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Operation and Maintenance

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7.1 HVAC System Commissioning

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Commissioning was originally used by the Navy to ensure that battleships and submarines functioned properly before they were sent out to sea. It has been adopted and adapted within the building construction industry to apply to many different building systems. ASHRAE provides a definition of building commissioning in its Guideline 1-1996 (ASHRAE, 1996, p. 23):

> Commissioning is the process of ensuring systems are designed, installed, functionally tested, and operated in conformance with the design intent. Commissioning begins with planning and includes design, construction, start-up, acceptance, and training and can be applied throughout the life of the building. Furthermore, the commissioning process encompasses and coordinates the traditionally separate functions of systems documentation, equipment start-up, control system calibration, testing and balancing, and performance testing.

The ASHRAE commissioning efforts were restricted to new buildings, but it later became evident that while initial start-up problems were not an issue in older buildings, most of the other problems which commissioning tackled were even more prevalent in older systems. Commissioning of HVAC systems has been growing in popularity over the last decade; however, it is still not the norm in construction practice or building operation. One of the recommendations in the National Strategy for Building Commissioning (PECI, 1999) is "to develop a standard definition of commissioning."

The principal motivation for commissioning HVAC systems is to achieve HVAC systems that work properly to provide comfort to all the occupants of a building in an unobtrusive manner and at low cost, and to optimize HVAC system operation with minimal energy and operational costs. When HVAC systems are commissioned based on the design intents for a new building, the process is called *new building commissioning*. When HVAC systems are commissioned based on initial design intents for an existing building, the process is called *existing building commissioning*. When HVAC systems are commissioned based on actual use and the HVAC systems operation are optimized for different load conditions, the process is called *continuous commissioning*.

In principle, all building systems should be designed, installed, documented, tested, and staffed by personnel trained in their use. In practice, competitive pressures, fee structures, and financial pressures to occupy new buildings as quickly as possible result in buildings that are handed over to the owners with minimal contact between designers and operators, and are characterized by minimal functional testing of systems, documentation largely consisting of manufacturer system or component manuals, and little or no training for operators. This has lead to numerous problems including: mold growth in walls of new buildings, rooms that never cool properly, and air quality and comfort problems.

It has been estimated that new building commissioning will save 8% in energy cost alone compared with the average building that is not commissioned (PECI, 1999). This offers a payback for the cost of commissioning in just over 4 years from the energy savings alone and provides improved comfort and air quality. Traditional commissioning of existing buildings typically provides 12% in energy savings, with a payback of just over 1 year (PECI, 1999). The enhanced commissioning process, or continuous commissioning, significantly improves building comfort and typically decreases energy costs by 20% (Claridge et al., 1998) with payback of the project cost often less than 1.5 years.

Although commissioning provides higher quality buildings and results in fewer initial and subsequent operational problems, the direct and rapid payback of the commissioning expense from lowered operating costs is often the principal motivation for many owners. Documenting these lower operational costs is much easier if a specific plan is implemented to monitor and verify the results of the commissioning process. This is sometimes done with utility bill information, but is often more effective if measurement equipment is used on a temporary or permanent basis to record hourly or daily energy use data. The last section in this chapter addresses effective ways to monitor and verify savings from commissioning projects.

7.1.1 Commissioning New HVAC Systems

The goal of the commissioning process for a new HVAC system is to achieve a properly operating system that provides design comfort levels in every room in a building from the first day it is occupied. The motivation for commissioning a building is sometimes the desire to achieve this state as quickly, painlessly, and inexpensively as possible. In other cases, the primary motivation is to achieve operating savings and secondarily to minimize operating problems, while the motivation is more complex in other cases.

Disney Development Corporation has constructed over $10 billion in new facilities over the last decade and has concluded that commissioning is an essential element for their company. The corporation often uses innovative construction techniques and creative designs in highly utilized facilities where the occupants have very high expectations. Most of their facilities are expected to be aesthetically and operationally at the cutting edge of technology (Odom and Parsons, 1998). Other major private sector property owners who have adopted commissioning include Westin Hotels, Boeing, Chevron, Kaiser Permanente, and Target. The U.S. General Services Administration has begun to integrate commissioning into its design and construction program (PECI, 1999). State and local governments have also been leaders in the move toward commissioning, with significant programs at the state or local level in Florida, Idaho, Maryland, Montana, New York, Oregon, Tennessee, Texas, and Washington (Haasl and Wilkinson, 1998).

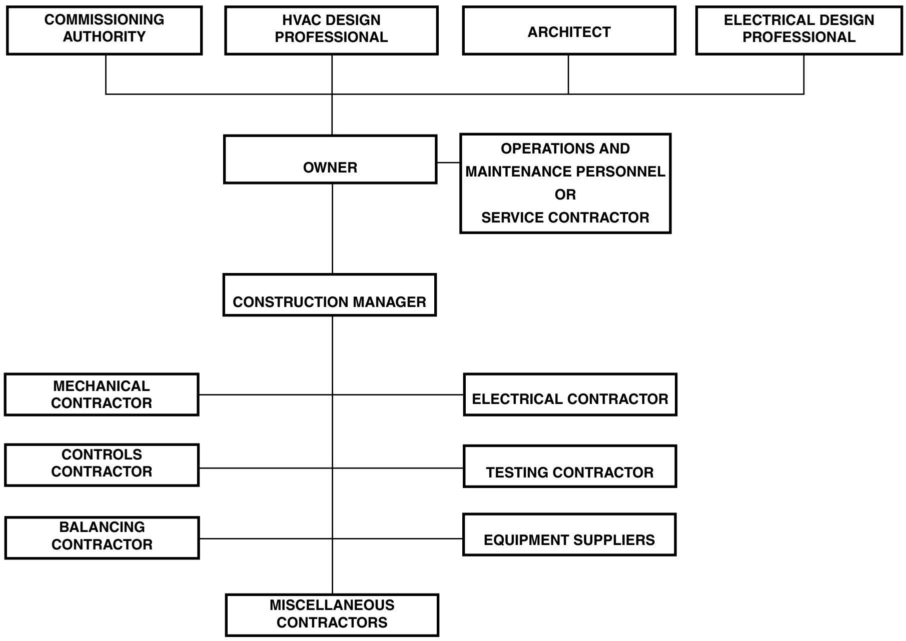

FIGURE 7.1.1 Commissioning organizational structure.

The Commissioning Process

Perhaps the major reason that commissioning is needed is that in many projects "commissioning" the project simply consists of turning everything on and verifying that all motors, chillers, and boilers run. The HVAC commissioning process ideally begins during the building programming phase and continues through the design phase, the construction phase, the acceptance phase, and into the post-acceptance phase. It requires the participation of the owner (or representative), the commissioning coordinator (or commissioning authority (CA)), design professionals, and the construction manager.

There is considerable agreement that a strong commissioning program requires a CA or a person or company who implements the overall commissioning process and coordinates commissioning related interactions between the other parties involved in the design, construction, and commissioning process.

The organizational structure of the commissioning process is shown in Figure 7.1.1. The CA reports to the owner and works with the other design professionals during the project. The construction manager then has primary responsibility of ensuring that the various contractors carry out the intent of the design developed, with the CA providing a detailed verification that the project, as built, does in fact meet the design intent.

