load is indicated to be higher than it really is because a mass flow rate is not measured properly, the predicted power can appear to be significantly higher than the measured power.

Methods A and C use statistical techniques which require several assumptions. The validity of these assumptions has to be checked if the tests are performed. These assumptions are discussed in detail in section 3.4.1. In this section, it is assumed that the assumptions are valid.

Methods D and E are not examined in the next sections but are mentioned here as further possibilities to be used in fault detection. Method D presents a straightforward test for faults in the system. Mass and energy balances around components or sets of components are checked. If the energy input to a component does not equal the energy output, a fault will be detected. However, this approach of fault detection requires many accurate measurements of flow rates, temperatures, humidities, etc.. In most systems, not all sensors necessary for that technique are employed. Thus, if this method were to be employed, additional measurement devices that are not normally found in an BEMCS may have to be installed.

Method E compares predicted powers obtained from different formulas. As discussed in section 2.5, formulas have to be developed to obtain optimal control laws. The formulas for the system power should be updated with time. If results from two successive formulas for the same forcing functions were significantly different, a fault could be detected. If the new formula predicts lower values of system power, either a fault is present or an improvement in near optimal control is achieved. Hence, this method can also be used to establish optimal control.

In the following sections, the methods A, B, and C for fault detection are presented in more detail. The fault parameter in equation (3.1) will be defined for each method so that it can be calculated for an actual problem. In the examples, no real weather data but randomly selected sets of forcing functions are used.

3.3.3 Instantaneous Evaluation (Method A)

A predicted value for the system power for a set of forcing functions is evaluated by first calculating the optimal control variables and then employing the regression formula. The measured value of system power without error is relatively close to the predicted value. Therefore a confidence interval is established in which the system power without error almost certainly lies.

The confidence interval for the system power can be calculated as follows:

$$P_{pred} \pm t_{\nu,\alpha/2} \frac{s}{\sqrt{n}} \tag{3.2}$$

where,

P_{pred} = power predicted from the formula

$t_{\nu,\alpha/2}$ = tabulated t-value for ν degrees of freedom and a tail area of $\alpha/2$ (two sided)

ν = degrees of freedom for evaluating the standard deviation = $n_{tot} - 1$

$\alpha/2$ = two sided tail area

s = standard deviation for the predicted values

n = number of observations for the predicted value = 1

T-values over a wide range of degrees of freedom and tail areas are tabulated in text books such as Box, et. al. [1979] or Draper [1981]. Because only one formula for the predicted value is developed and the formula is the only prediction for an observation, n is equal to one. S is the standard deviation for the predicted value, i.e. the standard deviation of values obtained from the regression formula. The value of the standard deviation is an output from the regression package. Because usually many data are employed for developing the regression formula, the number of degrees of freedom is very high. As mentioned earlier, if the degrees of freedom approach infinity, the t-distribution approaches the normal distribution of z. Hence, the process can be simplified by utilizing z values which are only a function of the tail area but no function of the degrees of freedom.

If a fault in the sensor of the chilled water temperature occurs, the measured power value is significantly higher than the predicted value, i.e. the residual might be located outside the confidence interval. However, not all residuals which represent power obtained with an error lie outside the confidence interval. Therefore, even if a fault is present, a fault is not indicated at every time step.

If a measured system power is not inside the confidence interval, a significant difference between predicted and measured power is indicated, i.e. a fault will be detected. The 95 % confidence interval (two sided tail area of $\alpha/2 = 0.05/2 = 0.025$) and the 99 % confidence interval (two sided tail area of $\alpha/2 = 0.01/2 = 0.005$) for the employed data are presented in Figure 3.10 together with residuals. The residuals are the same as in Figure 3.8. For a 99 % confidence interval, a fault can only be detected if a positive error in the chilled water temperature of at least 4 F occurs. This means that, if only this method for fault detection is utilized, much energy is wasted because no fault is detected. Therefore, other methods are necessary to detect smaller errors.

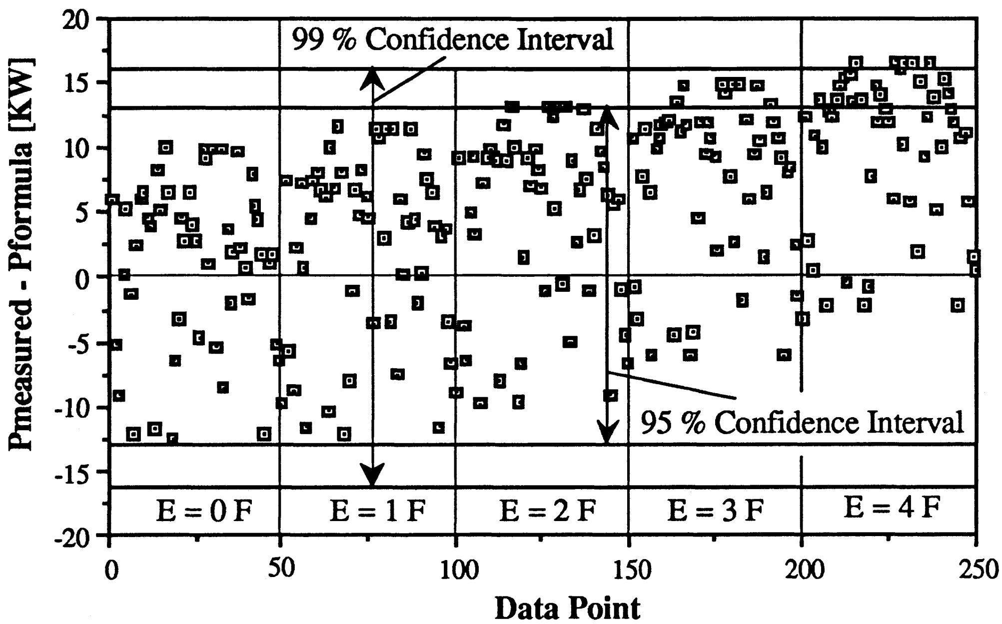


Figure 3.10 95 % and 99 % confidence intervals for residuals with bias error

3.3.4 Trends in Performance (Method B)

During operation of the air conditioning system, continuous measurements are taken. These could be stored by the BEMCS and continuous print outs from measurements can be created. For the total system power, plots could be made of the system power and residuals over time.

A plot could be created from the sum of cumulative power differences, i.e. for every data point a residual is calculated and is added to the old sum of residuals which starts with a value of zero at time step zero. With this plot, short and long term changes in the system can be shown.

In Figure 3.11, the cumulative sum of residuals for 100 randomly selected data points is presented as a function of the i-th data point. In an actual system, the i-th data point can be represented as time. Therefore, the terms time step or time are sometimes used in this chapter instead of the term data point.

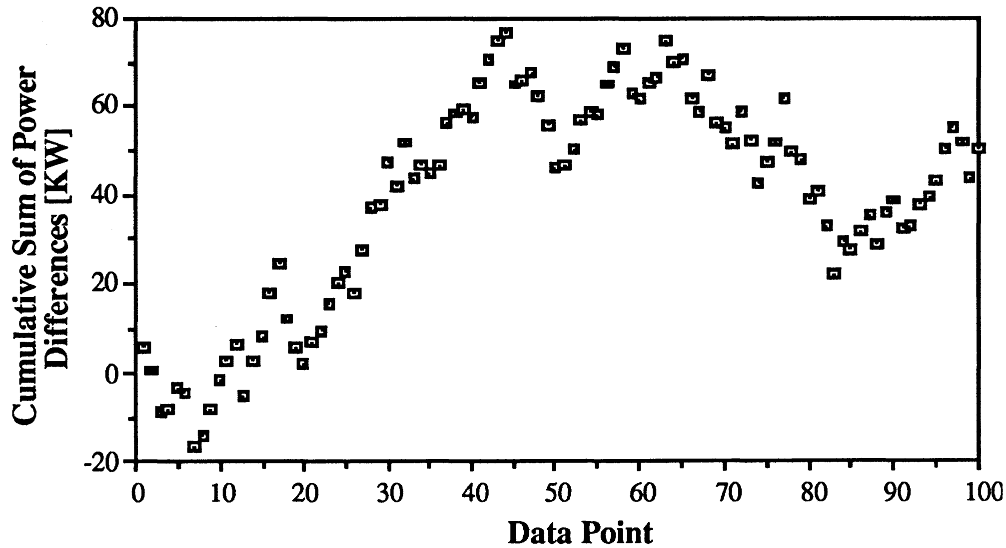


Figure 3.11 Cumulative sum of power differences for 100 random data points without error

No fault is present in the system for the data shown. The cumulative sum starts out with zero for time zero. As mentioned earlier, the cumulative sum should be close to zero if no fault occurs. However, as can be seen in the figure, the sum is rarely at exactly zero. If the cumulative sum of the residuals for the data which were employed for creating the regression formula is taken, the sum for the last point would be at exactly zero. Other data sets will probably yield cumulative sums which are not equal to zero. In the shown case, the cumulative sum of residuals is approximately 50 KW for 100 data points but reaches nearly 80 KW around data point 40.

If errors are introduced in the system, i.e. the system is not operating optimally, the cumulative sum would be expected to increase. However, many negative residuals may be computed if the measurements for load, wet bulb temperature, or sensible heat ratio include errors. Hence, the cumulative sum of power differences would decrease. In Figure 3.12, the cumulative sum of residuals is shown at every of the 250 data points whose absolute values are shown in Figure 3.8. The scale of the figure is much smaller than the scale for Figure 3.11. The first 50 data points correspond to the first 50 data points in Figure 3.11 where no fault is present. From data point 51 to data point 100, an error of 1 F is introduced in the chilled water temperature, from data point 101 to 151, an error of 2 F is introduced, etc.. As expected, the angle of a curve fit through the points increases with increasing error. Therefore, the error is more critical in terms of the power consumption for steeper curves.

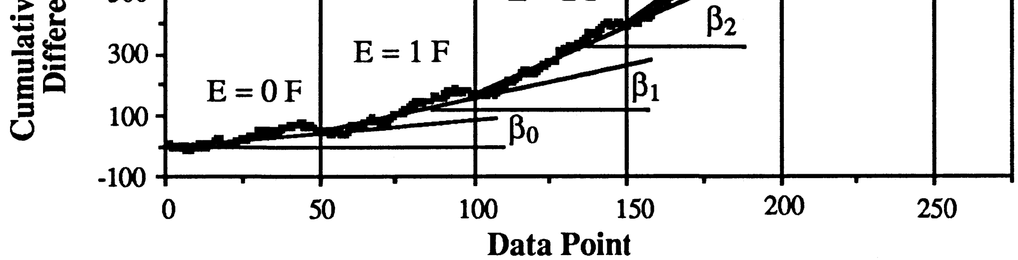


Figure 3.12 Cumulative sum of residuals with increasing error in Tchw,set

For the first 50 data points in Figure 3.12, the slope of the curve often changes. If only few data points are included, high slopes are sometimes reached. Thus, it can be difficult to distinguish between operation without and with small errors. Many data points have to be included if this method should provide information about troublesome operation of the air conditioning system.

The described method gives an indication to the building operator if a system fault occurred. If the slope of the line exceeds a limit value, it is clear that an error is present in the system. That limit value should be set slightly higher than the largest slope which was reached for operation without error. Long term as well as short term trends can be recognized. Furthermore, the seriousness of the fault in terms of increased energy use can be estimated qualitatively and quantitatively. If the slope increases for a short time period and then decreases again as in the first part of Figure 3.11, probably no immediate attention is needed.

In Figure 3.13, cumulative power differences are presented over a range of 250 time steps. Four different curves for errors in chilled water temperature of 0 F to 3 F are shown. The 250 data points for each of the curves are randomly chosen and are different for each of the curves. All curves are nearly straight lines and a clear difference between the lines can be recognized. Thus, over a long time period, it is not difficult to detect a significant difference for the upper lines.

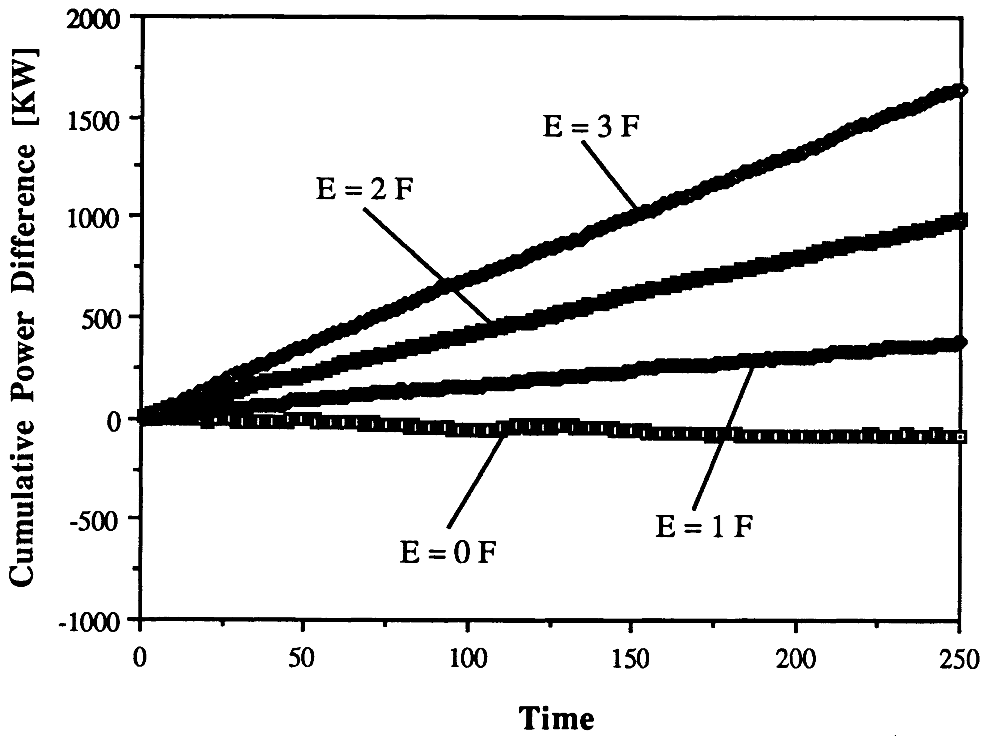


Figure 3.13 Cumulative sum of residuals for errors in Tchw,set of 0 F - 3 F

3.3.5 Evaluation of Sequences of Data (Method C)

Instead of comparing instantaneous values for the system power from the formula and measurements, as for method A, the averages for several data points are used in the comparison for method C. For this check, two sets of data have to be available. One set of data represents data during system operation. The other set is a reference data set and represents data from operation without error. The residuals for both sets of data are compared.

A statistical significance test is carried out. The null hypothesis is tested, i.e. it is assumed that no difference between the sets of data exists. Rejecting the null hypothesis means that there is significant evidence that a fault is present. If the null hypothesis is not rejected, there is not enough evidence that a fault occurred. The t-test is an appropriate test for performing such comparisons. The assumptions necessary for the test are discussed in section 3.4. It is important that the validity of the assumptions is checked. With,

$\bar{y}_A$ = average power difference ($\overline{P_{meas} - P_{pred}}$) yield in first sequence without error (treatment A) = $\dfrac{\sum_i (P_{meas,i} - P_{pred,i})}{n_A}$

$\bar{y}_B$ = average power difference ($\overline{P_{meas} - P_{pred}}$) yield in second sequence which should be examined (treatment B) = $\dfrac{\sum_i (P_{meas,i} - P_{pred,i})}{n_B}$

s_p = pooled variance

n_A = number of data points with treatment A

n_B = number of data points with treatment B

$t_{\nu,\alpha}$ = table t-value for ν degrees of freedom and a tail area of α

ν = total number of degrees of freedom = $n_A + n_B - 2$

α = tail area probability

ν_A = degrees of freedom for A = $n_A - 1$

ν_B = degrees of freedom for B = $n_B - 1$

s_A = standard deviation for treatment A

s_B = standard deviation for treatment B

a significant difference between treatment A (first sequence without error) and treatment

B (sequence which is being examined) is detected if

$$t = \frac{\bar{y}_B - \bar{y}_A}{s_p\sqrt{\frac{1}{n_A}+\frac{1}{n_B}}} = \frac{\overline{(P_{meas} - P_{pred})}_B - \overline{(P_{meas} - P_{pred})}_A}{s_p\sqrt{\frac{1}{n_A}+\frac{1}{n_B}}} > t_{\nu,\alpha} \tag{3.3}$$

where,

$$s_p = \frac{\nu_A s_A + \nu_B s_B}{\nu_A + \nu_B} \quad . \tag{3.4}$$

A pooled variance is calculated because it is assumed that observations or system powers for both sequences have the same population variance. Therefore, all available data is utilized to estimate the variance.

The data used to estimate the average power difference for the sequence which should be examined changes at every time step. If, for example, 30 data points are always included in the sequence, the first average is calculated from data points one to 30 where data point 30 represents the last actual measurement The next check is made by calculating the average residual from data point two to 31. The sequence including 30 or in general n_B data points is therefore always shifted. With i being the present time step, the average power residual can be calculated as:

$$\bar{y}_B = \sum_{i-n_B}^{i} (P_{meas,i} - P_{pred,i}) / n_B \tag{3.5}$$

Always the last measured n_B values are employed in the calculation. Every data point is used in n_B tests.

The data points representing the reference data set can be chosen in two different ways. The two different ways of performing the t-test are summarized in Table 3.2. In method C1, the reference data sequence is taken after the near optimal control strategy was installed. During operation without error, the reference data set is collected. The number of data points involved in both sequences is on the same order.

In method C2, the data which is employed for obtaining the regression formula is utilized. By doing so, several simplifications occur because the average residual for the reference data set is exactly equal to zero and the reference data set is much larger than the actual data set which is examined. The sample variance s_A^2 is assumed to be the pooled variance and the t-distribution approaches the z-distribution; z_α is the tabulated z-value for a tail area of α.

Method C1 should be used if small changes in the system occur but the control strategy is not changed. At that point, an average residual of zero, representing the operation without fault, may no longer be accurate. Therefore, an average residual for a reference data set has to be computed.

For the analyses in this thesis, method C2 is employed. The computational effort for method two is less because the pooled variance only has to be evaluated once instead of at every time step. The total number of degrees of freedom for method two is very high. Hence, the tabulated t-value is almost the same as the z-value and the number of data points included in the test does not have an influence on the tabulated value. The z-value depends only on the significance levels. Therefore, only a few z-values have to be stored.

Table 3.2 Procedures to perform t-test

Method C1:

- let a sequence of data points without error represent 'treatment A'
- evaluate the mean and variance for treatment A (stays the same for all checks)
- take sets of the most actual data during operation (treatment B)
- evaluate the mean and the variance for treatment B at every time step
- evaluate the pooled variance from equation (3.3) at every time step
- check for significant difference by using equation (3.2) at every time step

Method C2:

- let the data employed in the regression represent treatment A; average residual $\bar{y}_A = 0$
- take the variance for treatment A, s_A^2, from the regression output
- take a set of data during operation representing treatment B (for example 30 points)
- evaluate the mean for treatment B
- because $\frac{1}{n_A} << \frac{1}{n_B}$, $v_A >> v_B$, $\bar{y}_A = 0$, and $s_A^2 \approx s_p^2$, the evaluation of the t-value reduces to:

$$t = \frac{\bar{y}_B \sqrt{n_B}}{s_A} \quad (3.6)$$

and the tabulated t value can be simplified: $t_{v,\alpha} \approx t_{\infty,\alpha} = z_\alpha$

A fault is detected if:

$$t = \frac{\bar{y}_B \sqrt{n_B}}{s_A} > z_\alpha \quad (3.7)$$

In Figure 3.14, method C1 is illustrated. The average residual for the reference sequence A, $\bar{y}_A$, is, as indicated in the figure, zero because the residuals from the regression are utilized. During the first 50 time steps, no error is present while from time 51 to time 100 a bias error of 2 F in the chilled water temperature is present. T-tests are performed at every timestep. In the figure, only two of the tests are indicated. One of the shown tests was performed at time 55 and one at time 86. In both tests, the last ten data points, i.e. the power residuals from the last ten measurements, are included in the test.

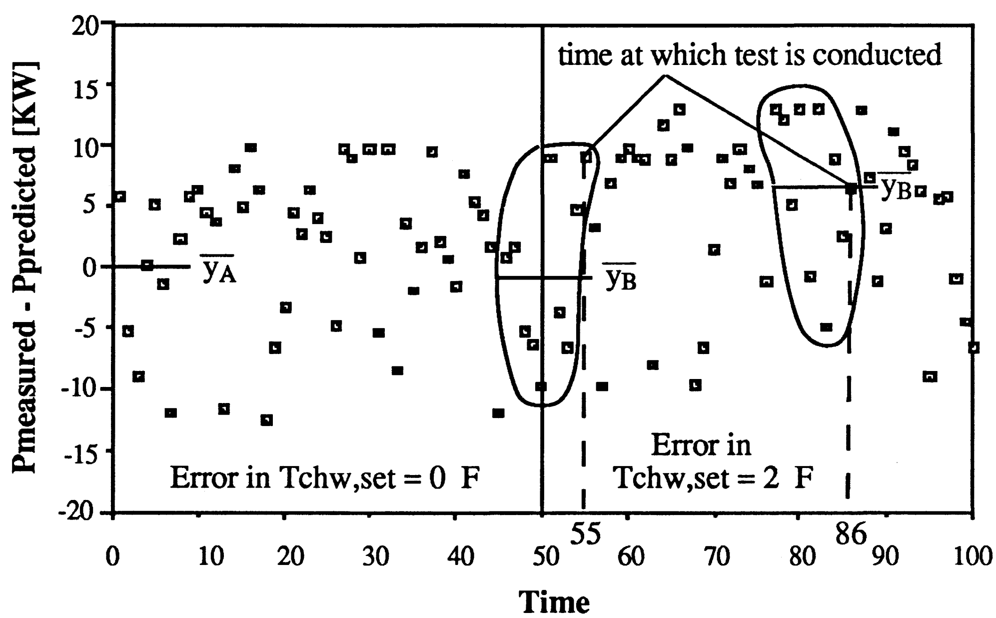


Figure 3.14 Residuals without error and with an error in Tchw,set of 2 F

In the first of the shown tests at time 55, five measurements without error and five measurements with error are included in the test. The average residual $\bar{y}_B$ is close to zero. Therefore, the system is probably not able to detect the fault at that time using the t-test. In the second test shown, at time 86, the average of the ten last residuals, $\bar{y}_B$, which are the residuals from time 77 to the present time 86, is well above zero, i.e. a fault might be detected. The test compares the reference set, characterized by $\overline{y}_A$ and s_A^2 (not shown in the figure), and the actual data set, characterized by $\overline{y}_B$. The standard deviation from the reference set A, s_A, and from the examined sequences, s_B, are assumed to be equal.