The many facets of the commissioning process are shown schematically in Figure 7.1.2, specifically identifying the responsibilities of the owner, the CA, the design professional, and the constructions manager as they relate to the commissioning process in the programming, design, construction, acceptance, and post-acceptance phases of the project. In many projects, the commissioning process is implemented later in the design and construction process, decreasing the benefits of commissioning.

To maximize the benefits of commissioning, the owner selects the CA early in the programming phase so he or she can participate in the programming phase and develop a preliminary commissioning plan before the design phase begins. During the design phase, the principal responsibility of the CA is to review and comment on the design as it evolves and to update the commissioning plan as necessary. During the construction phase, the full commissioning team comes on board, and training of the building staff begins, while the CA continues to closely observe the construction process. The major commissioning activity occurs during the acceptance phase, with a multitude of checks and tests performed, further staff training, and finally, reporting and documentation of the process.

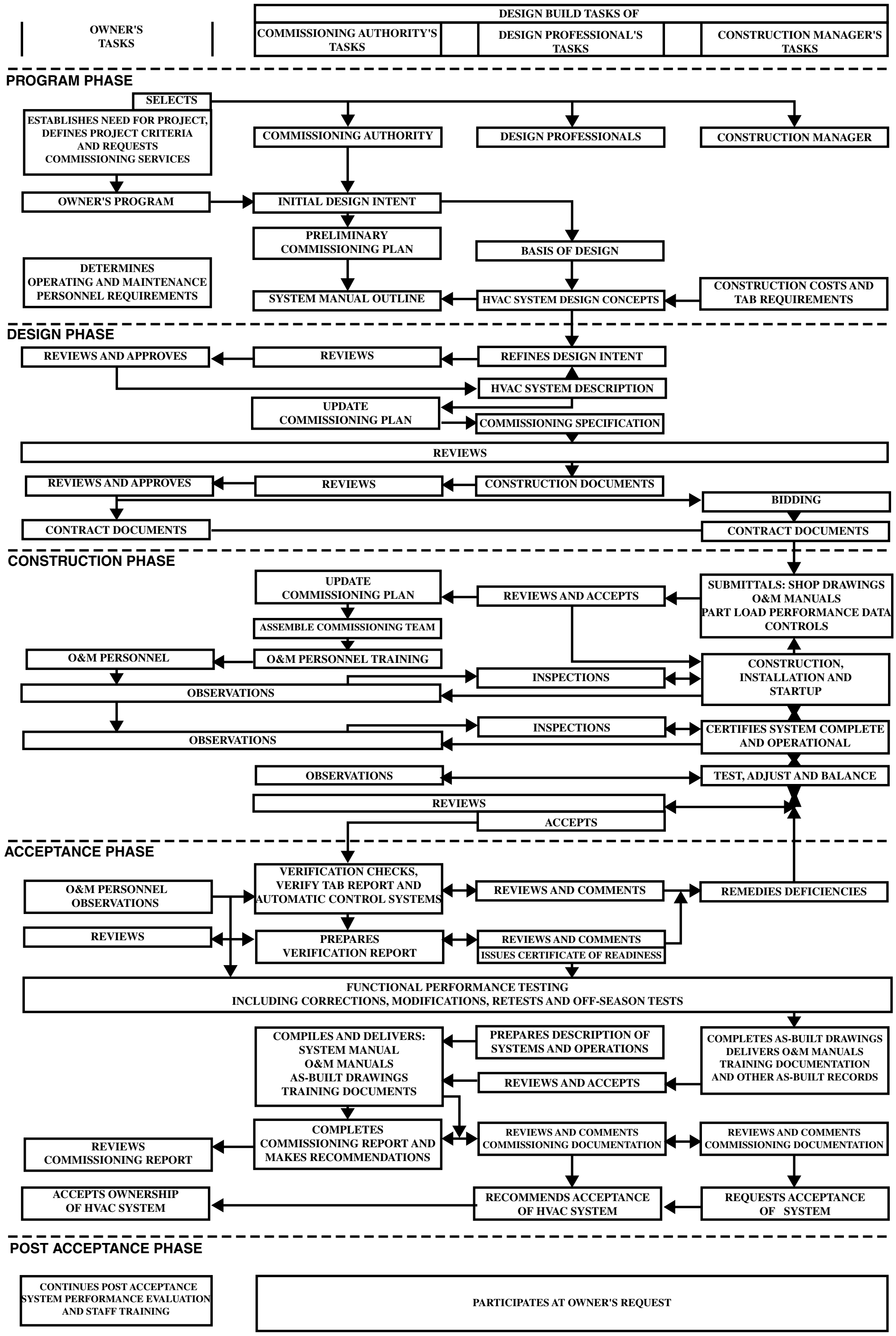

FIGURE 7.1.2 Commissioning process flow chart.

Commissioning Authority

The following is a more detailed listing of the duties of the commissioning authority (CA), as given by ASHRAE (1996):

1. Organize and lead the commissioning team.
2. Prepare the initial design intent document from the information contained in the owner's program.
3. Prepare a program-phase commissioning plan that describes in general the extent of the commissioning process to accomplish the owner's program and the initial design intent.
4. Develop the design-phase commissioning plan, which details the extent and activities of the commissioning process including commissioning team organization, schedule, training, and documentation requirements and all related testing, verification, and quality control procedures.
5. Review and comment on the impact of the design documents on the HVAC commissioning process for the mechanical, electrical, structural, plumbing, process, interior design, and other design professionals within the commissioning process, so that interfaces between systems are recognized and coordinated.
6. Prepare the construction-phase HVAC commissioning plan required as part of the commissioning specification. Include a list of all contractors for commissioning events by name, firm, and trade specialty.
7. Execute the HVAC commissioning process through organization of meetings, tests, demonstrations, training events, and performance verifications described in the contract documents and in the approved HVAC commissioning process. Organizational responsibilities include preparation of agendas, attendance lists, arrangements for facilities, and timely notification of participants for each commissioning event. The commissioning authority acts as chair at all commissioning events and ensures execution of all agenda items. The commissioning authority prepares minutes of every commissioning event and sends copies to all commissioning team members and attendees within five workdays of the event.
8. Review the plans and specifications with respect to their completeness in all areas relating to the HVAC commissioning process. This includes ensuring that the design phase commissioning plan is followed and adequate devices are included in the design in order to properly test, balance, and adjust the systems and to document the performance of each piece of equipment and each system. Any items required but not shown shall be brought to the attention of the construction manager prior to submittal of shop drawings.
9. Schedule the construction-phase coordination meeting within 90 days of the award of the contract at a convenient location and at a time suitable to the construction manager, the HVAC design professional, and the electrical design professional. This meeting is meant for reviewing the complete HVAC commissioning process and establishing tentative schedules for mechanical and electrical system orientation and inspections, O&M submittals, training sessions, system flushing and testing, job completion, testing, adjusting, and balancing (TAB) work, and functional performance testing.
10. Schedule the initial owner HVAC training session so that it is held immediately before the mechanical system orientation and inspection. This session is attended by the owner's O&M personnel, the HVAC design professional, the electrical design professional, the mechanical contractor, the electrical contractor, and the commissioning authority. The HVAC design professional will conduct this session with the assistance of the electrical design professional, giving an overview of the system, the system design goals, and the reasoning behind the selection of the equipment.
11. Coordinate the HVAC mechanical system orientation and inspection following the initial training session. The mechanical system orientation and inspection is conducted by the mechanical contractor. Its emphasis is on observation of the equipment's location with respect to accessibility. Prepare minutes of this meeting, with separate summaries of deficiency findings by the owner's staff and commissioning authority. Distribute to attendees and the owner.