The program which was developed for detecting faults from the simulation results is included in Appendix D. The user can specify a significance level and the number of data points included in the t-test (e.g. 30). Employing the level, the confidence intervals are calculated, and the z-value corresponding to the level is read from a data array. The first set of data points (e.g. 30) is read. For every data point, a residual is calculated. If the residual lies outside the confidence interval, a message will be printed. Furthermore, the described t-test is executed at every time step. Significant differences between the reference set and the examined set are indicated.

A graphical and qualitative way for comparing sequences of data is the comparison of frequency histograms. In Figure 3.8 and Figure 3.9, residuals are shown for increasing bias and random errors in Tchw,set, respectively. If the residuals of each set of 50 data points, representing data under a specific error, are collected, a frequency histogram of residuals can be created for every error. Figure 3.15 presents the frequency histograms for operation without error and for operation with bias errors in Tchw,set of 2 F and 4 F. The center of the histogram drifts towards higher residuals for larger errors. (This corresponds to the change in average residuals in equation (3.3)). If frequency histograms for residuals are created at specific times of operation,

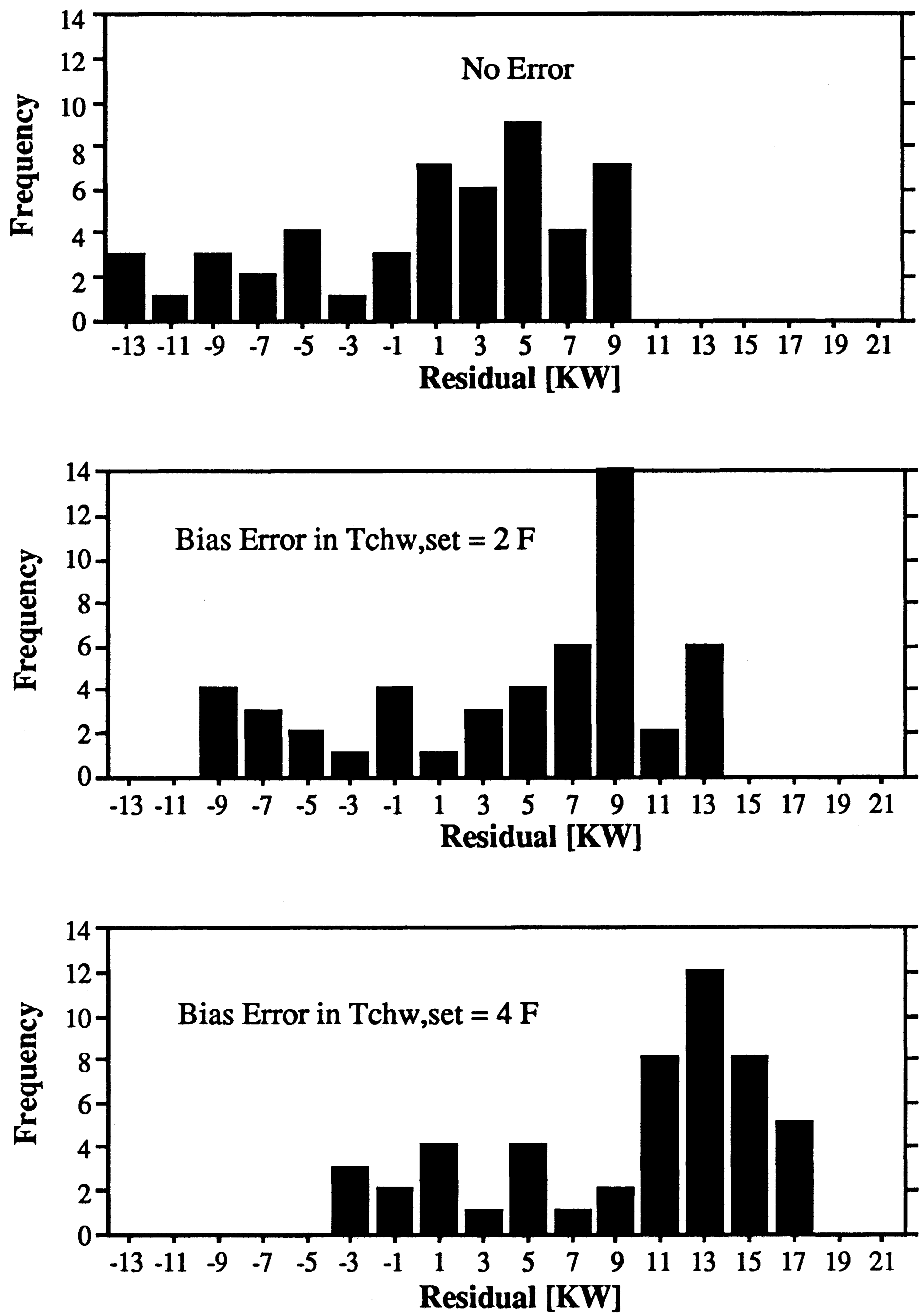
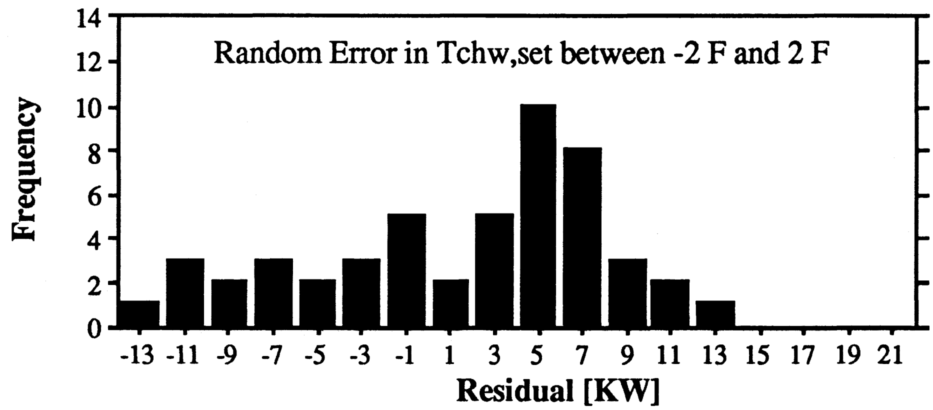


Figure 3.15 Residual frequency histogram for operation without error and bias errors in Tchw,set of 2 F and 4 F (50 random selected points)

and the histograms are compared, faults can be detected and trends can be recognized. The fact that the histogram does not form bell curves which characterize normal distributions is discussed in section 3.4.



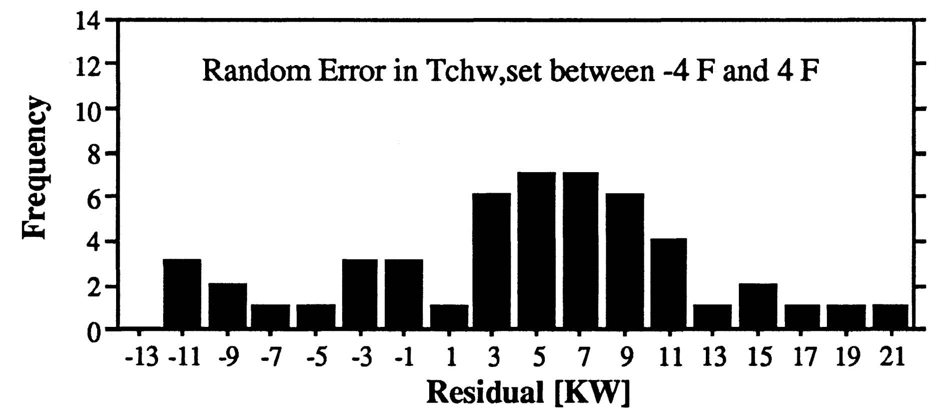


Figure 3.16 Residual frequency histogram for operation with random errors in Tchw,set between [-2,2] F and [-4,4] F (50 random selected points)

Figure 3.16 illustrates the histograms of residuals for random errors in Tchw,set between -2 F and 2 F, and -4 F and 4 F, respectively. As mentioned for Figure 3.9, the range of residuals increases if random errors are present. Low residuals, as in the histogram which represents trouble free operation, are present as well as higher residuals like in the histograms which represent bias errors. Very high residuals occur at high random error because the difference between set point temperatures decreases for negative errors. Large errors can yield not feasible points, i.e. the system is not able to maintain the set temperatures.

If a significant change in variance is observed, random errors could be detected because, as discussed earlier, the range of residuals increases with increasing random error. Furthermore, as will be discussed later, the range of residuals, especially for component powers, also increases rapidly also with bias errors. Examining these effects is recommended for further research. The change in the center of the histograms corresponds to the difference in average residual in the t-tests.

3.3.6 Quickness of Detecting a Fault (Methods A and C)

It can be seen from equation (3.7) that the calculated t-value increases with the number of data points included in the test, n_B. Therefore, the choice of n_B is important. A higher value of n_B increases the t-value even if the average residual $\bar{y}_B$ is small. Thus, even small errors can be detected if many data points are included in the test. On the other hand, a high average residual $\bar{y}_B$ is necessary to detect an error if n_B is small because the values of z_α and s_A are constant.

It is desirable to detect a fault in the system as fast as possible because the longer the system operates with the fault, the more energy is wasted. The first time a residual, representing a fault, is part of a t-test which includes many data points, the residual will not have a big influence on the average residual $\bar{y}_B$ even if the error is relatively large. Only when the fault is present over several time steps, it does have a large enough influence to be detected. Hence, including less data in the test will increase the quickness of detecting a fault.

A tradeoff between quickness of detection and sensitivity of detection exists. In a test run, 50 sets of forcing functions were input to a simulation, first without error (data points 1 - 50) and then with an error of 2 F in the chilled water temperature (data points 51 - 100). The total system power for the data was obtained.

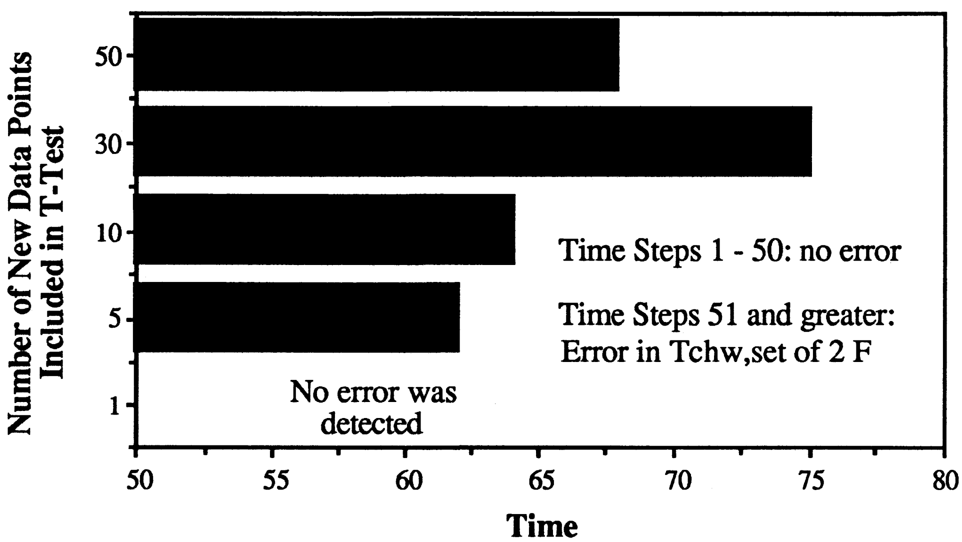


Figure 3.17 First time an error in Tchw,set of 2 F was detected for different numbers of data points included in the test

During the first 50 time steps or data points, representing operation without error, no fault was indicated for any of the tests. In Figure 3.17, the time steps are shown at which a fault was detected by the program the first time, for different numbers of data included in test. At these times and all other times when a fault is indicated, the calculated t-value in equation (3.6) is bigger than z_α. An indication of a fault at one time step does not necessarily mean that a fault was also indicated during all further time steps.

No fault was detected at any of the 50 time steps of operation with error when only one data point was included in the test. A t-test or z-test including only one data point is equivalent to checking if the single residual lies inside the confidence limits (99 % confidence interval). By including five or more data points in the test, a fault was detected at least once during the 50 timesteps of operation with a fault.

As expected, the time before a fault is detected generally increases if the number of data points included in the test increases. However, in the example, the time before a fault is detected is smaller when 50 points are included in the test than it is when 30 points are included. This could happen because many high residuals for operation without error are included in the 50 points but only low residuals for operation without error are included in the 30 points. The residuals for operation with error are the same at the beginning for both sets. Furthermore, the calculated t-value in equation (3.7) is higher if 50 points are included in the test and therefore reaches the threshold value z_α earlier.

If a fault were indicated once and after that no further indication of a fault were given, one might be sceptical about the detection. On the other hand, one can be relatively certain that a fault occurred if a fault is indicated at every time step. In Figure 3.18, the number of time steps, out of the 50 time step interval operating with an error in Tchw,set, for which a fault is indicated is presented for different numbers of data points N included in the t-test. For low numbers of data points in the test, the fault is only detected a few times. The fault is detected for every data point after the first detection when 50 data points are included in the test.

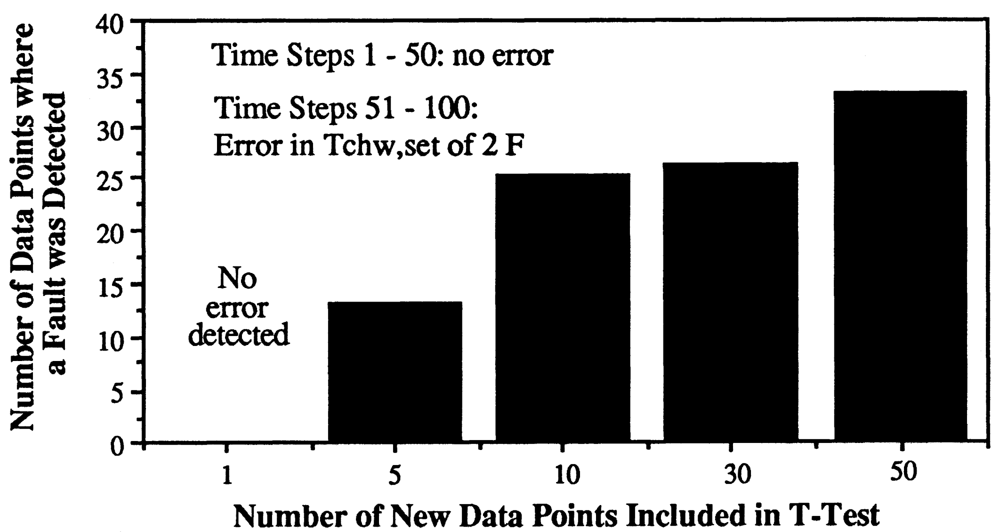


Figure 3.18 Number of times a fault was detected in a 50 hour time interval with an error in Tchw,set for different numbers of data points included in the test

Due to the tradeoff between quickness in the detection of faults and the ability to detect small faults and the certainty for having detected a fault, t-tests should be carried out with different numbers of points included in the test. By doing so, large and serious errors can be quickly detected and small errors representing only small energy losses can be recognized after a longer time period.

3.4 REFINEMENTS OF THE METHODOLOGY

At this point, some refinements on the methodology for fault detection are proposed. Assumptions necessary for the statistical analysis described in section 3.3 are discussed. Methods are presented for how to check the validity of the assumptions. Suggestions are given how to proceed if the assumptions are not valid. Although some refinements are made, the methodology for fault detection remains basically the same.

3.4.1 Assumptions Needed for the Validity of the t-Distribution

The quantity t in equation (3.3) has a t-distribution with ν degrees of freedom. The probability points for this distribution are tabulated in Box et. al. [1979]. Assumptions needed for the validity of the t-distribution are:

1) Observations are normally distributed about η with a variance σ^2
2) The standard deviation s is independent of the observation y, i.e. the variance is constant for all values of load, TWB, and SHR.
3) The sample variance s^2, which has ν degrees of freedom, is calculated from normally and independently distributed observations having variance σ^2.

Assumption one requires normally distributed data around a mean value. To check for the validity of this assumption, the residual plots have to be checked. For the test of normal distributed residuals, two residual plots are in common use: 1) the histogram frequency plot and 2) the normal score plot. The histograms of residuals without and with error were shown in Figure 3.15 - 3.16. It can be seen that the residuals do not build up to a bell curve which characterizes a normal distribution of the residuals. The residuals with the highest frequencies have high values instead of values near zero. The distribution of residuals is side loaded, i.e. the frequencies for high and low residuals are relatively high. In a normal distribution, the frequencies at low and high residuals are small. Therefore, the assumption of normal distributed residuals is not valid for the data used.

Assumption two requires a variance which is independent of the observation. This assumption can be checked if the residuals are plotted as a function of the predicted power. A range of residuals which stays constant for all predicted powers would characterize residuals with a constant variance. Figure 3.19 presents the 50 residuals shown in Figure 3.2 as a function of the predicted power. A clear dependence of the residual on the predicted power can be recognized. While at low predicted power, i.e. operation at low load, TWB, and SHR, the residuals are positive, the residuals at high load have negative values. If the air conditioning system is operated for a time period only at high or low loads, which may happen in a real case, a high positive or negative sum of residuals is obtained. Thus, a fault may be indicated although no fault is present. As tests showed, the sum of residuals for a complete day in the main cooling season is usually close to zero because high and low residuals are present over the day. However, on a moderate day with only low loads, it may happen that many high residuals are present. Therefore, a way should be found to stabilize the variance of the residuals.

Assumption three emphasizes that the data is independently distributed and randomly chosen. Random sampling requires that the probabilities for choosing any of the observations in the population are equal. Independent data requires that an observation is not influenced by other observations. In Appendix E, the residual plots of the data used in the regression are shown. There are roughly a constant variance and normal distributed residuals. The 50 residuals shown in Figure 3.19 represent a small part of the data used in the regression. If the 50 data points were picked randomly and independently from the population, their residual plots would look similar to the residual plots for the data set used for the regression. Thus, it is clear, that randomness and independence are not valid assumptions.

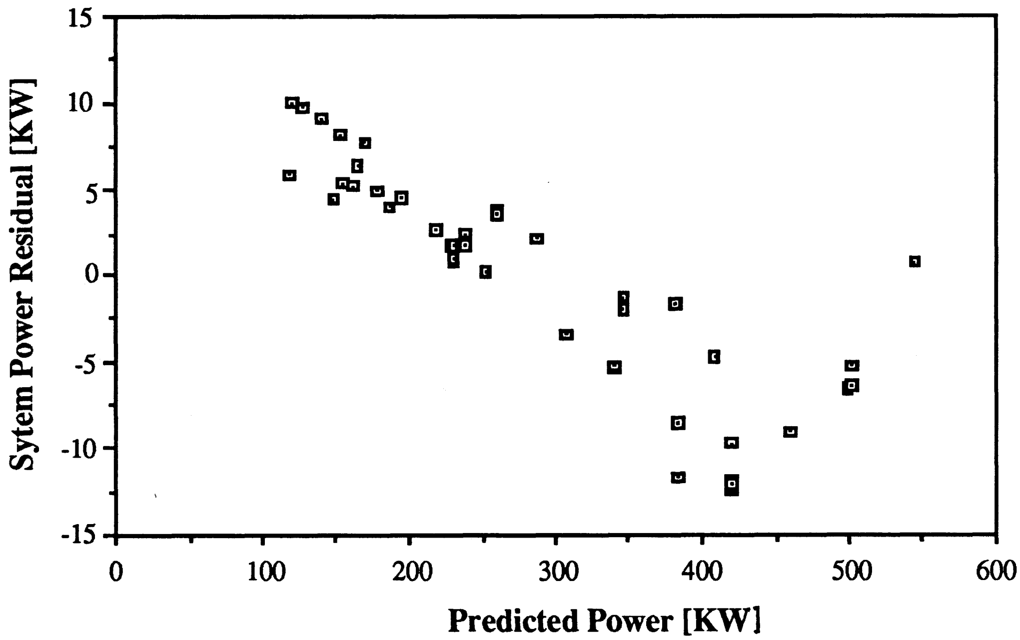


Figure 3.19 Residual plot for checking the assumption of constant variance

The reason, that random sampling and independence of the data are not valid is due to the procedure for control optimization. In the data set used for obtaining the regression formula, data around and away from the optimum are utilized. The data used during further operation, however, are obtained only under near optimal control. However, residuals representing near optimal control are differently distributed than the residuals for non-optimal control. Therefore, the residual plots show the invalidity of the assumptions.