12. Coordinate the HVAC electrical system orientation and inspection following the HVAC mechanical system orientation and inspection session. The electrical system orientation and inspection is conducted by the electrical contractor. Its emphasis is on observation of the equipment's location with respect to accessibility and function. Prepare minutes of this meeting, with separate summaries of deficiency findings by the owner and commissioning authority. Distribute to attendees and the owner.
13. Receive and review the operations and maintenance (O&M) manuals as submitted by the contractor. Ensure that they follow the specified outline and format. Insert the system's description as provided by the HVAC design professional in the Systems Manual.
14. Check the installation for adequate accessibility for maintenance and component replacement or repair.
15. Witness equipment, subsystem, and system start-up and testing. Ensure that the results are documented — including a summary of deficiencies — and incorporated in the O&M manuals.
16. Prior to initiating the TAB work, meet with the owner, mechanical contractor, HVAC design professional, and TAB contractor. The TAB contractor will outline TAB procedures and get concurrence from the HVAC design professional and commissioning authority. Ensure that the TAB contractor has all forms required for proper data collection and that he or she understands their importance and use.
17. Schedule the O&M training sessions. These training sessions are attended by the owner, the commissioning authority, the HVAC design professional, the electrical design professional, the construction manager, contractors, and equipment suppliers, as necessary. The format of these sessions follows the outline in the O&M manuals and includes hands-on training.
18. Upon receipt of notification from the construction manager that the HVAC system has been completed and is operational and the TAB report has been accepted by the HVAC design professional, proceed to verify the TAB report and the function of the control systems in accordance with the commissioning specification. Prepare a verification report, including all test data and identification of any deficiencies, and submit it to the owner and HVAC design professional for review.
19. Supervise the commissioning team members in the functional performance tests. The test data will be part of the commissioning report.
20. Review "as-built" drawings for accuracy with respect to the installed systems. Request revisions to achieve accuracy.
21. Ensure that the O&M manuals and all other "as-built" records have been updated to include all modifications made during the construction phase.
22. Prepare the Systems Manual.
23. Repeat functional performance tests to accommodate seasonal tests and/or correct any performance deficiencies. Revise and resubmit the commissioning report.
24. Assemble the final documentation, which will include the commissioning report, the Systems Manual, and all "as-built" records. Submit this documentation to the owner for review and acceptance.
25. Recommend acceptance of the HVAC system to the owner.

Commissioning Resources

Commissioning projects can be implemented at many levels of detail and a number of guidelines for implementing commissioning projects are available. *ASHRAE Guideline 1-1996: The HVAC Commissioning Process* (ASHRAE, 1996) is a product of the ASHRAE consensus process and as such has benefited from the input of all major stakeholders. It does not contain sets of forms and tables which are often helpful in scheduling and setting up the tests required in the process. The PECI guideline of Haasl and Sharp (1999) is helpful in this regard. They list 21 sources for commissioning guidelines, guide specifications, and sample functional performance tests. An abridged version of this list is provided in Table 7.1.1.

TABLE 7.1.1 Sources for Commissioning Guidelines, Guide Specifications, and Sample Functional Performance Tests

Source	Guidelines	Guide Specs	Sample Tests
Model Commissioning Plan and Guide Commissioning Specifications, USDOE/PECI, 1997. NTIS: # DE 97004564, 1-800-553-6847. PECI Web site: http://www.peci.org.	Some	Yes	Yes
The HVAC Commissioning Process, ASHRAE Guideline 1-1996, 1996. ASHRAE Publications Dept., 1791 Tullie Circle, NE, Atlanta, GA 30329.	Yes	Some	No
Engineering and Design Systems Commissioning Procedures, U.S. Army Corps of Engineers, 1995 (ER 1110-345-723). Department of the Army, U.S. Army Corps of Engineers, Washington, D.C. 20314-1000.	Some	Some	No
Commissioning Specifications, C-2000 Program, Canada, 1995. C-2000 Program, Energy Mines & Resources, Energy Efficiency Division, 7th Floor, 580 Booth St., Ottawa, Ontario, Canada K 1 A OE4.	No	Yes	No
Building Commissioning Guide, U.S. General Services Administration and USDOE, 1995. Prepared by Enviro-Management & Research, Inc., 703-642-5310.	Yes	No	No
Commissioning Guide Specification, Facility Management Office, University of Washington, 1993-6. http://weber.u.washington.edu/-fsesweb/	No	Yes	Some
Commissioning Guidelines, *Instructions for Architects and Engineers*, State of Washington, 1995. Dept. of General Administration, Div. of Engineering & Architectural Services, 360-902-7272.	Yes	No	No
Standard HVAC Control Systems Commissioning and Quality Verification User Guide, U.S. Army Const. Engineering Research Laboratories, 1994. Facilities Engineering Applications Program, U.S. Army Engineering and Housing Support Center, Ft. Belvoir, VA 22060-5516. FEAP-UG-GE-94/20.	No	No	Yes
Contractor Quality Control and Commissioning Program — Guidelines and Specification, Montgomery County Gov., State of Maryland, 1993. 301-217 6071.	Yes	Yes	Some
Procedural Standards for Building Systems Commissioning, National Environmental Balancing Bureau (NEBB), 1993. NEBB, 1385 Piccard Drive, Rockville, MD 20850. 301-977-3698	Yes	Some	Some
HVAC Systems Commissioning Manual, Sheet Metal and Air Conditioning Contractors' National Association (SMACNA), 1993. SMACNA, 4201 Lafayette Center Dr., Chantilly, VA 22021.	Yes	Some	Some
Guide Specification for Military Construction — Commissioning of HVAC Systems, Department of the Army, U.S. Army Corps of Engineers, January 1993. Department of the Army, U.S. Army Corps of Engineers, Washington, D.C. 20314-1000	No	Some	Yes
Commissioning Guide, Public Works Canada, Western Region, 1993. 403-497-3770.	Some	Yes	No
Building Commissioning Guidelines, Bonneville Power Administration/PECI, 1992. 503-230-7334.	Yes	Some	Some
The Building Commissioning Handbook, The Association of Higher Education Facilities Officers (APPA), written by John Heinz and Rick Casault, 1996. APPA, 1643 Prince Street, Alexandria, VA 22314.	Yes	Yes	No
HVAC Functional Inspection and Testing Guide, U.S. Dept. of Commerce and the General Services Administration, 1992. NTIS: 800-553-6847.	No	No	Yes
AABC Master Specification, Associated Air Balance Council (contains information on how the TAB fits into the commissioning process.) AABC National Headquarters, 202-737-0202.	No	Yes	No

Source: Abridged from Haasl and Sharp, 1999.