3.4.2 Improved Formula for Predicted Power

Because the assumptions necessary for the employed statistical tests are not valid for the regression formula which includes non-optimal data, a new predictor formula for the system power was developed. This formula is obtained by regressing only the data which represent optimal control conditions.

The procedure for obtaining the new formula is faster and simpler than the procedure for the old formula. For the old regression equation data set, data far away from the optimum has to be removed from the set. This procedure is not necessary for the new formula because only the data representing near optimal control is used.

The optimal control variables are calculated from the old regression formula. The system is then operated with these calculated values for the set point temperatures. The system powers for running the HVAC system are then stored over a period of time. Thus, a wide range of conditions is included in the data set. It is also possible to use that data from the old data set which represents optimal control; new and old data can also be combined to a new data set. The new data set is then regressed to obtain a new power formula.

A new formula for the power has several advantages over the old power formula which are listed below:

a) The data set for the new formula includes data obtained under near optimal control or optimal data from the old data set.
b) The new regression formula may be built into the supervisory computer.
c) The goal of constant variance and normal distributed residuals can usually be achieved (eventually after a transformation of data)
d) The formula does not have to be quadratic with the control variables.
e) A better fit can be obtained.

Because only near optimal data are included in the data set, the formula will have a better fit to the data and can therefore better predict the system power. The standard deviation is significantly reduced. Thus, even small errors in the system leading to higher power consumptions can be detected because the residual threshold value, at which a fault is detected, is significantly reduced.

A further improvement of the formula is sometimes reached if the form of the function is changed. Because no optimal control set points have to be evaluated with the new formula, the system power does not have to be quadratic with the control variables. Any real value function may be employed for the formula (e.g. higher order or exponential functions) and the fit may be very good. However, as stated before, the quadratic formula usually fits the data very well.

In Figure 3.20, the residuals for the old and the new power formula are shown as a function of the measured values. The residuals for the new formula are much smaller and the variance is stabilized. The new formula employed is also quadratic with the control variables. All possible variables in the quadratic equation were forced to be included in both formulas during the regression procedure (see section 2.5.3).

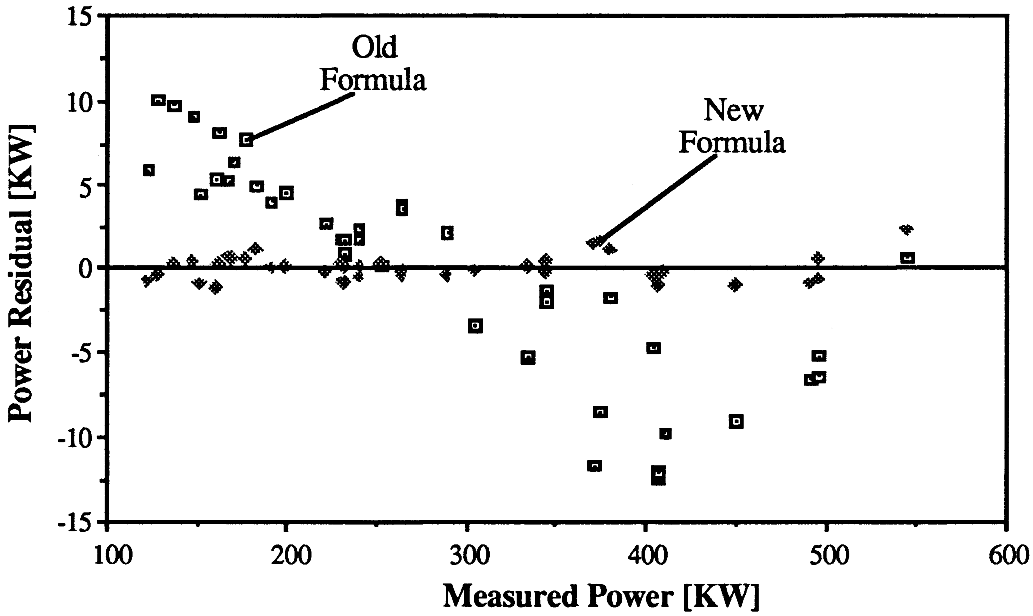


Figure 3.20 Residual plot for the old and the new power formula

The residuals obtained with the new formula are shown in Figure 3.21 to a larger scale. The assumption of constant variance for the residuals can assumed to be valid. Furthermore, the wet bulb temperatures for every data point are indicated in the figure. For every wet bulb temperature, the residuals are well distributed over the whole range of predicted values.

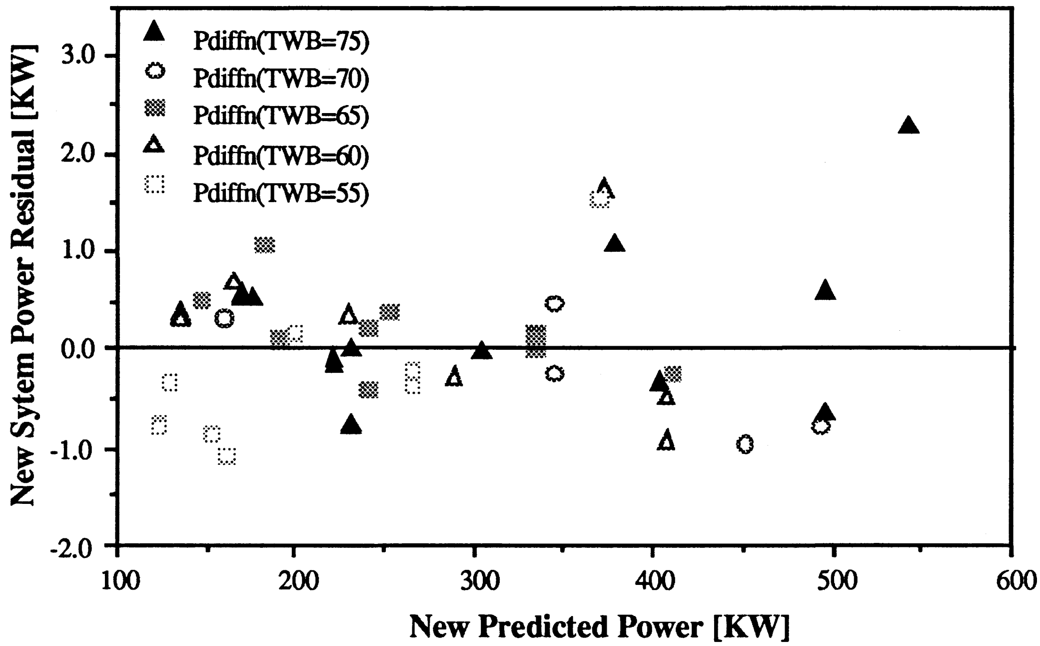


Figure 3.21 Residual plot for new formula showing the residuals at different wet bulb temperatures

On any day of the cooling season, the predicted power is usually high early in the morning after turning on the system and for several hours during midday and is lower during the morning and the evening. It is important, for operation without error, that the magnitude and sign of the residuals change as small changes in forcing function occur. If this is not the case and residuals over a day all have the same or similar residuals, the sum of these residual could be indicated to be significant in a test although no fault is present in the system.

On a day of the cooling season, the wet bulb temperature often does not change significantly. As shown in Figure 3.21, the residuals for the same wet bulb temperature but different predicted values, i.e. different loads and sensible heat ratios, have different residuals. Their average is almost equal to zero. Therefore, the new formula is well suited for the task of fault detection. The standard deviation is reduced to s = 0.6 KW.

Since weather data is involved in statistical procedures, the assumption of random and independent sampling is often not valid because an observation is dependent on the previous observation, i.e. the temperature changes continuously over the course of the day. Here however, residuals and not absolute values are utilized. As discussed earlier, the residuals change even if only small changes in forcing functions occur in a non-predictable manner. Hence, quasi-randomness and -independence of the data can assumed to be valid.

The assumption of normal distributed residuals has to be checked. As before, a frequency histogram is constructed for the differences between measured (simulated) powers and the powers predicted from the new formula. The histogram is presented in Figure 3.22. The bell curve which characterizes the normal distribution is well approximated with the residuals from the new formula. The residual which occurs most frequently is located in the middle of the spectrum of the residuals while low and high residuals are rare.

The variance is often found to be constant if the randomness and normality assumptions are valid. If the assumptions of constant variance or normal distributed residuals are not valid, a transformation can be performed (see section 3.4.3). Techniques to find the best transformation can be used. Often, if a constant variance is achieved, the residuals are also normally distributed.

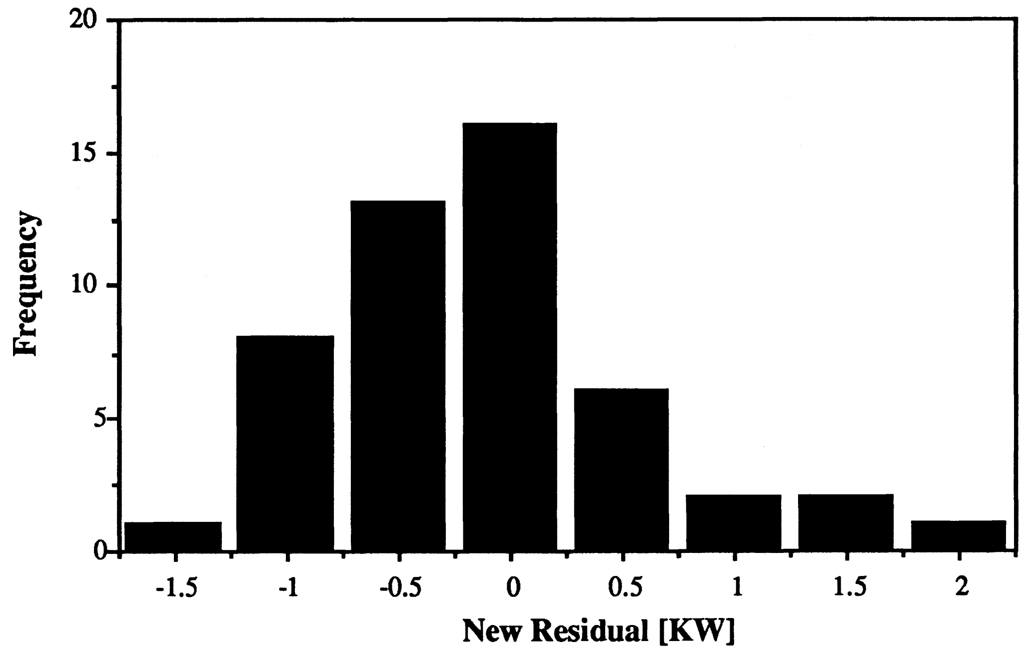


Figure 3.22 Frequency histogram of residuals for new formula

Because the assumptions needed for the validity of the t-distribution are only valid for the new formula, it should be used to determine predicted values. However, the old formula is still used to determine the near optimal control set points.

3.4.3 Transformation of Data

If methods A and C, described in section 3.3, are employed, the assumptions stated in section 3.4.1 have to be validated. In particular, the residuals should be normally and independently distributed with a constant variance. Section 3.4.2 discusses a way to obtain different residual plots which in the considered case validate the assumptions necessary for the t-distribution. However, in some cases even if the new formula is employed, the variance might still not be constant. At that point, a transformation of the data should be performed.

Transformation of data is a common way to stabilize the variance. It is necessary to find a data transformation Y = f(y) that has constant variance. The old observations, e.g. all values for the total system power, are transformed. A regression formula is then fit through the *new* data. The new observations are still a function of the controlled and uncontrolled variables in their original form. Residual plots for the new data should be created to check if the assumptions are valid with that transformation. After obtaining values from a new formula, these values can be transformed back to the original form, i.e. to powers in KW.

Different ways to find the right variance stabilizing transformation are discussed in statistical text books such as Box et al. [1979]. First, several transformations are tried. The methods then take information such as variance obtained for these transformation to determine the optimal possible transformation. The most common transformations which often stabilize the variance are Y = 1/y, Y = sqrt(y), Y = log(y), and Y = 1/sqrt(y).

The data points which are used to create the old regression formula can be used in a transformation. However, because the assumption of randomness is not valid for the old formula, as discussed before, the traditional ways to find a variance stabilizing transformation (e.g. Likelihood estimation of the transformation) can not be used.

Nevertheless, several transformations were tried in order to stabilize the variance. However, none of the transformations stabilized the variance significantly. Therefore, the new formula has to be used for the task of fault detection.

3.4.4 Further Adjustments

The better the formula predicts the actual measurements (i.e. simulation results), the smaller the threshold value is for residuals or for sets of residuals at which a fault is detected. The threshold value becomes higher if higher residuals for operation without error occur because no fault should be detected if no error occurs.

A way to improve the fit of the formula is to use more than one formula, i.e. several formulas fit to several parts of the data set. It was shown in section 2.5.1 that the power formula fits the data especially well in the medium range of the predicted value, i.e. at medium loads. The fit of the equation improves if the data is divided into two parts since the range of forcing functions is smaller for each of the two equations. The standard deviation for the two formulas was almost reduced by 50 %. Employing more than two formulas would improve the fit even more. However, to keep the procedure as simple as possible, only one equation is utilized in this thesis.

The results obtained from simulations do not contain any random noise, i.e. if the same set of forcing functions are input to the simulation twice, the exact same results occur. In an actual system, however, different results would be obtained due to measurement errors. Thus, if actual data is stored and regressed, the standard deviation will be higher than for simulated systems. The threshold value at which a fault can be detected will increase. Although the noise in the data will increase for real data, the method can still be applied.

3.5 LOCATING A FAULT IN THE SYSTEM

In section 3.3, a methodology for fault detection was described. Employing the method, a message from the supervisory computer could be used to indicate that a fault occurred. Besides knowing that a fault occurred in the system, it is also important that the fault is located. By immediately knowing the location of the fault, it can be repaired faster which will reduce the energy consumption.

3.5.1 Methodology for Locating a Fault

A methodology is presented that locates the detected faults in the system. The methodology follows closely the general methodology for fault detection described in section 3.3. Instead of creating a single power formula for the total system power, several formulas are developed, one for every power using component. Through the combination of fault messages for the single component powers, the fault can be located in the system. The procedure is described in the following section.

The component powers are determined from the simulation program similar to the measurements in an actual system. After collecting data under near optimal conditions without error, formulas are determined for each component power consumption. In the considered case, formulas for the air handling unit fan power, the chiller power, and the main water loop pump power, are determined using linear regression techniques. The powers necessary to operate the cooling tower fans and pump are not regressed because they are constant for all conditions.

The assumptions needed for the validity of the t-distribution have to be validated for every data set, i.e. the residual plots have to be checked for every component data set because significance tests are performed for every component power. For example, 50 random data points are used to obtain a regression equation for the total system power and the component powers under near optimal conditions. The residual plots for the single power consumption are checked for constant variance and normal distributed residuals, and are presented in Appendix E. All residual plots demonstrate a large improvement over the residual plots for the old formula, shown in Figures 3.15 and 3.19.

The tests described in section 3.3 for detecting faults are now used for every single component power. T-tests are performed and confidence intervals are checked for the component power residuals. The standard deviations necessary for the tests are taken from the regression output. The standard deviations are usually different for every component and for the total system power. Because only 50 values were included in the reference set, the degrees of freedom for the residuals are too low to assume a z-distribution. Thus the t-values, which are a function of the tail area and the degrees of freedom, are used. If the reference set is larger, a z-distribution can be assumed.

Faults may be indicated for every component. An error message from the supervisory controller could indicate a significantly higher power consumption, a significantly lower power consumption, or no significant difference between the measured and the predicted power. A flag may be used to signify a fault. If a significantly higher power consumption is detected, a value of unity is assigned to the fault indicator while a value of negative one is assigned if a significantly lower power consumption is detected. A fault indicator value of zero indicates that no significantly higher or lower power is consumed for that component.

Often, faults can be located earlier if not only the total system power but also the component powers are examined because significant power differences are often able to be detected earlier for a single component than for the total system. The total energy consumption can be reduced if the fault is repaired immediately.

Fault messages from the single component powers are combined to locate the fault. Specific faults cause significant power differences for several components, i.e. a specific fault causes an increase in some component powers while other component powers might be reduced or do not show a significant change. The influence of specific faults on the component power consumptions can be determined through the use of simulations or through experience. If a fault occurs, the significant changes in component powers are compared to the changes known for specific faults. If the actual component faults are equivalent to the component faults for a specific imperfection, then this fault may be the system fault. An example for a test of a fault is presented in Table 3.4 representing a positive error in the chilled water temperature sensor.

Table 3.3 Example for a statement that could be included in the supervisory controller in order to locate faults

If {[Fault (pump) = -1]
and [Fault (fan) = 0]
and [Fault (chiller) = 1]
and [Fault (system) = 1]}
Then
Positive error in the chilled water temperature

A positive error in the chilled water temperature, i.e. a lower chilled water temperature, reduces the efficiency of the chiller. Thus, the chiller requires more power. The supply air temperature remains at its optimal value. Therefore, no difference to the optimal behavior is indicated for the air handling unit fan power. Because the chilled water temperature is lower than for optimal conditions, the pump does not have to provide as much water flow rate to obtain the same supply air temperature as for the optimal control. Hence, the pump power requirement is lower than for optimal conditions.

Using the described method, faults can often be located. However, for a combination of faults, several locations are often possible. All of the possible faults have then to be checked. More knowledge about the error can be obtained if the magnitudes of the residuals are examined. Also, the spread of the residuals can be inspected by measuring the standard deviation or variance of the residuals. The variance can be compared to the variance obtained under conditions without error. Additional detectors should be developed to reduce the number of possible sources for a fault.

3.5.2 Examples

Throughout this thesis, errors in the sensors of the chilled water temperature and the supply air temperature are used as examples for locating faults. Figures 3.23 - 3. 26

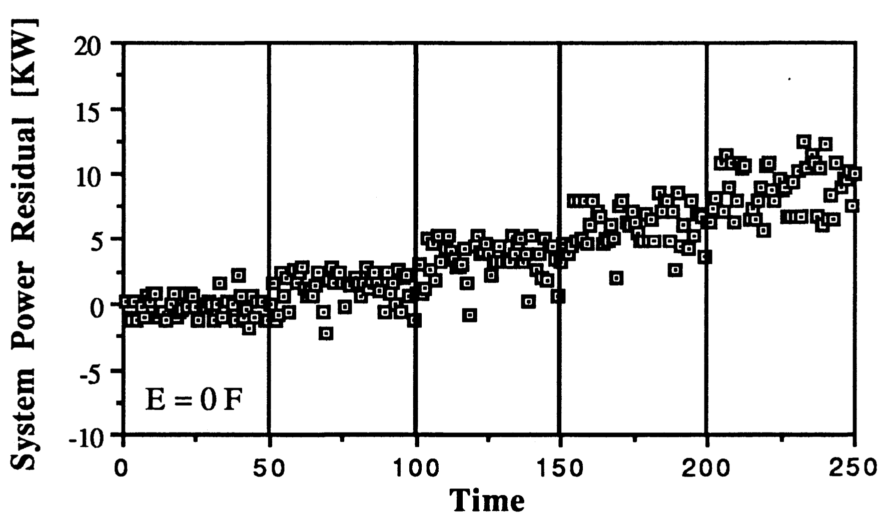


Figure 3.23 System power residuals for an increasing error in Tchw,set (same data points for every error)

show the residuals for total system power, chiller power, main water loop pump power, and air handling unit fan power, respectively, for an increasing error in the chilled water temperature. The 50 sets of forcing functions are the same for every

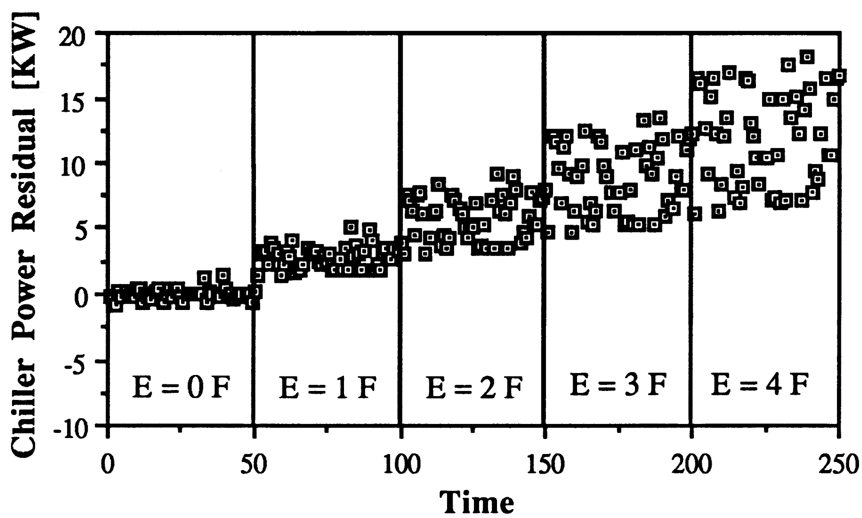


Figure 3.24 Chiller power residuals for an increasing error in Tchw,set (same data points for every error)

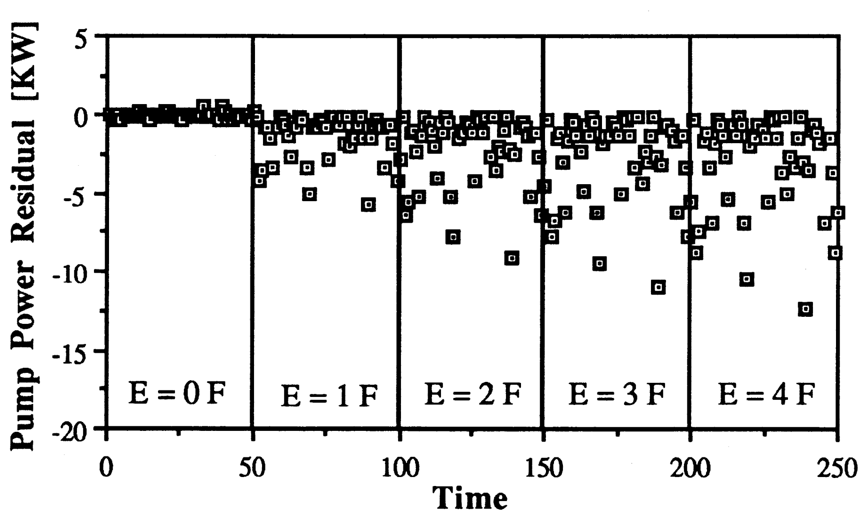


Figure 3.25 Main water loop pump power residuals for an increasing error in Tchw,set (same data points for every error)

error, i.e. the forcing functions employed at data points 1, 51, 101, 151, and 201, at data points 2, 52, 102, 152, and 202, etc. are the same.

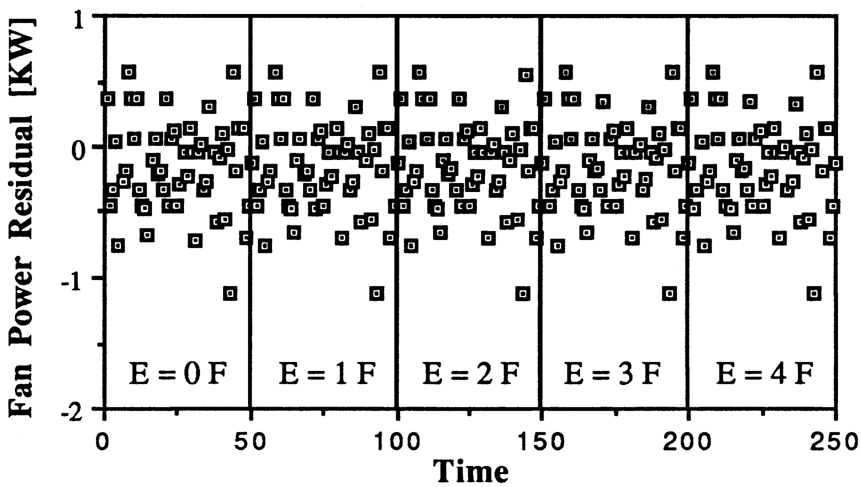


Figure 3.26 Air handling unit fan power residuals for an increasing error in Tchw,set (same data points for every error)

The range of chiller power and pump power residuals is much larger for high errors than for small errors. This is due to the higher sensitivity of the powers to changes in set temperatures at high loads, wet bulb temperatures, and sensible heat ratios. The range of residuals for the total power consumption does not change as much as the residuals for the component powers of chiller and pump because the component power for operating the pump decreases with increasing error while the chiller power increases. A high residual for the chiller power and a low residual for the pump power correspond to the same set of forcing functions. Thus, the range of residuals for the total system power is relatively small because the negative pump power residuals make up for a part of the positive chiller power residuals.

As stated earlier, the power requirements for the supply air fan does not change if an error in the chilled water temperature occurs. The residuals in Figure 3.26 are exactly the same for all errors. The fan power only depends on the temperature difference between the set point temperatures of supply air and zone.

In Figure 3.13, the cumulative sum of total system power residuals is shown for 1000 random sets of forcing functions, 250 sets for each case of no error and of errors in Tchw,set of 1 F, 2 F, and 3 F. It can be observed that even with changing forcing functions, as it is in an actual system, the difference in power consumption between operation with different errors can be clearly identified. In Figures 3.27 - 3.29, the corresponding cumulative sums of component power residuals for the sets of forcing functions are presented.

The curves representing the pump and chiller power, shown in Figures 3.27 - 3.28, are straight lines. As expected, the lines for the cumulative sum of pump power residuals have a negative slope while the lines for the cumulative sum of chiller power residuals have a positive slope. While the angle increase for lines of the cumulative sum from the chiller is approximately linear with the error, the angle increase for the lines representing the pump decreases with increasing error. This shows that the resistance due to friction in pipes, valves, and the evaporator increases with increasing flow rate but that this increase does not require linear increasing power.

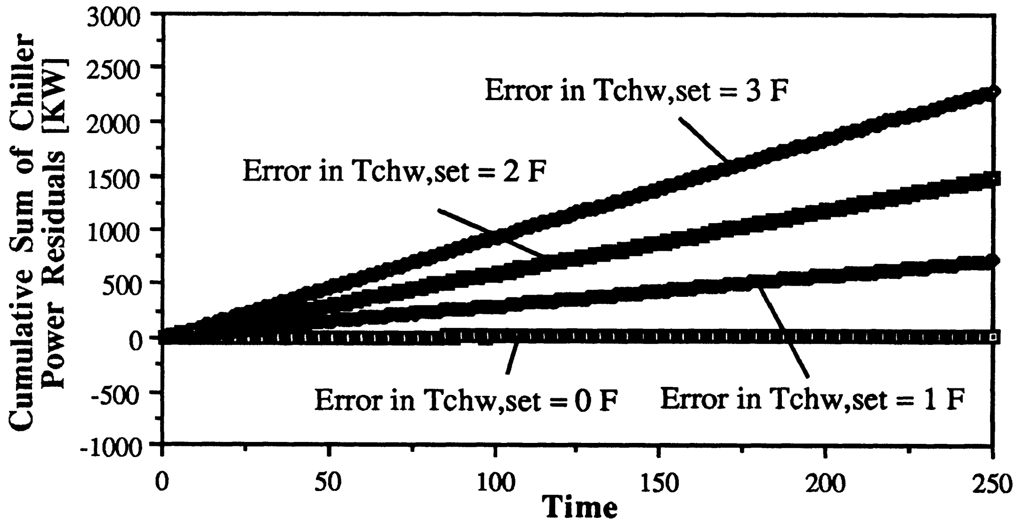


Figure 3.27 Cumulative sum of chiller power residuals for errors in Tchw,set

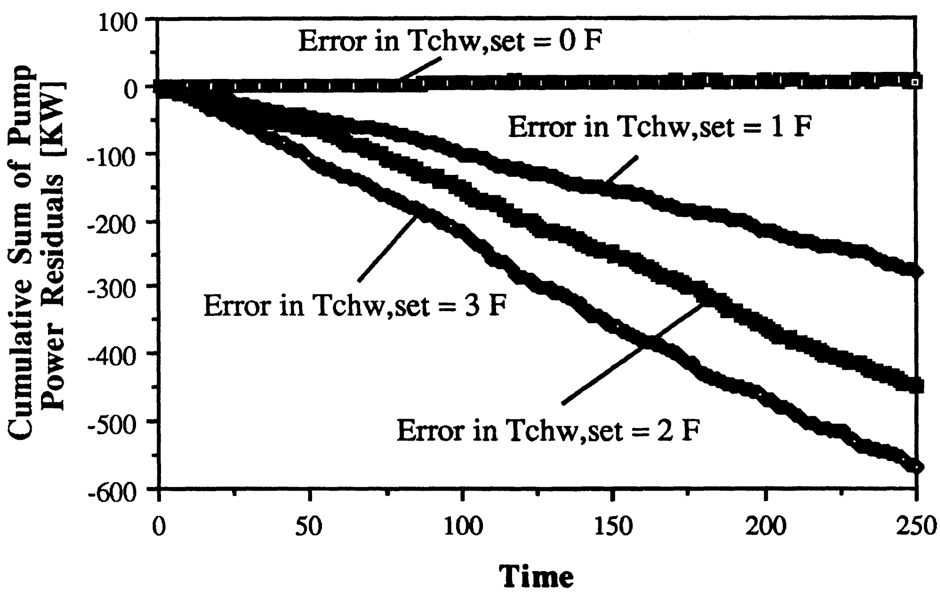


Figure 3.28 Cumulative sum of pump power residuals for errors in Tchw,set

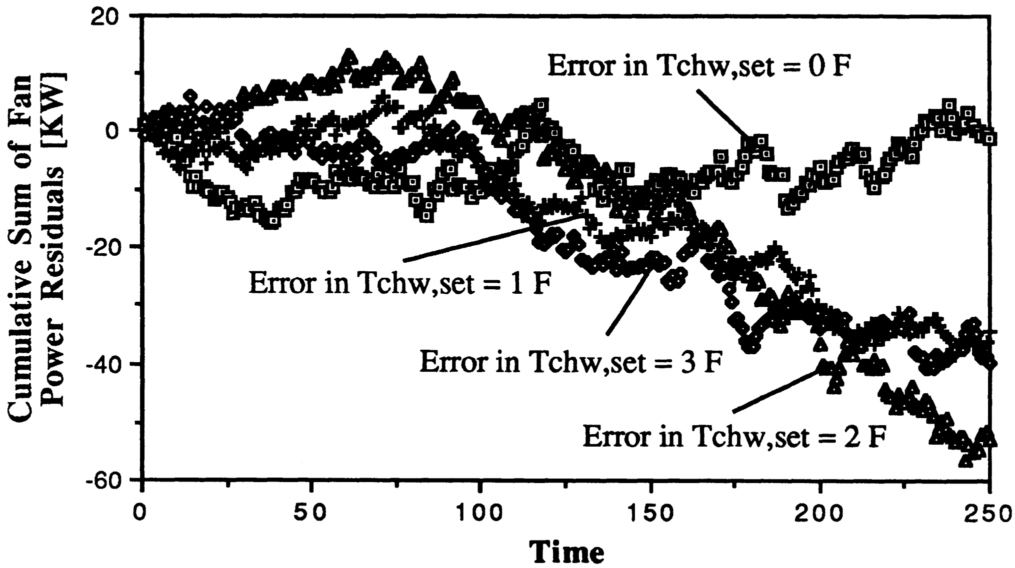


Figure 3.29 Cumulative sum of fan power residuals for errors in Tchw,set

In Figure 3.29, the cumulative sum of fan power residuals is illustrated. The curves representing different errors often cross each other. No significant difference in residuals can be found. The course of the curves depends on the data which is randomly selected. For some sets of forcing functions the residual is positive while for others, the residual is negative.

Tables 3.4 and 3.5 demonstrate how often component faults were indicated employing five and 30 data points in the t-test (method C) for different errors in Tchw,set. The same data points as in the Figures 3.23 - 3.26 are used. It generally can be seen that high errors are more often detected than small errors. While a small fault (error in Tchw,set = 1 F) is only indicated a few times for the total system power, the component powers for chiller and pump indicate errors at almost every time step. For high errors, the total system power indicates a system fault for almost all 50 time steps. As expected, no fault is ever indicated for the supply air fan power. When five data points were employed in the t-test, a fault in the chiller power is indicated once although no error is present. This might happen for special sequences of data because a confidence level of 99% is chosen. One can never be exactly certain that an indicated fault corresponds to a real fault. However, the more often a fault is indicated, the more certain one can be that a fault really occurred.

As a second example, an error in the supply air temperature is examined. Figures 3.30 - 3.33 demonstrate the dependence of the residuals in system power and component powers on errors in the supply air temperature. The spread of the residuals for increasing error increases rapidly. The influence on the residuals is different for different forcing functions. As discussed before, the power increases quickly for high loads and slowly for low loads if the error in Taoc,set increases. Hence, a spread of the residuals occurs.

An error in Taoc,set has the largest influence on the power requirements for the air handling unit fans. The fan power is a function of the air flow rate through the zones which itself is a function of the temperature difference between the supply air temperature and the zone temperature. Therefore, if a negative error in Taoc,set occurs, i.e. the supply air temperature increases, the flow rate and the fan power increase to provide the same zone temperatures (Figure 3.33).

Table 3.4 Number of data points at which fault is indicated using N = 5 data points in t-test for positive errors in Tchw,set (50 data points for every error)

Error in Tchw,set	Total System Power Fault = 1	Chiller Power Fault = 1	Pump Power Fault = 1	Supply Fan Power Fault = 1
Error = 0 F	0	1	0	0
Error = 1 F	3	47	49	0
Error = 2 F	29	50	50	0
Error = 3 F	47	50	50	0
Error = 4 F	50	50	50	0

Table 3.5 Number of data points at which fault is indicated using N = 30 data points in t-test for positive errors in Tchw,set (50 data points for every error)

Error in Tchw,set	Total System Power Fault = 1	Chiller Power Fault = 1	Pump Power Fault = 1	Supply Fan Power Fault = 1
Error = 0 F	0	0	0	0
Error = 1 F	10	44	48	0
Error = 2 F	45	50	50	0
Error = 3 F	50	50	50	0
Error = 4 F	50	50	50	0

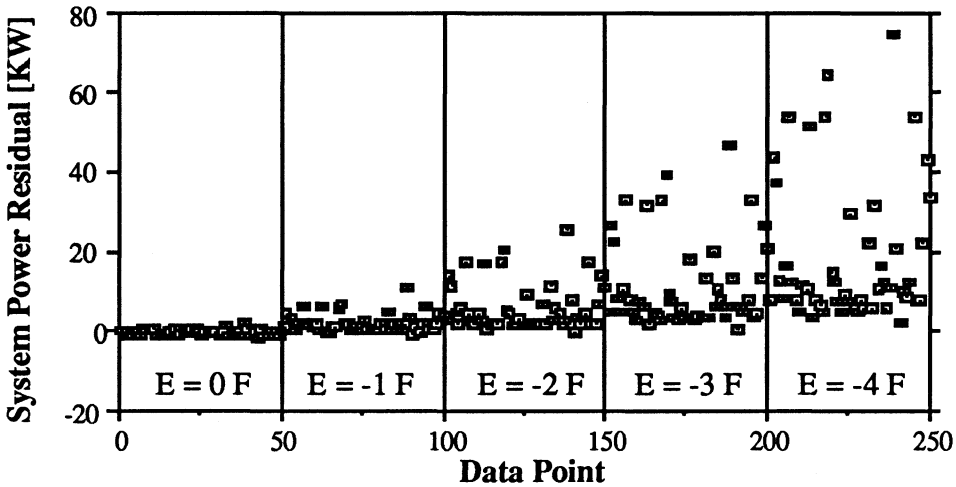


Figure 3.30 System power residuals for an increasing error in Taoc,set (same data points for every error)

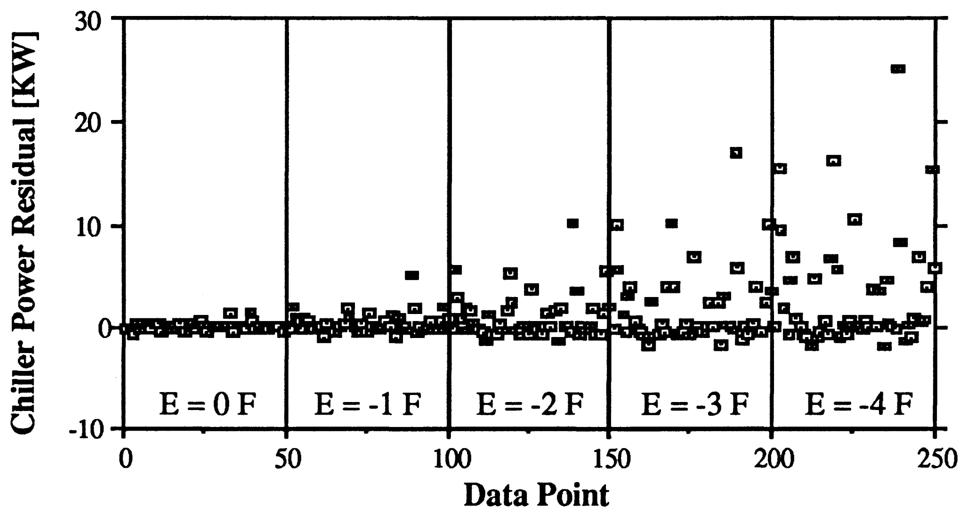


Figure 3.31 Chiller power residuals for an increasing error in Taoc,set (same data points for every error)

The chiller power, shown in Figure 3.31, and therefore the chiller power residuals also increase with increasing error in Taoc,set. An increase of the load on the chiller due to increases in fan and ventilation load are reasons for the increasing power consumption.

The band in which the residuals are located also becomes wider. For some sets of forcing functions the additional loads from fan and ventilation load are made up for by the decreasing pump power.

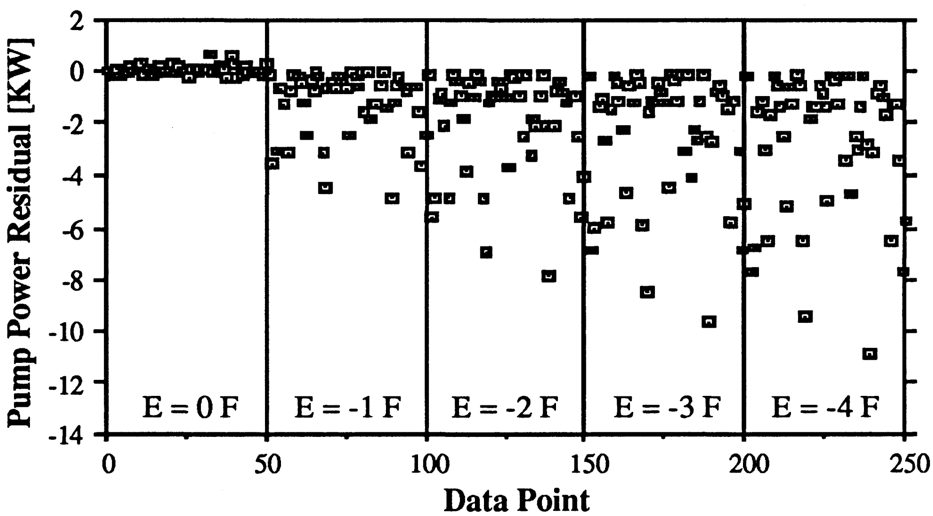


Figure 3.32 Main water loop pump power residuals for an increasing error in Taoc,set (same data points for every error)

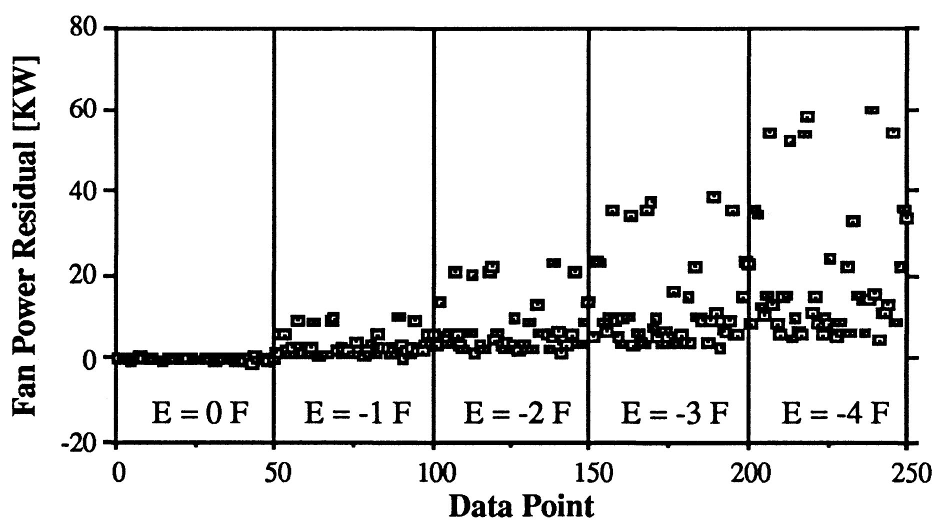


Figure 3.33 Air handling unit fan power residuals for an increasing error in Taoc,set (same data points for every error)

The pump power for errors in Taoc,set, shown in Figure 3.32, behaves similar to the pump power for errors in Tchw,set. Less water has to be provided for an increasing air outlet temperature. Again, the pump power decreases much more for high than for low loads and wet bulb temperatures.

A negative error in Taoc,set would therefore cause the following errors:

System power: Fault = 1

Chiller power: Fault = 1

Pump power: Fault = -1

Fan power : Fault = 1.

Table 3.6 demonstrates how often component faults were indicated employing five data points in the t-test (method B) for different negative errors in the supply air set point temperature. Faults in the pump and the fan component are indicated at almost every time step even for a small error in Taoc,set of 1 F. The increase in fan power has the main influence that faults are also indicated for the total system power. Faults in the chiller power are indicated the least because many of the residuals do not increase, as can be seen in Figure 3.31.

The described method for locating a fault in the HVAC system is an important part in the methodology for fault detection. Using the method, operators are able to locate and repair a fault quickly which can save energy and cost.

Table 3.6 Number of data points at which fault is indicated using N = 5 data points in t-test for negative errors in Taoc,set (50 data points for every error)

Error in Taoc,set	Total System Power Fault = 1	Chiller Power Fault = 1	Pump Power Fault = -1	Supply Fan Power Fault = 1
Error = 0 F	0	1	0	0
Error = -1 F	13	3	49	41
Error = -2 F	38	13	50	50
Error = -3 F	50	19	50	50
Error = -4 F	50	23	50	50

3.6 CHAPTER SUMMARY

In this chapter, a methodology for detecting faults in HVAC systems was proposed. It is based on the methodology for near optimal control discussed in section 2.5. A representative air conditioning system was simulated using the TRNSYS simulation program. Simulated faults in the system were detected by the fault detection techniques.

Errors in the chilled water temperature and the supply air temperature were used as examples for system faults. The influence of these faults on the total system power and the component powers was illustrated. Even small errors can have a significant impact on the system power specially at high loads, wet bulb temperatures, and sensible heat ratios.

A regression equation for the total system power and all component powers is fit through operational data representing near optimal operation conditions. The determination of the near optimal control variables is discussed in section 2.5. The new regression formulas are functions of the uncontrolled variables and the corresponding optimal control variables.