7.1.2 Case Study — Boeing Commercial Airplane Group Headquarters

Project Overview

The Boeing Company maintains and operates a large number of facilities in multiple locations. Over the years, Boeing has used many different methods to design, construct, and maintain its facilities. It currently uses an internal Facilities Asset Management Organization to handle the real estate, procurement, construction, maintenance, and asset accounting functions required to site, build, maintain, and manage all aspect of facilities infrastructure for the commercial airplane group.

The original case study description (Davenny, Doering, and McGuire, 1999), from which this description has been condensed and adapted, was written by two lead members of the Boeing project management team and the lead engineer for the commissioning agent.

The commissioning process used for this project is the result of many years of experience by Boeing's facilities personnel, and as such is not identical to the ASHRAE process. However, there are many common elements. The emphasis placed on the commissioning process is indicative of the direction in which the overall construction process at Boeing is headed. The company believes that the inherent benefits and efficiencies of the commissioning process increase staff effectiveness and help ensure success in the construction, operation, and maintenance of facilities.

The new commercial airplane group headquarters office building is a 309,000 square feet, 5-story office building located in Renton, Washington, and houses executive, administrative, and sales offices. The project was performed as a cost-plus-fixed-fee, design-build partnering effort. It began in October 1996 with initiation of the programming and preliminary design process. Ground was broken on May 14, 1997, and the building was occupied on October 2, 1998. (Costs below are for 1998.)

Commissioning Organizational Structure

The owner decided to expand the scope of the mechanical engineer's role to include the commissioning process. The mechanical engineer thus was assigned to act as the commissioning focal (CF), responsible for managing the commissioning work, in addition to being the owner's representative to the mechanical design and construction process, functioning as the liaison between the Boeing operating and maintenance staff and the design/construction team, reviewing design and equipment submittals, and resolving coordination problems and operational issues.

The owner then hired an independent commissioning agent who was assigned the responsibility of defining and executing the detailed quality assurance measures and system functional tests. Thus, the commissioning authority's (CA) responsibilities for the ASHRAE process were divided between the CF and the commissioning agent on this project. This allowed the CF to maintain an overview of the commissioning process, while still giving the required attention to other responsibilities. As the project developed, a commissioning team, which included representatives from the various contractor and facilities personnel, was formed. The coordination and communication role of the CA was identified, and the quality assurance and documentation duties which the company had traditionally viewed within the scope of commissioning were expanded to include organizing, scheduling, and reporting on the weekly commissioning team meetings, similar to the ASHRAE process recommendations. With a direct reporting line between the owner and the CA, the appropriate channel was available for decision making and problem resolution by the owner's staff.

Role and Responsibilities of a Commissioning Agent

The scope of work negotiated between the commissioning agent (CA) and the owner included the following specific responsibilities:

- Commissioning or Cx plan: This plan was prepared as a draft review document using input from all team members to establish respective roles, responsibilities, and communication pathways which were not articulated in the design/build contract documentation. The purpose was to clearly define the specifics of contractor relationships, reporting structures, and paper flow requirements relating to Cx. This plan became the focal point for the construction team to define, implement, and administer the Cx scope and process.
- Schedule: The CA assisted the general contractor with incorporating Cx into the master construction schedule. The Cx plan was translated into scheduled activities with specific milestones and scheduled time frames. These tasks were assigned work breakdown structure numbers to "nest" within the master schedule. Documentation requirements for each task were indicated on the MS project schedule document. This was to ensure that the Cx process enhanced project work flow as well as overall quality.

- Start-up documentation: The Cx team, led by the CA, reviewed and developed installation, start-up, and point-to-point checklists and appropriate follow-up documentation for subcontractor specialties. This step was incorporated into the Cx plan as the various specifications and responsibilities were reviewed.
- Test procedures and record sheets: Functional performance test procedures and record sheets for the various systems and components were written and executed. The systems included most of the mechanical and controls equipment within the building, including interface with other campus facilities. Electrical scope consisted of reviewing component test documentation by third party testing agents and witnessing emergency power system demonstrations.
- Quality assurance: Spot checking of test and balance scope for more than 400 VAV terminal boxes throughout the building was initially performed on 10% of the units. This QA scope expanded as a number of installation and operational irregularities were noted. Rather than having an adversarial role, the prefunctional testing allowed the team to resolve potential occupancy issues ahead of move-in.
- Cx meetings: The CA organized, scheduled, and conducted 38 regular meetings involving appropriate team members with a focus on the Cx process and related activities. These meetings supplemented other construction meetings as part of the Cx package and included the writing and distribution of meeting minutes, schedule generation and modifications, and task follow-up.
- Cx reports and Cx manuals: Reports were generated detailing site activities and items of importance during the construction and testing phases. These reports represented the summation of issues requiring resolution during construction and the performance of functional test procedures. Additionally, the final versions of all documentation relating to the scope outlined above were incorporated into appropriate format for a Cx manual.

Contract and Specification Issues

One of the biggest challenges presented to the commissioning effort was to revisit the client design criteria and review plans and specifications for enhanced compliance to Cx standards during construction. The design-build partnering aspects of the project facilitated the Cx in ways uncommon to bid-spec delivery, including such things as designated focals, time allotments, and extended cost mechanisms. The details, however, needed a fair amount of fleshing out. In some ways, the Cx team was playing a "catch-up" game by defining requirements as events occurred. Many times the Cx meeting forum identified technical issues during the job that were not addressed in the conventional construction meetings. The net effect was very positive.

Technical Issues

The building equipment, which was the focus of the HVAC commissioning work, included four custom air handling units (AHUs) with a total capacity of 350,000 cfm, associated fans with variable frequency drives (VFDs), pumps, coils and dampers, 400 VAV fan-powered terminal units, a building automation direct digital control system, and other miscellaneous systems and items.

One of the areas of greatest interest technically is that of VFDs. These devices control the air handler supply and return fan motors, and while they were provided by the electrical contractor, they are integral to the mechanical performance of the systems and are interfaced with the building automation system (BAS). Thus, there was great potential for conflict between various contractors as problems arose. Issues identified by the functional testing of these drives were added to a close-out punch list and resolved by the appropriate parties. These included:

- The need to provide additional wiring from the local unit disconnect back to the VFD to provide a shut down of the drive when the disconnect was open.
- Identification of proper VFD keypad operation to avoid conflict with the BAS.
- The need to repair fan intake damper closure so the drives did not fault due to inadvertent backward turning of the fans when disabled.

- Increase of minimum fan speed setting to avoid overvoltage occurrence at the drive when all flow was across a return fan in full recirculation mode.
- Identification of wiring problems at the motor controller when a drive was placed in bypass mode.

It was very beneficial to have these issue identified and resolved while all affected parties were still involved with project close-out.