To detect faults, an instantaneous comparison is made between the measured (simulated) power during operation and the power predicted from the formula. Two graphical and two quantitative approaches to using this difference in power are described. Trends in performance are checked by monitoring the cumulative sum of power differences. A clear difference between operation without error, with small errors, and with large error could be observed. These differences can also be recognized in frequency histograms for the residuals.

The statistical significance of individual measurements are examined. Furthermore, sequences of data are examined by performing statistical tests. The tests check for a significant difference between a sequence during operation and sequences without fault. A fault can be detected earlier if only a few data points are included in the statistical tests. However, if more data are included in the tests, smaller errors can be detected. Thus, tests including different numbers of data should be performed simultaneously. Using the t-tests, even small errors could be detected.

By performing the tests for every component power, the fault can often be located in the system. The supervisory computer indicates if a component requires significantly more or less power compared to the optimal behavior. Through the combination of these messages for every component, possible sources of the fault can be determined. Several assumptions are necessary for doing the statistical analysis. These assumptions have to be checked by creating residual plots. The assumptions of constant variance and normal distributed residuals are often critical. If these assumptions are not valid for any of the new formulas, a transformation of the data should be performed.

The developed method is able to detect all faults which have a significant impact on the system power or any component power. More with respect to the power consumption serious faults are easiest to detect. Small errors require more time to be detected. The proposed methodology offers a simple way to detect faults which can result in large energy savings.

Chapter 4

CONCLUSIONS AND RECOMMENDATIONS

In this chapter, the significant conclusions of this work are presented. The methodology for fault detection is summarized and recommendations are made for future work.

4.1 CONCLUSIONS

The main goal of this thesis was to develop a methodology for fault detection. The proposed methodology is based on a methodology for optimal control of the HVAC system. All faults which cause a power consumption significantly higher than the power required under optimal operation are detected. In order to demonstrate the procedures for optimal control and fault detection, a simple but representative air conditioning system was simulated with TRNSYS. In this system, the chilled water temperature and the supply air temperature were the only controlled variables.

To develop optimal control laws for the system, outputs from the energy management and control system are employed. A regression equation for the total system power in terms of the forcing functions and the control variables is fit through the operational (simulated) data collected under different values of the controlled and uncontrolled variables. The equation can be any real value function of the uncontrolled variables while it should be quadratic with the control variables.

The Jacobian of the equation with respect to the control variables is equated to zero. The resulting set of equations determine the optimal values of the controlled variables. These equations represent near optimal control at all times. The formula and the optimal control laws may be updated as new data becomes available.

Comparisons were made between the formula and the measured (simulated) system powers. A quadratic formula of both the controlled and uncontrolled variables usually fits the data well. The near optimal control variables which characterize the minimum power for the formula are always very close to the real optimal control variables which minimize the total power. Sometimes, the difference between the set point temperatures obtained with near optimal control occurred to be slightly larger than the real optimal temperature difference. However, the resulting difference in power for optimal and near optimal control is negligible. The difference in absolute values of the power for near optimal and optimal control, which is used for fault detection, might be significant.

To detect faults, an instantaneous comparison is made between the measured (simulated) system power and the power predicted from the formula. Various approaches to using this power residual are described. The statistical significance of individual residuals is examined. Furthermore, sequences of data are inspected. Statistical analyses check for a significant difference between these sequences and sequences without error.

There is a tradeoff between the quickness of detecting a fault and the level at which a fault can be detected. The larger the number of data points included in the significance test, the smaller the errors that can be detected. However, if only a few data points are employed in the test, faults can be detected earlier. Thus, tests with different numbers of data should be performed simultaneously.

Two other qualitative checks for system faults using the power residuals were discussed. The cumulative sum of power differences might indicate an imperfection in the system. If no fault is present in the system, the slope of a line, fit through the points which represent the cumulative sum of residuals, is close to zero. For non-optimal operation, the slope will be different than zero. Furthermore, frequency residual histograms for operational data can be created and be compared to histograms representing data without error.

Several assumptions are necessary in order to perform the statistical significance tests. The validity of these assumptions has to be checked. If the assumptions are found to be not valid, transformations of the data should be attempted. The assumptions were found to be not valid for the data set which included data away from the optimum. Furthermore, no transformation was found which would validate the assumptions.

Regression formulas were fit through operational data collected under near optimal conditions. The fit of the function improves significantly compared to the fit through data which employed a wide range of control variables. This permits small errors to be detected. In addition, the assumptions needed for statistical analyses are usually valid. Regression equations for the component powers were also fit through operational data. Checks for faults were made for the total system and for every component. Significantly lower or higher power consumptions compared to powers obtained under optimal operation are indicated. Often, faults are detected earlier for a component than for the total system. Through the combination of fault messages for every component, the fault can often be located.

The described methodology detects all faults which cause an increase in power consumption for the total system or any component. Quick repair of the faults can make a significant contribution to energy savings in HVAC systems.

4.2 METHODOLOGY SUMMARY FOR FAULT DETECTION

In this section, the methodology for fault detection is summarized.

1) Measurements of the controlled and uncontrolled variables and the total system power are taken while running the system as close as possible to the optimum.
2) After gathering data over a broad range of conditions, fit a regression equation for the total system power, which is quadratic with the controlled variables, through the data.
3) Develop near optimal control laws for the control variables as a function of the

forcing functions. Implement these control laws in the supervisory controller.

4) Run the system under near optimal conditions and store the data.

5) Repeat steps 1 - 4 until no improvement in control is made anymore.

6) Fit regression equations for the total system power and the component powers through near optimal data.

7) While running the system, check for faults by simultaneously

    - performing t-tests with different amounts of data
    - checking if data is inside the confidence interval
    - checking the slope of the cumulative power difference
    - checking the distribution of the residual histograms

8) a) If no faults are detected, regression formulas can be improved and updated with new data (old data that is far away from the optimum can be taken out)

   b) If a fault is detected, use a combination of component error messages to determine the location of the fault.

4.3 RECOMMENDATIONS FOR FUTURE WORK

The significant recommendations for future work in the area of optimal control and fault detection in HVAC systems are listed in this section. In the area of optimal or near optimal control, the recommendations are as follows:

1. Include one or several zone models in the simulation so that the forcing functions correspond to weather cycles. Let the load be different for different zones. Include reheat coils in the simulation.

2. Include an economizer cycle in the simulation so that the fraction of outdoor air may vary for different ambient conditions.
3. Examine the influence of system dynamics on the optimal control of the system.
4. Develop a TRNSYS model for the methodology of near optimal control. The user should be able to set the time before a first formula is regressed through the stored data. After differentiation, the optimal control laws can be automatically used (self-optimizing control).
5. Employ the discussed methodology for near optimal control to a real building.

Following recommendations can be made for future work in the area of fault detection:

1. Examine the possibility of using energy balances around components or sets of components for the task of fault detection.
2. Examine how changes in the regression formulas indicate system faults. Compute a predicted power with different formulas. Check for significant difference.
3. The methods for detecting faults by using the cumulative difference and the frequency histograms were used as a qualitative check in this thesis. Quantitative methods for these ideas should be developed so that it can be implemented on a computer or supervisory controller.
4. Examine the possibility of using the change in variance of a sequence of data for detecting faults. Possibly, random errors can be recognized.
5. Examine the effect of measurement errors on the methods for fault detection. If measurement errors occur, the standard deviation of the residuals for the sequence increases. However, small measurement errors (accuracy of the

measurement devices) should be allowed. No fault should be detected for these small errors.

6. Examine if time series models can be used to detect trends in the performance.
7. Examine the dynamics of the system for the task of fault detection.
8. Develop an expert system which can be employed for locating faults. Specific system faults have to be related to every possible combination of component fault messages, similar to Table 3.3.
9. Employ the discussed methodology for fault detection to a real building.

Appendix A

TRNSYS SIMULATION DECK

```
*****************************************************************************************
* CONFIGURATION ***********************************************************************
*****************************************************************************************

NOLIST
MAP
SIMULATION 1 10000 1
WIDTH 72
TOLERANCES .0001 .0001
LIMITS 40 5000

*****************************************************************************************
UNIT 1 TYPE 9 DATA READER (WET-BULB TEMPERATURE GENERATOR)
*****************************************************************************************
PARAMETERS 19
* Ndata  Tint  TWB  m   a   TDB  m   a    Q       m    a
*  (#)   (hr)  (F)  (X) (+) (F)  (X) (+) (Btu/hr) (x)  (+)
   6     1     -2   1   0   -3   1   0   -4       1    0

*  SHR    m   a  ERROR  m   a  LU   FRMT
*(x100%) (x) (+)  (F)   (x)  + (#)  (>0)
   -5     1   0   -6     1   0  21    1
(F5.0,2X,F5.1,2X,F5.1,2X,E8.3,2X,F4.2,F10.4)

*****************************************************************************************
UNIT 2  TYPE 75   SYSTEM CONTROLLER ***************************************************
*****************************************************************************************
PARAMETERS 9
* UNITS      TRSET    FOA       MAO,min     MACoil,max
* (2=Eng)     (F)    (0<#<1)    (lbm/hr)    (lbm/hr)
    2         75       .1        8.00E3      1.60E5
```

```
* MwCoil,max      Cp,evap        NCoils      MACoil,min
*  (lbm/hr)       (Btu/lbm F)     (#)         (lbm/hr)
  1.05E5            1.00          6            1.60E4

INPUTS 19
* TWB   TDB   Qload,bld   SHR     TAOCoil   MAOCoil   WOCoil
* (F)   (F)   (Btu/hr)  (0<#<1)    (F)       (lbm/hr)   (#)
  1,2   1,3     1,4       1,5      7,1        7,3       7,4

* TWOCoil      QCoilFan        QMWLPump      MWEvap
* (F)          (Btu/hr)        (btu/hr)      (lbm/hr)
  7,4             8,3             6,3           6,2

* Qcoil,tot  MWCoil   PCCFAN  ERROR PCHILLER  PMWLPUMP  PTFAN  PTPUMP
* (btu/hr)  (lbm/hr)   (KW)    (F)     (KW)      (KW)     (KW)    (KW)
    7,6        7,5      13,1    1,6     5,6       12,1     10,1    4,3

* INITIAL VALUES FOR INPUTS
  70.0    90.0     0.0    0.8    75.0    0.0    0.0085    50.0
  0.0   0.0   0.0   0.0   0.0  0.0   0.0   0.0  0.0    0.0    0.0

**********************************************************************************
UNIT 3 TYPE 51 COOLING TOWER ****************************************************
**********************************************************************************
PARAMETERS 11
* NOTE: Enter 12 parameters for mode 2, 11 parameters for mode 1.
* Units      Mode       Geom      Ncell  Va,cell,max  Pcell,max
* (2=Eng)  (2=Data)  (2=XFlow)   (#)     (ft3/hr)     (KW)
   2           1          2        2      3.726E6      11.19

* Va,off    Vs      Ti,sump   LU/c    Ndata/n    Print
* (ft3/hr)  (ft3)    (F)       (#)      (#)     (1=Print)
 5.589E5   0.0      85.0     3.767   -1.210        1

INPUTS 7
* Twi      Mw,i      Ta,i     Tewb     Tmain   g1      g2
* (F)     (lbm/hr)   (F)       (F)      (F)  (-1;0,1) (-1;0,1)
  5,3       5,4      1,3       1,2      0,0    2,4     2,5
  95.0    7.57E5   100.0     77.0     60.0    1.0     1.0

**********************************************************************************
UNIT 4 TYPE 3 PUMP (TOWER TO CHILLER; includes motor efficiency=.91) *****************
**********************************************************************************
PARAMETERS 2
* Mmax      Pmax
* (lbm/hr)  (KW)
 7.57E5     23.4
INPUTS 3
* Ti        Mi          g
* (F)       (lbm/hr)   (0,1)
```

```
 0,0        3,2       2,1
 85.0       7.57E5    1.0
* NOTE:  The control signal issued from the controller must be unity
*      for this pump (constant speed pump).

*************************************************************************************
UNIT 6 TYPE 3 PUMP (AIR HANDLER TO CHILLER) ***********************************
*************************************************************************************
PARAMETERS 6
* Mmax        Pmax       C0        C1       C2       C3
* (lbm/hr)    (KW)       (const)   (x)      (x2)     (x3)
 6.31E5       16.9       0.0       0.0      0.0      1.0
INPUTS 3
* Ti          Mi         g
* (F)         (lbm/hr)   (0,1)
 0,0          14,1       2,2
 60.0         6.31E5     1.0

*************************************************************************************
UNIT 5 TYPE 53 PARALLEL CHILLERS *********************************************
*************************************************************************************
PARAMETERS 12
* Units       Nmot       Qmax       Qmin       LU       Ndata
* (2=Eng)     (0,1)      (Btu/hr)   (Btu/hr)   (#)      (#)
   2          .95        8.80E6     0.0        23       50

* Qdes        DTdes      Pdes       Cp,cw         Cp,ew         Print
* (Btu/hr)    (F)        (KW)       (Btu/lbmF)    (Btu/lbmF)    (1=Print)
 6.72E6       50.0       353        .998          1.00          2

INPUTS 6
* Tchw,s      Tev,i      Mev        Tc,i      Mc          Nch
*  (F)        (F)        (lbm/hr)   (F)       (lbm/hr)    (#)
 2,6          2,10       6,2        3,1       4,2         2,7
 40.0         45.0       6.31E5     85.0      7.57E5      1.0
* NOTE:  The constants for the empirical equation used in this model
*      must be input into the fortran source code.

*************************************************************************************
UNIT 15  TYPE 65  FLOW CONVERTER II (Mode: Chiller==>AHU) **********************
*************************************************************************************
PARAMETERS 2
* MODE        NAHUS
* (1,2)       (#)
   1          6
INPUTS 1
* MI
* (lbm/hr)
 5,2
 6.31E5
```

```
*************************************************************************************
UNIT 8 TYPE 3 FAN (AIR HANDLING UNIT) ***********************************************
*************************************************************************************
PARAMETERS 6
* Mmax      Pstar    C0       C1    C2    C3
* (lbm/hr)  (KW)     (const)  (x)   (x2)  (x3)
  1.60E5    21.3     .0826    0.0   0.0   1.051

INPUTS 3
* Ti    Mi        g
* (F)   (lbm/hr)  (0,1)
  0,0   7,3       2,3
  75.0  1.60E5    1.0

*************************************************************************************
UNIT 7 TYPE 52 COOLING COIL (AIR HANDLING UNIT) *************************************
*************************************************************************************
PARAMETERS 20
* Mode         Units     Nrows   Ntubes   Ltube   Hduct
* (2=Detail)  (2=Eng)    (#)     (#)      (ft)    (ft)
  2            2         4       52       10.5    6.15

* Do      Di       Ktube        Fthick   Fspace   Nfin
* (ft)    (ft)     (Btu/hrftF)  (ft)     (ft)     (#/tube/pass)
  .0521   .04625   231.7        .00109   .00595   1764

* Kfin         FinMode       Dfin   Wcl,rows   MWC_max    DTdes   Re,laminar   F_full_circuit
* (Btu/hrftF)  (2=Annular)   (ft)   (ft)       (lbm/hr)   (F)     (#)          (.25,.5,1.0)
  136.9        2             .104   .139       1.05E5     10      1000.0       1.0

INPUTS 6
* Tidbc   Wic            Ma        Tw,i   Mw        TAOC_set
* (F)     (lbm,w/lbm,a)  (lbm/hr)  (F)    (lbm/hr)  (F)
  2,8     2,9            8,2       5,1    15,1      2,11
  80.0    .01003         1.60E5    40.0   1.05E5    50.

*************************************************************************************
UNIT 14  TYPE 65  FLOW CONVERTER (AIR HANDLING UNIT==>CHILLER) *************
*************************************************************************************
PARAMETERS 2
* MODE   NAHUS
* (1,2)  (#)
  2      6

INPUTS 1
* MI
* (lbm/hr)
  7,5
  1.05E5
```

```
**************************************************************************************
UNIT 10  TYPE 60   ELECTRIC MOTOR (TOWER FAN; VSD) ***************************
**************************************************************************************
PARAMETERS 6
* MODE            PShaft,rated     ServiceFactor    C1        C2        C3
* (2=3Constants)    (kW)            (0<#<1)        (const)    (x^2)     (const)
  2                 22.4              1.15         70.0      180.0      1.38
INPUTS 1
* PShaft
* (kW)
 3,3
 0.0

**************************************************************************************
UNIT 12  TYPE 60   ELECTRIC MOTOR (MAIN WATER LOOP PUMP; VSD) ***************
**************************************************************************************
PARAMETERS 6
* MODE            PShaft,rated     ServiceFactor    C1        C2        C3
* (2=3Constants)    (kW)            (0<#<1)        (const)    (x^2)     (const)
      2             18.7              1.15         70.0      180.0      1.38
INPUTS 1
* PShaft
* (kW)
 6,3
 0.0
**************************************************************************************
UNIT 13  TYPE 60   ELECTRIC MOTOR (COIL FAN; CSD) *****************************
**************************************************************************************
PARAMETERS 6
* MODE            PShaft,rated     ServiceFactor    C1        C2        C3
* (2=3Constants)    (kW)            (0<#<1)        (const)    (x^2)     (const)
  2                 22.4              1.15         20.0      300.0      1.125
INPUTS 1
* PShaft
* (kW)
 8,3
 0.0

**************************************************************************************
UNIT 44 TYPE 25 PRINTER (INPUT AND SUMPOWER) ********************************
**************************************************************************************
PARAMETERS 4
* Interval     Time,start     Time.stop     Output_Unit
*  (hr)          (hr)           (hr)           (#)
   1             1.0          10000.0          15
INPUTS 9
1,2    1,4   1,5     2,6       2,11      2,18       2,16       2,17    1,6
TWB LOAD SHR TCHWSET TAOCSET SUMPOW  PFORMULA   PDIFF  ERROR
**************************************************************************************
END
```

Appendix B

TRNSYS COMPONENTS

1) SUPERVISORY CONTROLLER

```
C************************************************************************************
C  THIS ROUTINE MODELS THE MAIN CONTROLLER FOR A HVAC SYSTEM. THE
C  SYSTEM INCLUDES VARIABLE SPEED MAIN WATER LOOP PUMP AND VARIABLE
C  SPEED FANS IN THE AIR HANDLING UNITS (VAV-SYSTEM).  IT IS USED TOGETHER
C  WITH ANOTHER CONTROLLER CONNECTED TO THE COOLING COIL ROUTINE.
C  THE COIL ROUTINE PROVIDES THE RIGHT COIL MASS FLOW RATE TO MEET THE
C  COIL AIR OUTLET TEMPERATURE.  IN THIS ROUTINE, THE STATUS OF THE POWER
C  DEVICES IS SET TO MEET THE SET POINT TEMPERATURES (CHILLED WATER
C  TEMPERATURE AND SUPPLY AIR TEMPERATURE)  (FLORIAN PAPE 4'89)
C************************************************************************************

      SUBROUTINE TYPE75(TIME,XIN,OUT,T,DTDT,PAR,INFO)
      DIMENSION XIN(19),OUT(14),PAR(9),INFO(10)
      CHARACTER*4 MODE
      INTEGER ROUND,UNITS
      REAL MAOMIN,MACMAX,MWCMAX,MAC,MWC,MWEVAPMAX,MWEVAP,MACMIN,L
      COMMON /SIM/ TIME0,TFINAL,DELT
      PARAMETER (WROOMS=.01,TOL=.0001)

C*** NOMENCLATURE ************************************************************
C  CPW           = SPECIFIC HEAT OF WATER
C  CPA           = SPECIFIC HEAT OF AIR
C  DIFF          = DIFFERENCE BETWEEN POWER FROM SIMULATION AND FORMULA
C  ERROR         = ERROR INTRODUCED IN THE SYSTEM
C  FAO           = FRACTION OF OUTDOOR AIR USED IN RETURN AIR
```

```
C  F1G        = SUPPLY FAN CONTROL VARIABLE
C  F2G, F3G   = COOLING TOWER FAN CONTROL VARIABLES
C  HFG        = HEAT OF VOPORIZATION FOR WATER
C  MACMIN     = MINIMUM AIR MASS FLOW RATE THROUGH COOLING COL
C  MAC        = AIR MASS FLOW RATE THROUGH THE COIL
C  MACMAX     = MAXIMUM AIR MASS FLOW RATE PROVIDED BY FAN
C  MWC        = WATER MASS FLOW RATE THROUGH EVERY COIL
C  MWEVAP     = TOTAL WATER MASS FLOW RATE THROUGH EVAPORATOR
C  MAOMIN     = MINIMUM OUTSIDE VENTILATION AIR MASS FLOW RATE
C  MWCMAX     = MAXIMUM WATER MASS FLOW RATE THROUGH EACH COIL
C  NCOILS     = NUMBER OF COOLING COILS
C  NCH        = NUMBER OF OPERATING CHILLERS
C  PFORMULA   = POWER PREDICTED FROM THE FORMULA
C  P1G        = COOLING TOWER LOOP PUMP CONTROL VARIABLE
C  P2G        = MAIN WATER LOOP PUMP CONTROL VARIABLE
C  QCCFAN     = LOAD INTRODUCED BY FAN (=POWER)
C  QMWLPUMP   = LOAD INTRODUCED BY MAIN WATER LOOP PUMP (=POWER)
C  QCHILLER   = LOAD MEET BY THE CHILLER
C  QCHILLMAX  = MAXIMUM LOAD WHICH CON BE MEET BY CHILLER
C  QCOIL      = LOAD ON COOLING COIL
C  Q          = BUILDING LAOD
C  SHR        = SENSIBLE HEAT RATIO (QSENS/QTOT)
C  SUMPOWER   = TOTAL POWER NECESSARY TO OPERATE THE SYSTEM
C  TRSET      = ROOM SET POINT TEMPERATURE
C  TSI        = TEMPERATURE IN SI-UNITS
C  TABS       = ABSOLUTE TEMPERATURE
C  TAIC       = COOLING COIL AIR INLET TEMPERATURE
C  TAOCSET    = COOLING COIL AIR OUTLET SET POINT TEMPERATURE
C  TAOC       = COOLING COIL AIR OUTLET TEMPERATURE
C  TENG       = TEMPERATURE IN ENGLISH UNITS
C  TWOC       = WATER COIL OUTLET TEMPERATURE
C  TCHWSET    = CHILLED WATER SET POINT TEMPERATURE
C  TWB        = OUTDOOR WETBULB TEMPERATURE
C  TDB        = OUTDOOR DRYBULB TEMPERATURE
C  WAMB       = AMBIENT HUMIDITY
C  WIC        = HUMIDITY OF AIR IN FRONT OF THE COIL
C  WOC        = HUMIDITY OF AIR BEHIND THE COIL
C  WROOMS     = STARTING HUMIDITY IN ROOMS FOR ITERATION

C*** STATEMENT FUNCTIONS ****************************************************
   ROUND(RNUM)=NINT(RNUM)
   TSI(TEMP,UNITS)=(TEMP-32)/1.8*(UNITS-1)+TEMP*(2-UNITS)
   TENG(TEMP,UNITS)=(1.8*TEMP+32)*(2-UNITS)+TEMP*(UNITS-1)
   TABS(UNITS)=459.67*(UNITS-1)+273.15*(2-UNITS)
   HFG(UNITS)=1050.*((UNITS-1)+(2-UNITS)/.42995)
   CPA(UNITS)=.244*((UNITS-1)+(2-UNITS)/.23886)
   QCHILLMAX(UNITS)=560.0*((UNITS-1)*12000.+(2-UNITS)*12000./.94787)

C*** FIRST CALL OF THE SIMULATION ****************************************************
   IF(INFO(7).EQ.-1)THEN
```

```
      NI=19
      NP=9
      ND=0
      INFO(6)=11
      INFO(9)=1
      CALL TYPECK(1,INFO,NI,NP,ND)
      MODE='OFF'
      K=K+1
      WRITE(*,*) K
     ENDIF

     IF(IUNIT .EQ. INFO(1))GO TO 100
     IUNIT=INFO(1)

C*** SET PARAMETERS **************************************************************
     UNITS      =ROUND(PAR(1))
     TRSET      =PAR(2)
     FAO        =PAR(3)
     MAOMIN     =PAR(4)
     MACMAX     =PAR(5)
     MWCMAX     =PAR(6)
     CPW        =PAR(7)
     NCOILS     =ROUND(PAR(8))
     MACMIN     =PAR(9)

C*** SET CONSTANTS (FOR EVALUATION OF HUMIDITY) ***************************
     C8=-5800.2206
     C9=1.3914993
     C10=-.04860239
     C11=.41764768E-4
     C12=-.14452093E-7
     C13=6.5459673

C*** EFFECT CALCULATIONS ***********************************************************
100  TWB        =XIN(1)
     TDB        =XIN(2)
     Q          =XIN(3)
     SHR        =XIN(4)
     TAOC       =XIN(5)
     MAC        =XIN(6)
     WOC        =XIN(7)
     TWOC       =XIN(8)
     QCCFAN     =XIN(9)*3413.0
     QMWLPUMP   =XIN(10)*3413.0
     MWEVAP     =XIN(11)
     QCOIL      =XIN(12)
     MWC        =XIN(13)
     PCCFAN     =XIN(14)
     ERROR      =XIN(15)
     PCHILLER   =XIN(16)
```

```
      PMWPUMP   =XIN(17)
      PTFAN     =XIN(18)
      PTPUMP    =XIN(19)

C ******* TOTAL SYSTEM POWER FROM COMPONENT POWERS *********************
      SUMPOW=PCHILLER+PMWPUMP+PTFAN+PTPUMP+6*PCCFAN

      IF ((INFO(7).EQ.0).OR.(INFO(7).EQ.-1)) THEN
C ****** EVALUATION OF NEAR OPTIMAL CONTROLLED VARIABLES *****************
       L=Q/12000.
       TAOCSET=(1./(3.34224/2./1.86808-1.89675*2./3.34224))*((1./2./
     +    1.86808*(-41.141+0.172373*TWB+0.080169*L+17.6379*SHR))+
     +    1./3.34224*(-30.689-0.107878*TWB-0.033831*L+0.5504*SHR))

       TCHWSET=1./2./1.86808*(41.141-0.172373*TWB-0.080169*L
     +        -17.6379*SHR+3.34224*TAOCSET)

C ****************** CONSTRAINTS ON TCHW,SET ********************************
        IF (TCHWSET.LT.38.) THEN
           TCHWSET=38.
           TAOCSET=1./1.89675/2.*(30.689+0.107878*TWB+0.033831*L
     +     -0.5504*SHR+3.34224*TCHWSET)
        ELSEIF (TCW.GT.55.) THEN
           TCHWSET=55.
           TAOCSET=1./1.89675/2.*(30.689+0.107878*TWB+0.033831*L
     +          -0.5504*SHR+3.34224*TCHWSET)
        END IF

C ******* REGRESSION FORMULA PREDICTING THE TOTAL SYSTEM POWER *********
       PFORMULA=3542.62-14.4488*TWB-1726.65*SHR-41.141*TCHWSET-30.689
     + *TAOCSET-5.73989*L+0.05808*TWB*TWB+0.00328938*L*L+173.41*SHR*SHR
     + +1.86808*TCHWSET^2+1.89675*TAOCSET^2+0.0221688*TWB*L+3.8827
     + *TWB*SHR+0.172373*TWB*TCHWSET-0.107878*TWB*TAOCSET+1.91033*L*SHR
     + +0.080169*L*TCHWSET-0.033831*L*TAOCSET+17.6379*SHR*TCHWSET+0.5504*SHR
     + *TAOCSET-3.34224*TCHWSET*TAOCSET

C **************** INTRODUCTION OF AN ERROR **********************************
        TCHWSET=TCHWSET-ERROR

      END IF

C **************** DIFFERENCE BETWEEN SIMULATION AND FORMULA *************
      DIFF=SUMPOW-PFORMULA

      OPEN (55,FILE='HUM.DAT')
      I=I+1
      IF (INFO(7).EQ.0) THEN
         WRITE(*,110)I
110      FORMAT(I4)
```

```
C *************** CHECK OF HUMIDITY LEVEL FROM TIMESTEP BEFORE ************
        IF (WROOM.GT.0.012) THEN
             WRITE(55,*)'HUMIDITY TOO HIGH BEFORE TWB,Q,SHR,TCHW,TAC',
     +           TWB,Q,SHR,TCHWSET,TAOCSET
        ENDIF
        J=J+1
     ENDIF

C*** NO LOAD *********************************************************************
     IF(Q.EQ.0) THEN
       MODE='OFF'
     ELSE IF ((Q.GT.0).AND.(MAC.LT. .1 .OR. MWC.LT. .1
     +         .OR. MWEVAP.LT. .1)) THEN
C*** START DEVICES FOR A LOAD NOT EQUAL TO ZERO ****************************
       MODE='ON'
       P2G  =.1
       F1G  =.1
       P1G  =1.0
       F2G  =1.0
       F3G  =1.0
       NCH  =1
       TAIC =TRSET
       WIC  =WROOM
       TWIEV =TWOC

     ELSE IF ((Q.GT.0).AND.(MAC.GE. .1 .OR. MWC.GE. .1)) THEN
C*** RUNNING MODE **************************************************************
C*** TOWER PUMP AND TOWER FANS ARE RUNNING WITH CONSTANT SPEED *******
       MODE='ON'

        P1G =1.0
        P2G =MWC/MWCMAX
        F2G =1.0
        F3G =1.0
        NCH =1

C*********************************************************************************
C*** EVALUATION OF FAN SPEED NECESSARY TO MEET THE LOAD ******************
        QSENS=SHR*Q+QCCFAN*NCOILS
       MAC=MAX(QSENS/NCOILS/(CPA(UNITS)*(TROOM-TAOC)),MACMIN)
       MACSET=MAX(QSENS/NCOILS/(CPA(UNITS)*(TROOM-TAOCSET)),MACMIN)
        F1G=MAC/MACMAX
       TWIEV=TWOC+QMWLPUMP/(MWEVAP*CPW)
       QCHILLER=QCOIL*NCOILS+QMWLPUMP
C       IF(QCHILLER.GT.QCHILLMAX(UNITS))THEN
C         TCHWSET=TWIEV-QCHILLMAX(UNITS)/(MWEVAP*CPW)
C       ENDIF

C*** EVALUATION OF VENTILATION LOAD ****************************************
       TT=TSI(TWB,UNITS)+273.15
```

```
      PSAT=EXP(C8/TT+C9+C10*TT+C11*TT**2+C12*TT**3+C13*LOG(TT))
      P=.101325E6
      PV=PSAT-(P-PSAT)*(TDB-TWB)/(2800.0-TWB)
      WAMB=.622*PV/(P-PV)
      QLAT=(1-SHR)*Q
      IF(INFO(7).EQ.0)THEN
        WROOM=WROOMS
      ELSE
        WROOM=WOC+QLAT/(MAC*NCOILS*HFG(UNITS))
      ENDIF
      TROOM=TRSET
      IF(FAO*MAC.GT.MAOMIN)THEN
        F=FAO
      ELSE
        F=MAOMIN/MAC
      ENDIF
      TAIC=F*TDB+(1-F)*TROOM
      WIC=F*WAMB+(1-F)*WROOM
    ENDIF

C*** SHUT OFF MODE ************************************************************
    IF(MODE.EQ.'OFF')THEN
      P1G=0.0
      P2G=0.0
      F1G=0.0
      F2G=0.0
      F3G=0.0
      NCH=0
      TAIC=TRSET
      WIC=WOC
      TWIEV=TCHWSET
    ENDIF

C*** SET OUTPUTS ***************************************************************
    OUT(1) =P1G
    OUT(2) =P2G
    OUT(3) =F1G
    OUT(4) =F2G
    OUT(5) =F3G
    OUT(6) =TCHWSET
    OUT(7) =NCH
    OUT(8) =TAIC
    OUT(9) =WIC
    OUT(10)=TWIEV
    OUT(11)=TAOCSET
    OUT(12)=ERROR
    OUT(13)=DIFF
    OUT(14)=SUMPOW
    RETURN
    END
```

2) LOCAL LOOP CONTROLLER

```
C**********************************************************************************
C  THIS ROUTINE MODELS A LOCAL LOOP CONTROLLER FOR THE COOLING COIL.  IT
C  RECEIVES THE COIL AIR OUTLET TEMPERATURE FROM THE COIL ROUTINE AND
C  COMPARES IT WITH THE COIL AIR OUTLET SET POINT TEMPERATURE.  EMPLOYING
C  THE SECANT'S ITERATION METHOD, THE RIGHT FLOW CONDITIONS ARE FOUND.
C  THE CORRESPONDING WATER MASS FLOW RATE THROUGH THE COIL IS GIVEN
C  BACK TO THE SUPERVISORY CONTROLLER.
C**********************************************************************************

      SUBROUTINE TYPE52(TIME,XIN,OUT,T,DTDT,PAR,INFO)
      DIMENSION XIN(6),OUT(9),PAR(20),INFO(10)
      REAL MWC,MWC_MAX,MWC_OLD

C     OPEN (55,FILE='OUT.DAT')
C*** FIRST CALL OF THE SIMULATION *********************************************
      IF(INFO(7).EQ.-1)THEN
        NI=6
        NP=20
        ND=0
        INFO(6)=9
        INFO(9)=1
        CALL TYPECK(1,INFO,NI,NP,ND)
      ENDIF

C*** SET PARAMETERS ***********************************************************
      MWC_MAX=PAR(17)

C*** EFFECT CALCULATIONS ******************************************************
      MWC    =XIN(5)
      TAOSET =XIN(6)

C*** IF NO LOAD AND PUMP IS OFF, GO BACK **************************************
      IF(MWC.EQ.0.0)RETURN

      IF(INFO(7).EQ.O) ITER_SECANT=0
      TAO=51.7

C*** ITERATION FOR THE AIR OUTLET TEMPERATURE (SECANT METHOD) ***********
      DO WHILE(ABS((TAOSET-TAO)/TAOSET).GT..00005)
        CALL TYPE50(TIME,XIN,OUT,T,DTDT,PAR,INFO)
        TAO=OUT(1)
        IF(ITER_SECANT.GT.0)THEN
          E1=TAOSET-TAO_OLD
          E2=TAOSET-TAO
```

```
        SLOPE=(E2-E1)/(MWC-MWC_OLD)
        IF(SLOPE.EQ.0.0)GOTO 150
        TAO_OLD=TAO
        MWC_OLD=MWC
        MWC=MWC-E2/SLOPE
      ELSE
150     TAO_OLD=TAO
        MWC_OLD=MWC
        MWC=MWC+.01*MWC_MAX
      ENDIF
170   CONTINUE
      XIN(5)=MWC

      ITER_SECANT=ITER_SECANT+1
    END DO
    RETURN
    END
```

3) ELECTRIC MOTOR

```
C*********************************************************************************
C  THIS COMPONENT MODELS THE PERFORMANCE OF AN ELECTRIC MOTOR
C  OPERATING AT PART LOAD.  THE PART LOAD PERFORMANCE CHARACTERISTIC OF
C  A  CONSTANT SPEED DRIVE OR A VARIABLE SPEED DRIVE IS CURVE FIT TO THE
C  SELECTED EXPRESSIONS BY THE USER.  THE COEFFICIENTS DETERMINED BY THIS
C  PROCESS ARE THEN INPUT AS PARAMETERS TO THIS MODEL.
C*******************************************************************************

      SUBROUTINE TYPE60(TIME,XIN,OUT,T,DTDT,PAR,INFO)
      DIMENSION XIN(1), OUT(3), PAR(6), INFO(10)
      REAL L, N
      INTEGER ROUND
      COMMON /LUNITS/ LUR,LUW,IFORM

C*************** STATEMENT FUNCTIONS *****************************************
C==> ROUND-OFF REAL NUMBERS TO THE NEAREST INTEGER
      ROUND(RNUM)=NINT(RNUM)

C*************** FIRST CALL OF THE SIMULATION *********************************
C CALL TYPECK TO SET UP THE UNIT AND, IF NECESSARY, PRINT ERROR MESSAGES
      IF(INFO(7).EQ.-1)THEN
         NI=1            ! NUMBER OF INPUTS IS ONE
         NP=INFO(4)      ! NUMBER OF PARAMETERS IS CONTAINED IN THE INFO ARRAY
         ND=0            ! NUMBER OF DERIVATIVES IS ZERO
         INFO(6)=3       ! NUMBER OF OUTPUTS IS THREE
         INFO(9)=0       ! UNIT'S OUTPUTS ONLY A FUNCTION ITS INPUTS (NOT OF t)
         CALL TYPECK(1,INFO,NI,NP,ND)   ! CHECK THE USER'S TRNSYS DECK
         MODE = ROUND(PAR(1))
         IF(MODE.NE.1 .AND. MODE.NE.2)CALL TYPECK(-4,INFO,0,0,0)
         IF(MODE.EQ.2 .AND. NP.NE.6)CALL TYPECK(-4,INFO,0,0,0)
         OUT(1)=XIN(1)
         OUT(2)=100.0
         OUT(3)=100.0
         RETURN
      ENDIF

C==> CHECK FOR MORE THAN ONE ELECTRIC MOTOR UNIT
      IF(IUNIT .EQ. INFO(1))GO TO 100
      IUNIT = INFO(1)   ! UNIT NUMBER

C*************** SET PARAMETERS **********************************************
C  MODE     = VARABLE SPEED DRIVE (1) OR CONSTANT SPEED DRIVE (2)
C  PSMAX    = SHAFT POWER (KW) REQUIRED FROM THE MOTOR AT FULL
C               LOADING CONDITIONS
C  SF       = MOTOR SERVICE FACTOR (INDICATES THE AMOUNT OF CONTINUOUS
```

```
C              OVERLOAD PERMISSIBLE)
C  C1        = CONSTANT IN EXPRESSION FOR MOTOR EFFICIENCY UNDER VARIABLE
C              SPEED OPERATION AND CONSTANT SPEED OPERATION
C  C2, C3    = CONSTANT IN EXPRESSION FOR MOTOR EFFICIENCY UNDER CONSTANT
C              SPEED OPERATION

   MODE  =ROUND(PAR(1))
   PSMAX =PAR(2)
   SF    =PAR(3)
   C1    =PAR(4)
   C2    =PAR(5)
   C3    =PAR(6)

C*************** EFFECT CALCULATIONS ******************************************
C  PS    = SHAFT POWER (KW) REQUIRED BY THE PUMP/FAN WHICH IS TO BE
C          SUPPLIED BY THE MOTOR
C  PE    = ELECTRICAL POWER (KW) SUPPLIED BY THE UTILIY GRID
C  L     = PERCENT FULL-LOAD ON THE MOTOR
C  N     = MOTOR EFFICIENCY (%)

100 PS=XIN(1)
    L=PS/PSMAX*100.
   IF(L.GT.SF*100)WRITE(LUW,1001)INFO(1),INFO(2),L/100
   IF(MODE .EQ. 1)THEN
     N=L/(C1+L)*100
   ENDIF
   IF(MODE .EQ. 2)THEN
     N=C3*L/(L+(L**2/C2+C1)/2)*100
   ENDIF
   IF(N.EQ.0)THEN
    PE=0.0
   ELSE
    PE=PS/(N/100.)
   ENDIF

C*************** SET OUTPUTS ****************************************************
   OUT(1)=PE
   OUT(2)=N
   OUT(3)=L

   RETURN

C*************** FORMATS ********************************************************
1001 FORMAT(//2X,'**** ERROR **** UNIT ',I2,'  TYPE ',I2,'  ELECTRIC
   . MOTOR',/2X,'LOAD FRACTION, ',F7.2,', EXCEEDS MOTOR SERVICE
   . FACTOR')
   END
```

4) FLOW CONVERTER

```
      SUBROUTINE TYPE65(TIME,XIN,OUT,T,DTDT,PAR,INFO)
      DIMENSION XIN(1),OUT(1),PAR(2),INFO(10)
      CHARACTER*12 CONFIGURATION
      INTEGER ROUND
      REAL MI,MO

C*** STATEMENT FUNCTIONS ****************************************************
      ROUND(RNUM)=NINT(RNUM)

C*** FIRST CALL OF THE SIMULATION ********************************************
      IF(INFO(7).EQ.-1)THEN
        NI=1
        NP=2
        ND=0
        INFO(6)=1
        INFO(9)=0
        CALL TYPECK(1,INFO,NI,NP,ND)
      ENDIF

C*** SET PARAMETERS **********************************************************
      MODE  =ROUND(PAR(1))
      NAHUS =ROUND(PAR(2))

      IF(2-MODE)3,2,1
3        GOTO 4
2        CONFIGURATION='AHU==>CHILL'
         GOTO 4
1       CONFIGURATION='CHILL==>AHU'
4        CONTINUE

C*** EFFECT CALCULATIONS *****************************************************
100  MI =XIN(1)

      IF(CONFIGURATION.EQ.'CHILL==>AHU')MO=MI/NAHUS
      IF(CONFIGURATION.EQ.'AHU==>CHILL')MO=MI*NAHUS

C*** SET OUTPUTS *************************************************************
      OUT(1)=MO
      RETURN
      END
```

MINITAB COMMAND FILE AND EXAMPLE OUTPUT

```
execute 'reg.dat'
MTB > ECHO
MTB > BATCH
MTB > READ 'RTOTN2.DAT' C1-C7
  3919 ROWS READ
* 23514 NUMBERS READ IN EXPONENTIAL NOTATION

 ROW   C1   C2      C3    C4   C5   C6    C7

   1    2   50  1800000   0.7   49   55  118.1
   2    3   50  1800000   0.7   49   54  117.6
   3    4   50  1800000   0.7   49   53  117.3
   4    5   50  1800000   0.7   49   52  117.3
  . . .
MTB > LET C8=C3/12000.
MTB > LET C9=C2*C2
MTB > LET C10=C8*C8
MTB > LET C11=C4*C4
MTB > LET C12=C5*C5
MTB > LET C13=C6*C6
MTB > LET C14=C2*C8
MTB > LET C15=C2*C4
MTB > LET C16=C2*C5
MTB > LET C17=C2*C6
MTB > LET C18=C8*C4
MTB > LET C19=C8*C5
MTB > LET C20=C8*C6
MTB > LET C21=C4*C5
MTB > LET C22=C4*C6
```

```
MTB > LET C23=C5*C6
MTB > SAVE 'REG.ALL'

Worksheet saved into file: REG.ALL
MTB > REGR C7 20 C2 C4-C6 C8-C23 c24-c25;
SUBC> TOLER 0.000001;
SUBC> residual c26.
* NOTE *   C2 is highly correlated with other predictor variables
* NOTE *   C4 is highly correlated with other predictor variables
* NOTE *   C5 is highly correlated with other predictor variables
* NOTE *   C6 is highly correlated with other predictor variables
* NOTE *   C8 is highly correlated with other predictor variables
* NOTE *   C9 is highly correlated with other predictor variables
* NOTE *  C10 is highly correlated with other predictor variables
* NOTE *  C11 is highly correlated with other predictor variables
* NOTE *  C12 is highly correlated with other predictor variables
* NOTE *  C13 is highly correlated with other predictor variables
* NOTE *  C14 is highly correlated with other predictor variables
* NOTE *  C15 is highly correlated with other predictor variables
* NOTE *  C16 is highly correlated with other predictor variables
* NOTE *  C17 is highly correlated with other predictor variables
* NOTE *  C18 is highly correlated with other predictor variables
* NOTE *  C19 is highly correlated with other predictor variables
* NOTE *  C20 is highly correlated with other predictor variables
* NOTE *  C21 is highly correlated with other predictor variables
* NOTE *  C22 is highly correlated with other predictor variables
* NOTE *  C23 is highly correlated with other predictor variables


The regression equation is
C7 = 3443 - 14.1 C2 - 1715 C4 - 36.3 C5 - 32.2 C6 - 5.62 C8 + 0.0574 C9
       + 0.00315 C10 + 176 C11 + 1.81 C12 + 1.86 C13 + 0.0223 C14
       + 3.70 C15 + 0.170 C16 - 0.110 C17 + 1.93 C18 + 0.0743 C19
       - 0.0299 C20 + 16.1 C21 + 1.57 C22 - 3.27 C23
```