The quality assurance scope included sampling the test and balance work performed at variable air volume terminal units throughout the space. This was particularly important to make sure that the staged building occupancy could proceed on a floor-by-floor basis with a minimum of disruption and comfort callbacks. This included checking the diffuser proportioning, primary air valve operation, and control of the air valves by the unit air flow sensors. Groups of terminal units were checked by changing control set points and trending zone responses in heating and cooling modes. Problems identified and corrected included:

- Improper installation of duct mounted air flow sensors
- Faulty proportioning of some terminal unit air flows
- Connection of a few zone temperature sensors to the wrong terminal units
- Improper setpoints at some terminal units

As a result of the problems identified, the scope was expanded to test more sample boxes. This process was repeated until all parties were comfortable with the performance of the equipment.

The commissioning process for this project also included the electrical systems and the fire alarms and smoke control systems.

Costs and Benefits of Commissioning on this Project

The services and deliverables described in the CA scope of work, as well as the ancillary support and testing work cost $0.58 per square foot. The overall cost picture should include the subcontractor costs associated with commissioning. Those figures were not available at the time of publication.

Some of the individual problems identified and corrected by the commissioning process have already been mentioned. During the construction process, the team initiated weekly commissioning meetings attended by designated representatives from the various contractors, subcontractors, and Boeing departments. These proved to be a valuable auxiliary forum for communication between partnering staff and the affected parties and facilitated the identification and resolution of technical and operational issues in a proactive fashion. The Cx team meetings complemented weekly foreman and owner's meetings and added depth and focus to many areas that are traditionally problematic. The meetings continued until well after the building was occupied and ensured post-construction continuity of design intent and owner satisfaction.

The Boeing project managers contend that:

> The benefits of Cx work are easily recognizable to those involved with construction, operating, and maintaining buildings and related systems. That perspective is not always as easy to demonstrate to the business and financial entities within organizations. Placing a monetary value on items such as fewer change orders and contractor call-backs, expending less O&M staff time, and having fewer building occupant complaints, "sick" building scenarios, systems outages, and equipment warranty issued can be difficult. The best case for any owner can usually be made internally, when the total costs of projects performed without Cx are analyzed. This usually requires identifying and isolating costs encountered after the construction project is closed out. This can be a somewhat cumbersome and painful, but beneficial, undertaking for any company. In today's business climate, the value of avoided litigation should also be considered. When the total value of such avoided costs and realized benefits is truly accounted for, Cx is recognized as one of the best bargains in the construction marketplace today.

7.1.3 Commissioning Existing HVAC Systems: Continuous Commissioning

Commissioning of HVAC systems in existing buildings is intended to identify and correct any construction problems that have not been rectified, just as commissioning does in a new building. However, it is also intended to identify and correct other problems that develop during subsequent operation of the building.

Operators and maintenance personnel often increase utility consumption when dealing with an immediate problem. For example, the chilled water temperature might be decreased from 42°F to 39°F if one of the AHUs cannot provide 55°F cold air with 42°F chilled water since the control valve is stuck in a partially closed position. Or the static pressure of the VAV systems is set at a higher level than needed instead of locating the kink in the flex duct that limits flow and cooling in one zone. The efficiency issues associated with these solutions are ignored. During building operation, resolving comfort problems is a top priority. However, inefficient solutions such as those noted above tend to accumulate as time passes, and these solutions often lead to additional comfort problems. It is generally true that an older building has more comfort problems and opportunities to improve HVAC efficiency than a new building.

Commissioning of existing buildings is called by various names including: continuous commissioning (CC), retro-commissioning, and recommissioning. Common practice when commissioning an existing building emphasizes bringing the building operation into compliance with design intent. However, changes occur in most buildings as time passes so the operation of an existing building which is commissioned will generally differ from the original design intent. Some practitioners started using the term "recommissioning" to distinguish between the commissioning of new buildings and existing buildings, but this has met some resistance since it implies that the building was originally commissioned, which is seldom the case. The term "retro-commissioning" is used by many to indicate that commissioning was performed as a "retrofit" to an existing building.

"Continuous commissioning" (CC) is a term applied to the commissioning process developed by a group of researchers at the Energy Systems Laboratory at Texas A&M University. The continuous commissioning process assumes that building use and operation are sufficiently different from the original design intent; therefore, a new optimum operating strategy should be regularly identified and implemented. This process uses advanced approaches to optimize the HVAC system operation to meet the current needs of the building. An additional feature of the CC process is ongoing follow-up after the initial CC activities to maintain and continuously improve the facility operation. The CC process will be the commissioning process for existing buildings which is described in this chapter.

Benefits of Commissioning Existing Buildings

The specific benefits of commissioning existing buildings can be summarized as follows:

1. Identifies and solves system operating, control, and maintenance problems.
2. Provides cost savings that rapidly pay back the commissioning cost.
3. Normally provides a healthier, more comfortable, and productive working environment for occupants.
4. Optimizes the efficiency of the energy-using equipment subject to the comfort requirements of the building.
5. Reduces maintenance costs and premature equipment failure.
6. Provides better building documentation which expedites troubleshooting.
7. Provides training to operating staff, increasing skill levels.
8. Provides the basis for accurate retrofit recommendations to upgrade the facility.

Commissioning of existing buildings is very attractive economically, even if the only benefit considered is energy savings. Gregerson (1997) presented results from commissioning 44 existing buildings that showed simple paybacks which ranged from 0.1 years to 4.2 years, with 28 having a payback of less than one year, 12 between 1.0 and 2.0 years, and only 4 with a payback longer than 2.0 years. The buildings in this study were generally large buildings, with the smallest having 48,000 square feet, and only 12 were less than 100,000 square feet. Energy use in these buildings was reduced by 2% to 49% with an average reduction of 17.5%. The cost of commissioning was quite evenly distributed over the range from \$0.03/square feet to \$0.43/square feet with 11 buildings less than \$0.10/square feet and 9 at more than \$0.30/square feet.

Evaluating an Existing Building for Commissioning

The most effective way to evaluate the commissioning potential of an existing building is to conduct a commissioning screening survey of the building. The following characteristics typically indicate a building with high commissioning potential:

1. A significant level of comfort complaints. The systems in buildings that do not produce uniform comfort have generally been adjusted in ways that reduce efficiency in attempts to deal with the comfort complaints.
2. A high level of energy use for the building type. A building which uses more energy than similar buildings with comparable use patterns is generally a prime candidate to benefit from commissioning.
3. Indoor air quality problems. Buildings that experience complaints about indoor air quality often have HVAC systems adjusted in ways that may or may not resolve the IAQ problem, but that compromise effective and efficient operation.
4. Buildings with energy management and control systems (EMCS). The EMCSs installed in buildings are rarely used to the full extent of their capabilities. This may be due to one or more of the following: (a) failure of the operating staff to fully understand the system, (b) failure of the control contractor to adequately understand the HVAC system in the building, and/or (c) poor design specification from the mechanical engineers.

The presence of one or more of these characteristics, coupled with any other known operating problems, is normally good justification for performing a screening study for the commissioning potential of a building. A commissioning screening will generally cost approximately \$0.01–\$0.03/square foot for medium to large facilities.

The Process of Commissioning Existing Buildings

The process of commissioning an existing building can be viewed in terms of four phases: planning, investigation, implementation, and follow-up phases as shown in Table 7.1.2. The planning phase commissioning activities most closely parallel those during the conceptual or predesign phase for a new building. Some activities during the investigation phase overlap with the construction phase, while others overlap with the acceptance phase for a new building. Implementation phase activities generally parallel some of those in the acceptance phase for a new building, and the hand-off parallels the post-acceptance phase.

Planning Phase

The first step in planning the commissioning of an existing building is to evaluate the need for commissioning. The operating staff may be aware of problems in the building that have never been properly resolved due to time constraints or other factors. There may also be a strong sense that commissioning or tune-up of the building is likely to provide significant benefits. This should generally be followed by a screening visit by one or more experienced providers of commissioning services. This will typically require a few hours to a few days (depending on the size of the facility) to examine the systems and operating practices of a large building, examine selected EMCS settings, and make selective system measurements. Examination of available building documentation and analysis of historical utility data are normally part of the screening visit. After consultation with the facility staff, a commissioning proposal tailored to the needs of the building should be provided. The proposal includes a price, services to be provided, and specific benefits to be expected.

Investigation Phase

The investigation phase should begin with meetings with the facility manager and any members of the facility operating staff who have been assigned to be part of the commissioning team. They will review

TABLE 7.1.2 Process Comparison for Commissioning Existing Buildings and New Buildings

Existing Buildings	New Construction
1. Planning phase (a) Determine need for commissioning. (b) Review available documentation and obtain historical utility data. (c) Conduct commissioning screening study. (d) Hire commissioning provider. (e) Develop commissioning plan.	**1. Conception or predesign phase** (a) Develop commissioning objectives. (b) Hire commissioning provider. (c) Develop design phase commissioning requirements. (d) Choose the design team.
No design phase activities	**2. Design phase** (a) Do a commissioning review of design intent. (b) Write commissioning specifications for bid documents. (c) Award job to contractor. (d) Develop commissioning plan.
2. Investigation phase (a) Obtain and develop missing documentation. (b) Develop and implement M&V plan. (c) Develop and execute diagnostic monitoring and test plans. (d) Develop and execute functional test plans. (e) Analyze results. (f) Develop master list of deficiencies and improvements. (g) Develop optimized operating plan for implementation.	**3. Construction/installation phase** (a) Gather and review documentation. (b) Hold commissioning scoping meeting and finalize plan. (c) Develop pretest checklists. (d) Start up equipment or perform pretest checklists to ensure readiness for functional testing during acceptance.
3. Implementation phase (a) Implement repairs and improvements. (b) Retest and monitor for results. (c) Fine-tune improvements if needed. (d) Determine short-term energy savings.	**4. Acceptance phase** (a) Execute functional test and diagnostics. (b) Fix deficiencies. (c) Retest and monitor as needed. (d) Verify operator training. (e) Review O&M manuals. (f) Have building accepted by owner.
4. Project hand-off/integration phase (a) Prepare and submit final report. (b) Document savings. (c) Provide ongoing services.	**5. Post-acceptance phase** (a) Prepare and submit final report. (b) Perform deferred tests (if needed). (c) Develop recommissioning plan/schedule.

Source: Modified from Haasl and Sharp, 1999.

building operating practices, special client needs, and all known operating problems in the building. It may be necessary at this point to search for or develop additional documentation — for example, obtain manufacturer information specifications for chillers, AHUs, or other equipment. A request may be sent to the utility for 15-minute electrical data if it is recorded, but not routinely provided. A plan should be developed for verification of the results of the commissioning effort and additional instrumentation should be installed if needed. The commissioning provider must determine the diagnostic and functional tests needed, and then execute them with participation and assistance of the building operating staff. These tests will typically consist of some combination of setting up trend logs on the EMCS, a series of spot measurements on the building systems, and/or installation of temporary portable loggers to record critical system parameters for a day or more.

The results of these tests will be analyzed and a list of operating changes, equipment maintenance, and possibly equipment retrofit recommendations will be generated. This list should include the expected comfort improvements and/or operating savings that will result from these changes. The list may also include items that were evaluated, but that do not appear to be cost effective or offer significant comfort and other benefits.

Implementation Phase

The recommendations will be discussed with the operating staff or an owner's representative who will decide which recommendations will be implemented. Implementation may be handled by the building staff, the commissioning provider, or a third party, depending on the skills and preferences of the owner. It is desirable to use EMCS data, or other data collected on an hourly basis, to verify the impact of the changes in the first days following implementation. This often provides near-term positive feedback to the operating staff on the impact of the changes. It can also give rapid feedback to the provider if the changes are not as effective as anticipated, and provide the basis for further fine tuning. The short-term savings determined from monitored data can then be used for comparison with the original savings estimates, and revisions can be made as necessary.

Project Follow-up/Integration Phase

Report: At this point, a final report on the commissioning effort is prepared and delivered to the owner. This report should provide a clear explanation of the optimum operating strategy which has been implemented in a concise format useful for the operators.

Document savings: The savings should be documented with the measured hourly data or utility bills. The savings analysis will consider the impacts of weather variation, usage schedules, and occupancy changes. The savings should be documented as soon as possible after the procedures are implemented. Monthly or quarterly reports are desirable.

Provide ongoing services: After completing the initial commissioning process, the commission engineers should provide assistance whenever the building operating staff needs it. This assistance is often needed when there is a change in occupancy, equipment, or schedule. It is a good "rule of thumb" for the operating staff to seek input from the commissioning engineers any time they are ready to revert to earlier practices to resolve an occupant complaint or component malfunction.

7.1.4 Continuous Commissioning Guidelines

Continuous commissioning (CC) guidelines should define the objectives of the commissioning process and provide procedures a checklist to follow, and documentation requirements. The commissioning team should follow the guideline to provide quality services. An abbreviated set of example guidelines is provided next using air handlers as an example.

Sample CC Guidelines for AHU Commissioning

These guidelines include the following sections: objectives, common AHU problems, AHU information requirements, CC procedures, and CC documentation.

Objectives

Optimize the deck and static pressure reset schedules to maintain room comfort conditions; improve electrical and mechanical equipment operation; minimize the fan power, chilled water, and hot water consumption.

Common AHU Problems

1. Inefficient deck and static pressure reset schedules
2. Inability to maintain room comfort (temperature and/or RH)
3. VFD and valve hunting
4. Low differential temperature across the coils
5. Inability to maintain the deck setpoints
6. Too much cold and hot air leakage through dampers in the terminal boxes

AHU Information Requirements

1. Sketch a single line diagram for each AHU (fill in standard forms)
2. Fan: hp, type (VFD, inlet guide vane, eddy switch, or other)
3. VFD: type, hp, brand, working condition (% speed, hunting)
4. Automatic valve description: type (normally open or closed), range (3–8 psi or 0–13 psi), working condition, and control (by EMCS or stand alone controller, DDC or pneumatic)

5. Coil data: inlet and outlet temperature (design and measured) and differential pressure
6. Damper data: working condition (adjustable or not), actuator condition
7. Temperature sensors: EMCS readings and hand meter readings
8. Controller condition: working or disabled
9. Air flow: note setting for outside air flow, return air flow, maximum total flow, and minimum total flow
10. Condition of system air flows: measure temperature and CO_2 level for outside air, return air, and supply air
11. Control sequence: determine cold and hot deck setpoints, economizer control sequence, and static pressure control sequence

CC Procedures

Step 1: Commission temperature and pressure sensors.
Use a hand meter to verify accuracy of discharge air temperature sensors and differential pressure sensors. Make sure the readings from the EMCS or the control system agree with the field measurements. If the control system readings do not agree with the hand meter readings, repair or replacement should be performed. If a systematic bias exists, a software correction may be used but is not recommended.