Predictor	Coef	Stdev	t-ratio	p
Constant	3443.13	56.47	60.97	0.000
C2	-14.0558	0.3076	-45.69	0.000
C4	-1714.87	49.23	-34.83	0.000
C5	-36.278	1.933	-18.77	0.000
C6	-32.238	1.564	-20.61	0.000
C8	-5.61591	0.08601	-65.29	0.000
C9	0.057444	0.001259	45.62	0.000
C10	0.00314815	0.00004424	71.17	0.000
C11	176.12	22.74	7.75	0.000
C12	1.80855	0.04120	43.89	0.000
C13	1.86205	0.03746	49.71	0.000
C14	0.0222823	0.0002284	97.57	0.000
C15	3.7003	0.1376	26.89	0.000
C16	0.170138	0.007174	23.72	0.000

C17	-0.110360	0.006531	-16.90	0.000
C18	1.92794	0.02882	66.89	0.000
C19	0.074310	0.002012	36.94	0.000
C20	-0.029873	0.001566	-19.08	0.000
C21	16.1417	0.8589	18.79	0.000
C22	1.5734	0.7810	2.01	0.044
C23	-3.27202	0.07519	-43.52	0.000

s = 6.679   R-sq = 99.6%   R-sq(adj) = 99.6%

Analysis of Variance

SOURCE	DF	SS	MS	F	p
Regression	20	49451380	2472569	55420.34	0.000
Error	3898	173909	45		
Total	3918	49625288			

Unusual Observations

Obs.	C2	C7	Fit	Stdev.Fit	Residual	St.Resid
3	50.0	117.300	131.583	0.674	-14.283	-2.15R
4	50.0	117.300	137.533	0.721	-20.233	-3.05R
5	50.0	118.400	147.207	0.824	-28.807	-4.35R
6	50.0	116.700	141.109	0.752	-24.409	-3.68R
7	50.0	115.700	131.887	0.651	-16.187	-2.43R
11	50.0	117.200	132.240	0.704	-15.040	-2.26R
17	50.0	115.800	135.808	0.700	-20.008	-3.01R
18	50.0	114.400	131.304	0.665	-16.904	-2.54R
29	50.0	113.600	127.598	0.647	-13.998	-2.11R
39	50.0	121.900	136.677	0.665	-14.777	-2.22R
117	55.0	125.300	139.489	0.613	-14.189	-2.13R
123	55.0	124.600	139.421	0.697	-14.821	-2.23R
124	55.0	124.200	137.929	0.680	-13.729	-2.07R
474	65.0	170.400	156.055	0.547	14.345	2.15R
475	65.0	171.800	156.788	0.540	15.012	2.25R
488	65.0	174.700	158.319	0.548	16.381	2.46R
489	65.0	177.200	160.646	0.574	16.554	2.49R
499	65.0	181.600	163.771	0.619	17.829	2.68R
500	65.0	186.400	167.693	0.686	18.707	2.82R
501	65.0	146.800	160.294	0.575	-13.494	-2.03R
574	70.0	181.700	165.963	0.483	15.737	2.36R
.	.	.	.	.	.	.
.	.	.	.	.	.	.

R denotes an obs. with a large st. resid.
X denotes an obs. whose X value gives it large influence.

MTB > END
MTB > STOP
*** Minitab Release 7.1 *** Minitab, Inc. ***
Storage available 1897261

FAULT DETECTION PROGRAM

```
C ***********************************************************************************
C THIS PROGRAM EVALUATES THE STANDARD DEVIATION AND THE CONFIDENCE
C INTERVALS OF THE DIFFENRENCE BETWEEN THE SIMULATION POWER AND THE
C PRIDICTED POWER FROM THE FORMULA.  IT CHECKS FOR SIGNIFICANT
C DIFFERENCE BETWEEN THE POWERS INSTANTANEOUSLY AND IN SEQUENCES.
C THE STANDARD DEVIATION OF THE REGRESSION IS USED AS THE POOLED
C VARIANCE (Florian Pape 1989)
C T   - VALUES IN T-TABLE FOR EVALUATING THE CONFIDENCE INTERVALS (2-SIDED)
C TT    VALUES IN T-TABLE FOR FOR THE T-TEST (ONE SIDED)
C ***********************************************************************************

      PROGRAM STAT
      IMPLICIT NONE
      REAL DIFF(100),T(4),TT(4),DELTA,DELSQ,STDEV,HOUR,CONFINT,TAP
      REAL DIFFLOW,DIFFHIGH,SUMDIFF,ERROR,END,SUM,DIFFAV
      REAL DIFFOLD,TTEST,TCONF,TDATA,DIFFAVNEW,TAP2,PSIM,PFOR
      INTEGER I,N,NU,NU2,CONF,CHOICE,FAULT,J,K,L
      DATA T(1)/1.96/,T(2)/2.576/,T(3)/2.807/,T(4)/3.291/
      DATA TT(1)/1.645/,TT(2)/2.326/,TT(3)/2.576/,TT(4)/3.09/
      OPEN (17,FILE='[FLORIAN.TRNSYS]PDALLPPETAC.DAT',STATUS='OLD')
      OPEN (31,FILE='CONF.DAT',STATUS='NEW')

C ************ INPUTS FROM KEYBOARD ******************************************
      WRITE(*,*)'TYPE IN THE NUMBER OF DATA POINTS REQUIRED FOR ',
     +          'FAULT DETECTION'
      READ(5,*)N
      NU=N-1
C ************ STANDARD DEVIATION FROM THE REGRESSION *********************
      STDEV=6.63
C **************** SET CONFIDENCE LIMITS ***************************************
25    CONTINUE
```

```
      WRITE(*,*)'WHAT CONFIDENCE INTERVAL SHOULD BE ASSUMED (IN %)?'
       WRITE(*,*)'FOR 95% TYPE    1'
       WRITE(*,*)'FOR 99% TYPE    2'
       WRITE(*,*)'FOR 99.5% TYPE  3'
       WRITE(*,*)'FOR 99.9% TYPE  4'
       WRITE(*,*)'FOR OTHERS TYPE 5'
       READ(5,*)CONF
       IF (CONF.EQ.1) THEN
         CONFINT=95.
       ELSEIF (CONF.EQ.2) THEN
         CONFINT=99.
       ELSEIF (CONF.EQ.3) THEN
         CONFINT=99.5
       ELSEIF (CONF.EQ.4) THEN
         CONFINT=99.9
       ELSEIF (CONF.EQ.5) THEN
         WRITE (*,*)'TYPE IN CONFIDENCE INTERVAL'
         READ(5,*)CONFINT
       ELSE
         WRITE(*,*)'WRONG INPUT'
         GOTO 25
       END IF
       TAP=(100.-CONFINT)/200.
       IF (CONF.LE.4) THEN
         TCONF=T(CONF)
         TTEST=TT(CONF)
       ELSE
        WRITE(*,160)TAP
        READ(5,*)TCONF
        WRITE(*,165)TAP
        READ(5,*)TTEST
       END IF
C **************** CONFIDENCE INTERVALS *****************************************
      DIFFLOW=-STDEV*TCONF
      DIFFHIGH=+STDEV*TCONF
      WRITE(31,110)STDEV,CONFINT,DIFFLOW,DIFFHIGH
      WRITE(*,110)STDEV,CONFINT,DIFFLOW,DIFFHIGH
      WRITE(31,115)N
55     CONTINUE
C *************** FIRST VALUES TAKEN FOR T-TESTS ******************************
       SUM=0.
      DO 60 I=1,N
         READ(17,130)HOUR,PSIM,PFOR,DIFF(I),ERROR
         SUMDIFF=SUMDIFF+DIFF(I)
60     CONTINUE
      DIFFAVNEW=SUMDIFF/REAL(N)
C ******* CHANGE OLD DIFFERENCE WITH THE ONE FROM THE ACTUAL HOUR ******
      DO 65 J=1,100
       DO 65 K=1,N
        I=J*N+K
```

```
        FAULT=0
        DIFFOLD=DIFF(K)
         READ(17,130)HOUR,PSIM,PFOR,DIFF(K),ERROR
        IF (DIFF(K).GT.DIFFHIGH) THEN
         WRITE(31,*)'DATA OUTSIDE CONFIDENCE INTERVAL'
        END IF
        SUMDIFF=SUMDIFF-DIFFOLD+DIFF(K)
        DIFFAVNEW=SUMDIFF/REAL(N)

C ****************** T-VALUE AND TEST FOR SEQUENCE ***************************
        TDATA=DIFFAVNEW/STDEV*SQRT(REAL(N))
        IF(TDATA.GT.TTEST) FAULT=1
        IF (K.EQ.1) THEN
         WRITE(31,*)'  I    DIFF    DIFFOLD  DIFFAVNEW    ',
     +        'TDATA    TTEST  FAULT   ERROR'
        END IF
        WRITE(31,170)I,DIFF(K),DIFFOLD,DIFFAVNEW,TDATA,TTEST,
     +            FAULT,ERROR
65    CONTINUE
      WRITE(*,*)'IF YOU WANT A DIFFERENT CONFIDENCE INTERVAL TYPE 1'
      WRITE(*,*)'IF YOU WANT TO QUIT TYPE                        2'
      READ(5,*)CHOICE
      IF(CHOICE.EQ.1)THEN
       GOTO 25
      ELSEIF(CHOICE.EQ.2)THEN
       CONTINUE
      ELSE
       WRITE(*,*)'WRONG INPUT'
       GOTO 55
      END IF
      CLOSE(31,STATUS='KEEP')
      CLOSE(33)
      CLOSE(17)

100    FORMAT(9X,'HOUR   POWDIFF     AVER_POWDIFF     DELTA')
110   FORMAT(2X,'The standard deviation received from the regression is'/,5x,
     +  ' 'STDEV = ',F7.4,//,',2x,'The average difference from the regression is zero'//,
     +  2X,'The ',F5.2,'% confidence interval for differences in'/,
     +   2x,'power yield from simulation and formula is:'/,5x   '[',f8.4,';',f8.4,']'/)
115   FORMAT(2X,'The number of data points employed for fault',
     +        ' detection at the same time is'/,5x,'N =',I3,//)
120    FORMAT(3X,F6.4,2X,E8.3)
130    FORMAT(F10.4,4(E11.3))
160   FORMAT(3X,'TYPE IN THE T-RATIO FOR TAIL AREA PROBABILITY'
     +      ' ALPHA/2 =',F6.5)
165   FORMAT(3X,'TYPE IN THE T-RATIO FOR TAIL AREA PROBABILITY',
     +      ' ALPHA =',F6.5)
170     FORMAT(3X,I3,X,F9.4,F11.4,F11.5,3X,F7.4,3X,F7.4,3X,I2,3X,F7.3)
      END
```

Appendix E

RESIDUAL PLOTS

In this appendix, residual plots are shown. Figures E.1 - E.3 demonstrate the fit of the regression equation for approximately 4000 sets of controlled and uncontrolled variables. For these points, the system power was evaluated by the simulation. Data representing non-optimal control is included in this set.

In Figure E.1, the predicted power obtained from the quadratic regression equation is presented as a function of the simulated power. As expected, a straight line occurs which characterizes a good fit. Only very few points are off the line; these points represent conditions which are far away from the optimal control.

In Figure E.2, the residuals, i.e. the differences between measured and predicted power, are shown as a function of the predicted values. The variance for different fitted values is examined. Most of the residuals have small values and are equally distributed over the whole range of predicted values. However, some residuals have very low or very high values which characterizes a heavy tailed distribution. Most of these residuals represent control far off the optimum.

Figure E.3 demonstrates the normal score plot. If the residuals in the normal score plot can be approximated by a straight line, the residuals are normally distributed which corresponds to a histogram of residuals shaped as a normal curve. Most of the residuals are on the straight line. However, the heavy tailed distribution can be recognized again. Most of the residuals which are not located on the straight line represent non-optimal control.

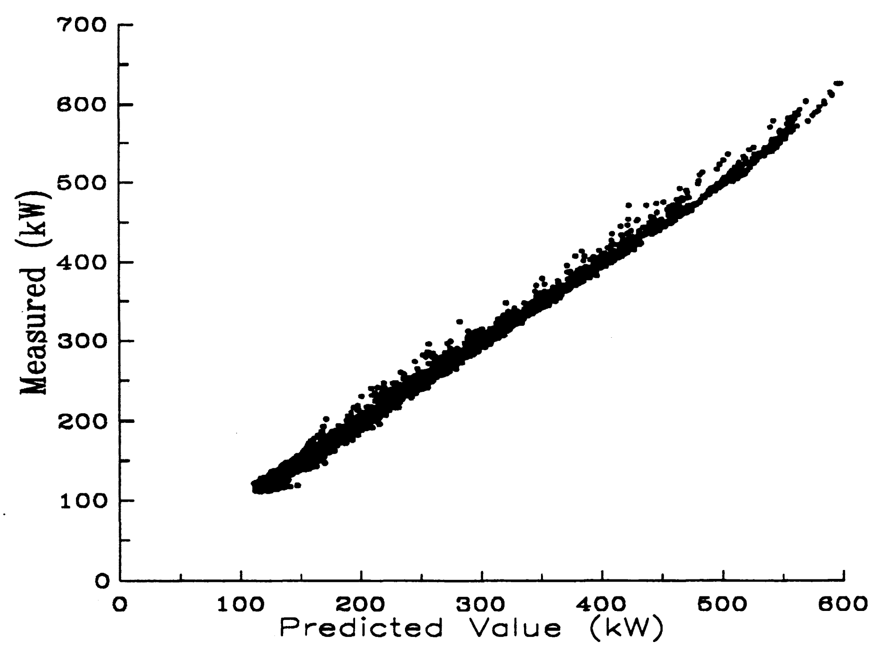


Figure E.1 Measured power as a function of the predicted power

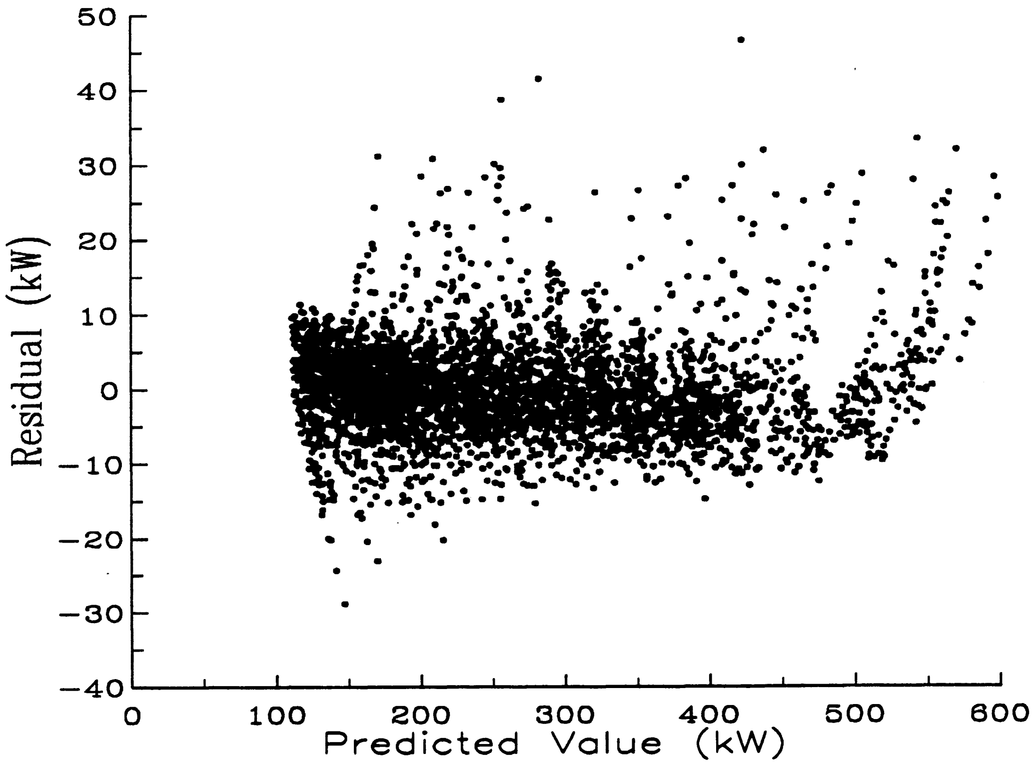


Figure E.2 Residuals as a function of the predicted value

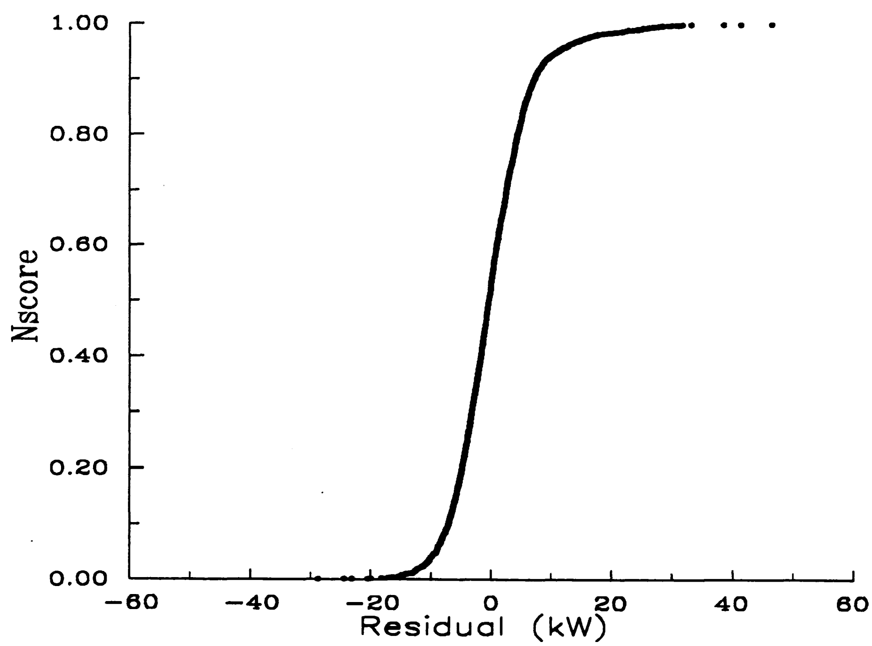
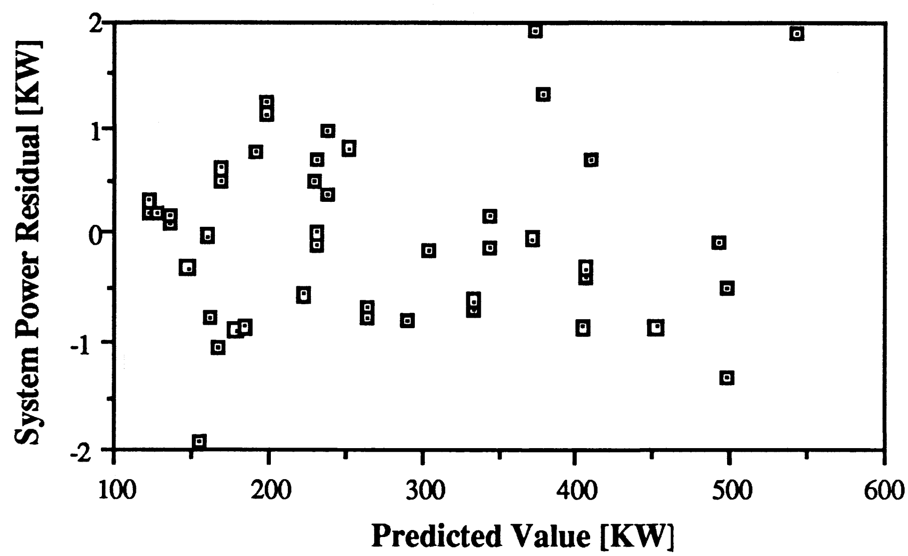


Figure E.3 Normal score plot for the power residuals

In Figures E.4 - E.7, the residual plots for the total system power, the chiller power, the pump power, and the fan power, respectively, are presented. The first of the two plots for every component and for the system checks if the assumption of constant variance is valid while the second plot checks for normally distributed residuals. The residuals have to be equally distributed for all predicted values. If in the normal score plots the points approximate a straight line, the residual can assumed to be normally distributed.

All of the plots show a large improvement to the residual plot representing the old regression formula in Figure 3.22. The residual plots for the total system power, the pump power, and the fan power in Figures E.4, E.6, and E.7 show that the statistical tests can assumed to be valid. The variance of the residuals does not seem to depend on the predicted value. The normal score plots can be approximated as straight lines which means that the residuals are roughly normally distributed.

The plot showing the residuals as a function of the predicted power for the chiller, shown in Figure E.5, exhibit a slight increase in variance with the predicted power. In the normal score plot, two values are located clearly off the line. Due to these patterns, a transformation for the chiller power is performed. The reciprocal power transformation is the best possible transformation, i.e. all powers are transformed into their reciprocal values and are then again regressed. The residual plots after the transformation are shown in Figure E.8. They are slightly improved.



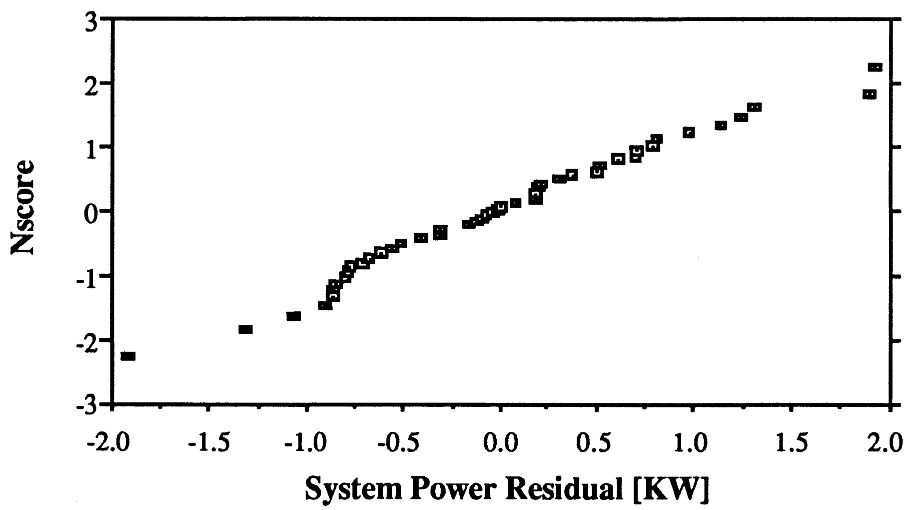
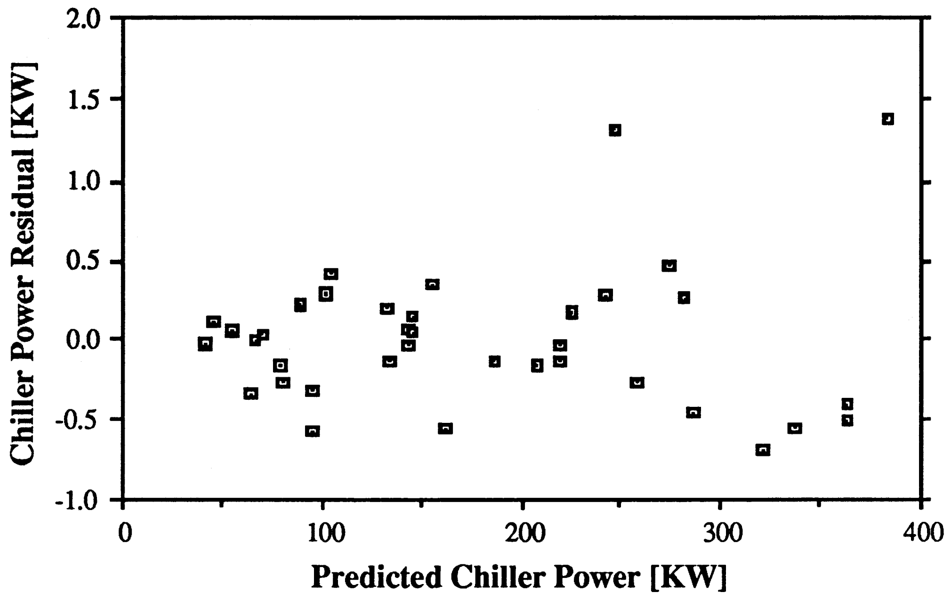


Figure E.4 Residual plots for the total system power for 50 random data points



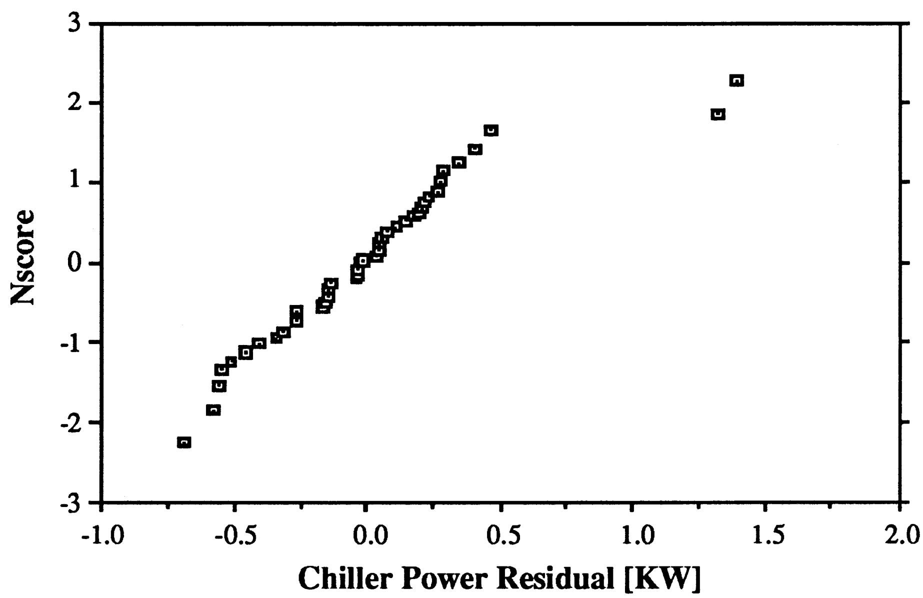
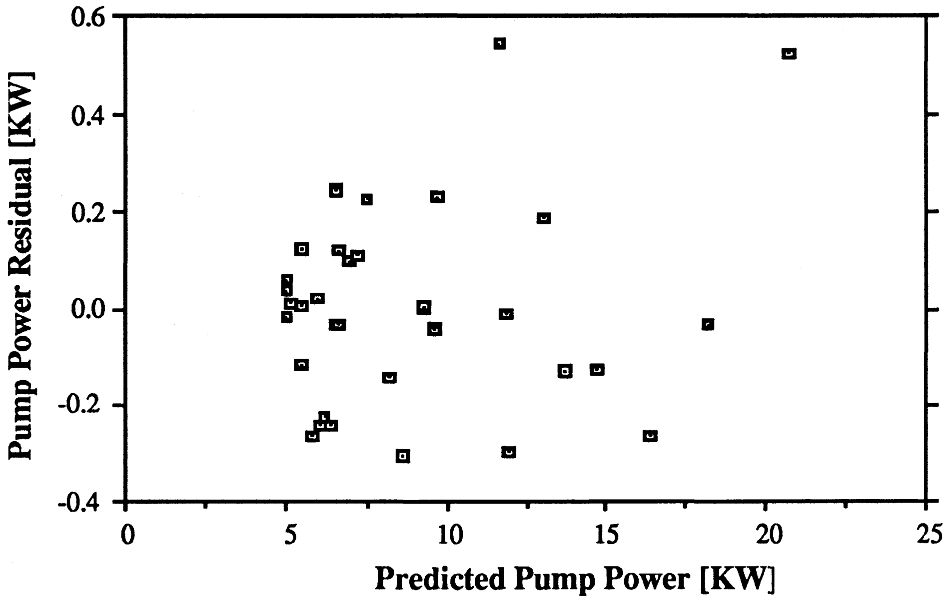


Figure E.5 Residual plots for the chiller power for 50 random data points



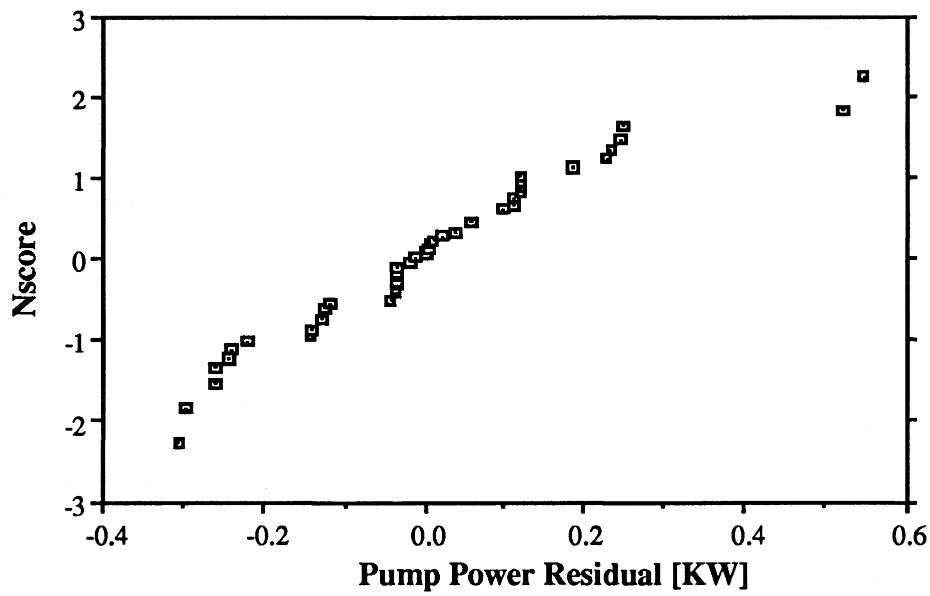
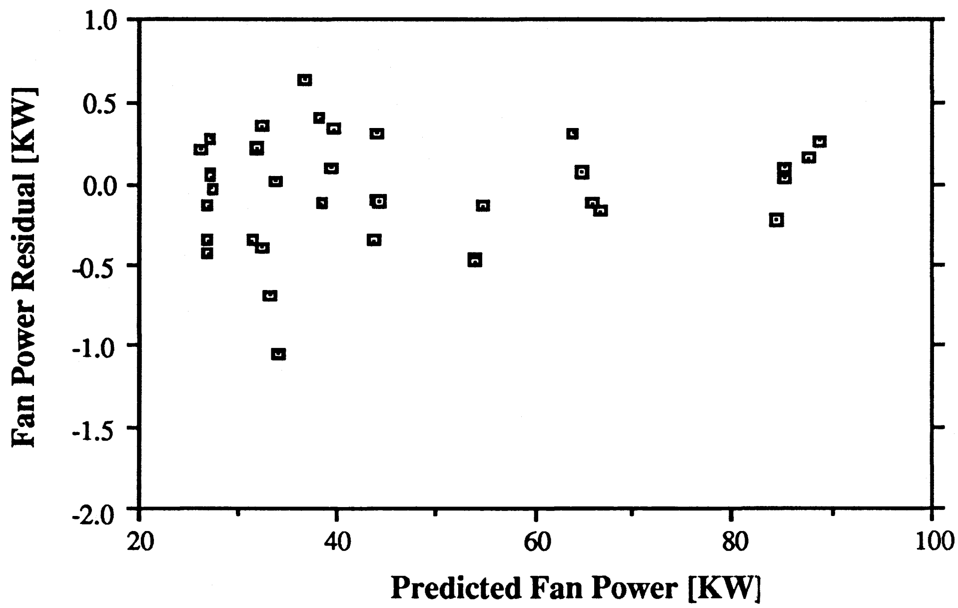


Figure E.6 Residual plots for the pump power for 50 random data points



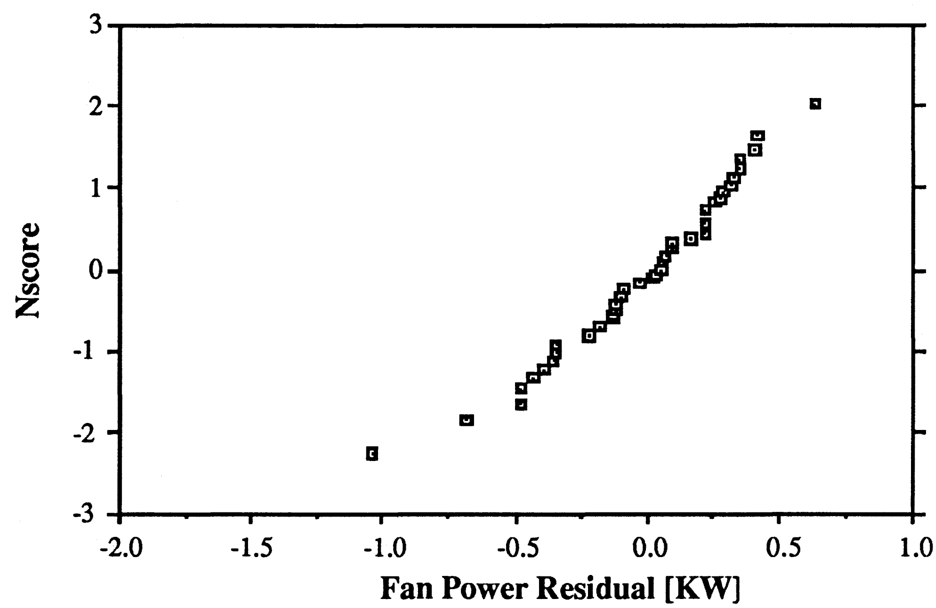
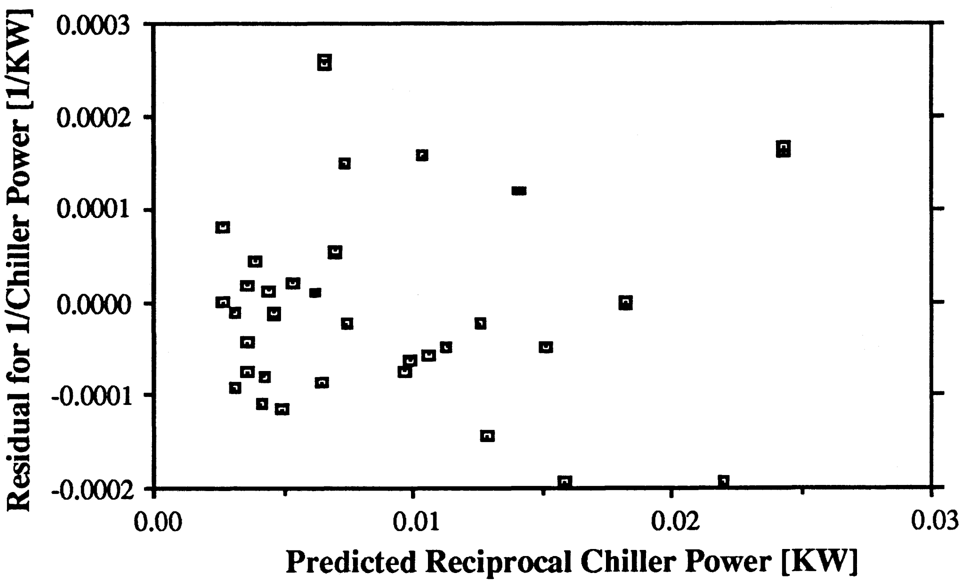


Figure E.7 Residual plot for the supply fan power for 50 random data points



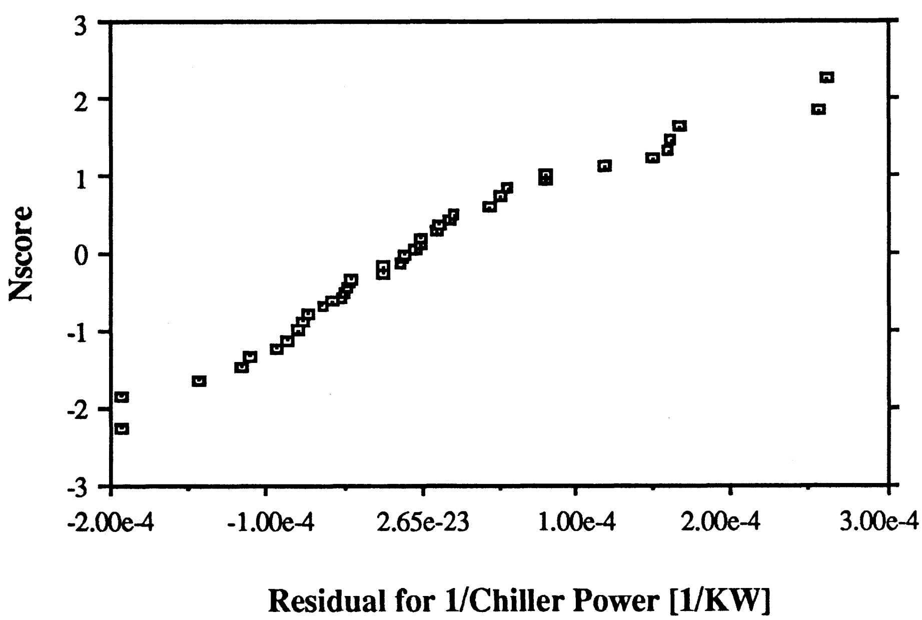


Figure E.8 Residual plots for the chiller power after a transformation Y = 1/y

REFERENCES

Anderson, D., et al., "A Quasi-Real-Time Expert System for Commercial Building HVAC Diagnostics", ASHRAE *Transactions*, Volume 95, Part 2, 1989.

ASHRAE *Handbook, Equipment Volume*, American Society of Heating , Refrigerating and Air Conditioning Engineers, Incorporated, Atlanta, Georgia, 1988.

ASHRAE *Handbook, Fundamentals Volume*, American Society of Heating , Refrigerating and Air Conditioning Engineers, Incorporated, Atlanta, Georgia, 1985.

ASHRAE *Handbook, Systems and Applicantions Volume*, American Society of Heating , Refrigerating and Air Conditioning Engineers, Incorporated, Atlanta, Georgia, 1987.

Box, G. E. P., W. G. Hunter, and J. S. Hunter, *Statistics for Experimenters*, An Introduction to Design, Data Analysis, and Model Building, John Wiley & Sons, New York, 1979.

Braun, J. E., J. W. Mitchell, S. A. Klein, and W. A. Beckman, "Methodologies for Optimal Control of Chilled Water Systems without Storage", ASHRAE Summer Annual Meeting, Ottawa, Canada, 1988.

Braun, J. E., "Methodologies for the Design and Control of Contral Cooling Plants", Ph.D. Thesis, University of Wisconsin-Madison, 1988.

Computer Controls Corporation, "Direct Digital Control Systems", Engineering Guide, Wilmington, Massachusetts.

Cummings, M. S., "Modeling, Design, and Control of Partial Ice-Storage Air-Conditioning Systems", M.S. Thesis, University of Wisconsin-Madison, 1989.

Draper, N. R., and H. Smith, *Applied Regression Analysis*, Second Edition, John Wiley & Sons, New York, 1981.

Haberl, J. S., L. K. Norford, and J. V. Spadaro, "Diagnosing Building Operational Problems", ASHRAE *Journal*, June 1989.

Hittle, D. C., et al., "Theory Meets Practice In A Full-Scale Heating, Ventilating and Air-Conditioning Laboratory", ASHRAE *Journal*, November 1982.

Hittle, D. C., *The Building Loads Analysis and System Thermodynamics (BLAST) Program*, Version 2.0, Volume 1, U.S. Army Construction Engineering Research Laboratory, 1979.

Hubbard, L. M., "Simplified Models of HVAC System Performance in Large Buildings", M.S. Thesis, University of Wisconsin-Madison, 1985.

Incropera, F. P., and D. P. DeWitt, *Introduction to Heat Transfer*, John Wiley & Sons, New York, 1985.

Kao, J. Y. and Pierce, E. T., "Sensor Errors - Their Effects On Building Energy Consumption", ASHRAE *Journal*, December 1983.

Kao, J. Y., "Sensor Errors - Some Possible Sources, Suggested Remedies", ASHRAE Journal, January 1985.

Klein, S. A., et al., *TRNSYS: A Transsient Simulation Program*, University of Wisconsin-Madison, Engineering Experiment Station Report 38-12, Version 12.2, 1988.

Klein, S. A., et al., *TRNSYS User's Manual*, University of Wisconsin-Madison, Engineering Experiment Station Report 38-12, 1988.

Liu, S. T. and G. E. Kelly, "Rule-Based Diagnostic Method for HVAC Fault Detection", Proceedings of Building Simulation '89, Vancouver, British Columbia, Canada, June 23 - 24, 1989.

McQuiston, F. C., and J. D. Parker, *Heating, Ventilation and Air Conditioning: Analysis and Design*, Second Edition, John Wiley & Sons, New York, 1982.

MINITAB, Statistical Software, Reference Manual, Release 7, April 1989.

Mitchell, J. W., *Energy Engineering*, John Wiley & Sons, New York, 1983.

National Research Council, Committe on Controls for Heating, Ventilating, and Air-Conditioning Systems, "Controls for Heating, Ventilating, and Air-Conditioning Systems, National Academy Press, Washington, D.C., 1988

Ryan, B. R., B. L. Joiner, and T. A. Ryan, Jr., MINITAB, Handbook, Second Edition, Revised Printing, PWS-KENT Publishing Company, Boston, 1985.

Schneider, R. K., *Control Systems*, John Wiley & Sons, New York, 1981.

Usoro, P. B., I. C. Schick, and S. Negahdaripour, "HVAC System Fault Detection and Diagnosis", American Control Conference, Volume 1, 1985.

Usoro, P. B., and I. C. Schick, "A Hierarchical Approach to HVAC System Fault Detection and Identification", Dynamic Systems: Modelling and Control, ASME DSC-1, p.285, 1985.

Wilkinson, L., SYSTAT: The System for Statistics, Third Version, Evanston, Il, SYSTAT, Inc., 1987.

Wilkinson, L., SYGRAPH, Evanston, Il, SYSTAT, Inc., 1988.

White, F. M., *Fluid Mechanics*, Second Edition, McGraw-Hill Book Company, New York, 1986.