Step 2: Determine the optimal static pressure for a VAV system.
Modulate the variable flow device, such as the VFD, eddy switch, or the inlet guide vane, to maintain the minimum static pressure level at preselected terminal boxes. Record the static pressure in the main duct as read by the control system. This pressure should be the setpoint for the current load condition.

Step 3: Test the optimal static pressure setpoint.
If the optimal setpoint is very different from the existing setpoint, reset the static pressure to the optimal level and wait for a while to see if any problems occur. If comfort problems occur in another area, correct the problem at the local level.

Step 4: Determine the cold and hot deck setpoints under the current conditions.
Field testing method: the optimal cold and hot deck setpoints can be determined by following an engineering procedure developed by the ESL.
Analytical method: both optimal hot and cold deck reset schedules can be determined by model simulation using AirModel.

Step 5: Determine the cold and hot deck reset schedules.

Step 6: Determine the outside air intake. Measure outside air, return air, and total supply air flow rates. Measure return air CO_2 levels. If the outside air intake is lower than the design value and the return air CO_2 level is lower than 800 ppm when the building is occupied, no minimum outside air increase is suggested. However, a spot check is suggested for the CO_2 levels in individual rooms. If the outside air intake is higher than the design value and the CO_2 levels are lower than 800 ppm, the minimum outside air flow should be adjusted based on the current standard. Make sure that the CO_2 level in the return air is not higher than 800 ppm when the building is occupied. Inspect damper actuators.

Step 7: Select a control sequence. Locate each sensor position and draw a schematic diagram. Draw a block diagram of the AHUs and control systems. Select a control sequence. This step is strongly system dependent. Commissioning engineers should be able to perform the task independently. Summarize the current control sequence and the proposed control sequence.

Step 8: Implement the optimal reset schedule. Inspect valve and VFD operation and trend data with a time interval of 10 sec. If any valve or VFD is hunting, PID fine tuning should be performed first. Change the control program and trending control parameters. Compare the setpoint and the measured data. If there are any problems, troubleshooting should be performed immediately.

CC Documentation

In addition to the physical characteristics and operational parameters noted in the Documentation Guidelines, the following information must be recorded when an AHU is commissioned:

1. Pre-CC and post-CC reset schedules
2. Repair list
3. Suggestions
4. Operational procedures

CC Guidelines for Water Loop Commissioning

These guidelines include the following sections: objectives, common waterside problems, water loop information requirements, CC procedures, and CC documentation.

Objectives

Identify optimal pump operating points or control schedules to (a) supply adequate water to each coil, (b) minimize pump energy consumption, and (c) maintain optimal differential temperature.

Common Waterside Problems

1. Coexistence of over-flow and under-flow
2. Low differential temperature for the whole building loop
3. Lack of flow in some coils
4. Poor automatic valve control performance due to high pressure
5. Over-pressurization of building loop
6. VFD hunting

Water Loop Information Requirements

1. Water loop riser diagram: differential pressure sensor position, temperature sensor position, automatic valve position, building bypass, coil bypass
2. Pump: single line diagram of pump and pipe line connections, hp, VFD, differential pressure across pump
3. VFD: operating conditions (working, manual, bypassed, damaged), % of speed or Hz, control logic
4. Automatic valves: operating condition (working, bypassed), type (normally open or closed), operating range, location, function, and position
5. Control: loop control logic, differential pressure reset schedule, return temperature reset schedule, automatic control valve control schedule
6. Water conditions: building supply and return temperature, coil supply and return temperature, differential pressure across building and each coil

CC Procedures

Step 1: Valve commissioning. Connect all valves to the control system or controllers. Troubleshoot malfunctioning controllers or control system. Fine tune PID gains to eliminate hunting.

Step 2: Verify valve working conditions. Measure air discharge temperature. If the discharge air temperature setpoint is maintained, the valves are working. If the discharge air temperature cannot be maintained in more than half of the coils, repeat step 1.

Step 3: Reset balance valves to adjust differential pressure to a correct level.

Step 4: Determine the minimum differential pressure under current conditions.

Step 5: Determine the reset schedules. Measure the building water return and supply temperatures and flow rate under the optimal differential pressure. The building energy consumption can be determined from the measured data. Determine the maximum load on the building and the differential temperature under the maximum load condition.

If a VFD is installed, the maximum differential pressure is then determined by the following formula:

$$\Delta P_{\max} = \Delta P_{\text{current}}\left(\frac{Q_{\max} \times \Delta T_{\text{current}}}{Q_{\text{current}} \times \Delta T_{\max}}\right)^2$$

The ΔP_{max} is the maximum differential pressure setpoint at the maximum load, Q_{max} is the maximum load, ΔT_{max} is the differential temperature under the maximum load conditions, and $\Delta T_{current}$ is the differential temperature under the current load conditions. When there is no VFD in the loop, determine the minimum differential pressure; it is the same as the maximum pressure if a building bypass is used.

If there is no building bypass and VFD, the maximum differential pressure can be determined by the above equation.

Step 6: Implement the reset schedule. When a VFD exists, correlate the differential pressure with the outside air temperature. A linear equation is suggested. Program it into the controller. When neither VFD nor building bypass exist, modulate the balance valve in the main line to maintain the differential pressure at the maximum value. The impact of the main loop pressure variation can be considered by adding a possible drop to the maximum setpoint.

When a building bypass exists without VFD, the minimum differential pressure should be maintained. Note that the main loop impact on the building loop can be considered by adding a possible drop to the minimum setpoint.

CC Documentation

The following information should be documented:

1. Pre-CC control and post-CC control sequence
2. Valve and VFD performance
3. Energy performance
4. Operation procedures
5. Problem and repair lists
6. Other suggestions

CC Case Study — Texas Capitol Extension Building

The Texas Capitol Extension Building was built in 1992 as an energy-efficient building intended to surpass the performance of other buildings in the complex. It is located next to the State Capitol and is entirely below grade to preserve open space around the Capitol. The two upper floors are built around a covered atrium and House legislative offices and hearing rooms. Two lower floors are a parking garage. Total floor area is 55,100 m^2, while the conditioned area (the two upper floors) is 33,500 m^2.

The building receives both chilled water and steam from a central plant. Three secondary chilled water pumps (50 hp each) are used to circulate chilled water in the building. Heat exchangers are used to convert steam to hot water. Three hot water pumps circulate hot water to provide heating for the building.

Twenty-one dual duct VAV systems (DDVAV) are used to condition the office area. Eight single duct VAV systems (SDVAV) are used to condition 16 hearing rooms. Twelve single duct constant volume systems (SDCV) serve the central court area, one auditorium, and a pump room. Five constant volume units serve the kitchen and dining area. Outside air is pretreated by four variable volume units (OAHU-VFD) and supplied to each mechanical room. Four supply fans and four exhaust fans serve the two-story parking garage. A total of fifty AHUs and eight fans serve the building.

The modern DDC energy management and control system (EMCS) is used to control the operation of HVAC systems. When commissioning was begun, it was found that the EMCS was being used to implement:

1. Hot water supply temperature reset
2. Chilled water and hot water pump lead-lag sequence control
3. Static pressure control for AHUs
4. Cold deck reset for SDVAV
5. Cold deck reset and hot deck control for DDVAV systems

The measured energy consumption before CC was 8,798,275 kWh/yr ($306,444) for electricity; 54,007 MMBtu/yr ($175,524) for chilled water; and 14,931 MMBtu/yr ($57,340) for hot water. The energy cost index was $1.5/ft^2/yr based on conditioned floor area or $0.91/ft^2/yr based on gross area. The building was operated 24 hours a day and seven days a week.

The building was controlled at a satisfactory level except that the hearing rooms needed to be overcooled before a meeting. Discomfort occurred when an unexpected meeting was scheduled at the last minute, leaving no time for the operating staff to react. To solve this problem, the room temperature was kept at 19°C to 21°C during unoccupied hours. However, when the hearing room was packed with people, the AHU could not cool the room satisfactorily. The problem persisted despite repeated attempts to deal with it.

CC Measures Implemented

The CC effort led to implementation of the following changes in the operation of this relatively new and efficient building:

1. *Set back VFD static pressure.* To maintain comfort conditions while minimizing energy consumption, the static pressure and minimum VFD speed were reduced to about half their normal values during the nominally unoccupied hours.
2. *Change control to maintain hearing room comfort.* Hearing rooms were being maintained at 66°F to 69°F during unoccupied hours, and the operators frequently changed the room temperature setpoint in an attempt to maintain room comfort conditions. Even so, room temperatures sometimes reached uncomfortably high levels when the rooms were packed with people. This was determined to be the result of inadequate cooling energy to the hearing rooms.

   After a detailed analysis, it was proposed that cooling energy to the room should be increased under full load conditions, while using the terminal box damper position to reset the static pressure and the cold deck temperature to maintain comfort and reduce energy use at part-load levels. The post-commissioning schedules provide more cooling energy to a room than the old schedules under maximum load conditions; they lower the static pressure and increase the cold deck temperature to reduce energy consumption as soon as the load decreases.

   The control schedule was first tested in one AHU and then implemented in all 8 SDVAVs. After these schedules were implemented, the complaints disappeared and room temperature was maintained in a range of 21°C to 22°C.
3. *Optimize the dual duct VAV system reset schedules.* Twenty-one dual duct VFD AHUs with VAV boxes condition all the offices which comprise 60% of the conditioned area in the building. The hot deck temperature set point was originally 27°C year-round. The cold deck temperature setpoint varied from 13°C to 18°C using a standard algorithm from the control company.

   After a field inspection, it was proposed that both cold and hot deck temperatures be reset based on the highest and lowest supply air temperatures required at the time in any zone. These schedules set the cold deck temperature to 13°C if the minimum supply temperature (T_{supmin}) needed by any zone is less than or equal to 13°C, to T_{supmin} if between 13°C and 18°C, and hold it at 18°C when T_{supmin} goes above 18°C. A similar schedule is used for the hot deck. The proposed schedules were tested first in one AHU, then were implemented in all 21 AHUs within a month.

   Since implementing these schedules, the hot deck temperatures have varied from 21°C to 24°C. There has been almost no heating consumption.

4. *Separate hot water control loops and reset supply temperature.* The Capitol building (CPB) and the Capitol extension (CPX) building have used the same hot water supply temperature control loop since the CPX Building was built. The CPB is an above-ground building with a lot of exterior surface, and the CPX is an underground building with very little surface exposed to ambient conditions. The outside air conditions play an important role in the CPB heating load but have little influence on loads in the CPX building. If hot water supply temperature satisfies the CPB, the consumption of steam for the CPX will increase when outside air temperature decreases.

   In order to satisfy the requirements of the CPB without increasing steam consumption for the CPX building, the following recommendations were implemented:
   a. Provide separate control of hot water supply temperature for the CPB and CPX.
   b. Lower hot water supply temperature from the range 27°C–38°C to the range 27°C–32°C.
5. *Shut down the AHUs that serve the central court area at night.* Eight single duct constant volume AHUs (SDCV) serve the central court area which is about 10% of the conditioned area of the building. Very few occupants are in the central court area at night, especially when the legislature is not in session. The eight SDCVs were shut down at night during nonsession periods. It was found that the space temperature in the central court area increased by about 2°F. The cooling and electricity consumption were reduced at night as expected.
6. *Implement delta-T control for the chilled water loop bypass valve.* Three constant volume chilled water pumps supply the chilled water to the AHUs. The control sequence keeps only one pump on-line most of the time. There is one bypass line with a bypass valve in parallel with the pumps. The chilled water flow typically ranged from 900 gpm to about 1150 gpm with a 2°C to 5.5°C building temperature differential. This caused some chilled water leakage through the coil valves and sometimes resulted in loss of control. ΔT control with a ΔT of 6.7°C was implemented instead of ΔP control. The chilled water flow was reduced to the range of 750 gpm to 1000 gpm. ΔT was maintained between 6.1°C and 6.7°C.
7. *Shut off steam during the summer.* Steam was provided from the central plant continuously. On June 25, 1996, the steam to the heat exchanger was shut off. The measured hot water consumption data showed that this measure reduced hot water consumption by up to 1 MMBtu/hr on days when the daily average temperature was above 24°C.
8. *Optimize outside air intake.* Four AHUs equipped with VFDs supply about 0.2 CFM/square foot of outside air to the building following the design specifications. The CO_2 levels in the building were measured in several rooms and ranged from 400 ppm to 550 ppm. This indicated that more outside air was being supplied to the building during nonsession periods than necessary, with a corresponding energy cost. On July 1, 1996, the speeds of the four AHUs were reduced by about 50% for nonsession periods. The CO_2 level generally increased to 550 ppm to 750 ppm with an average of 650 ppm. The maximum CO_2 level was found in a fully occupied hearing room where it was 950 ppm. The reduced outside air flows again reduced the electricity, the cooling, and the heating consumption.

Project Duration, Cost, and Savings

The project started in July 1995, and initial commissioning ended on July 1, 1996. During this 12-month period, the commissioning engineer's effort spanned over 5 months, and the measured savings were about $100,000.

The building had meters installed to measure hourly whole building electricity, chilled water consumption, and hot water consumption. The initial cost of these meter installations was approximately $15,000. The costs of the metering and savings analysis were about $8,000 for two years. The costs were paid back before the completion of the project.

Figure 7.1.3 compares the measured chilled water and hot water consumption for both the pre-CC and the post-CC period. The implementation of CC measures has significantly reduced the heating and cooling energy consumption.

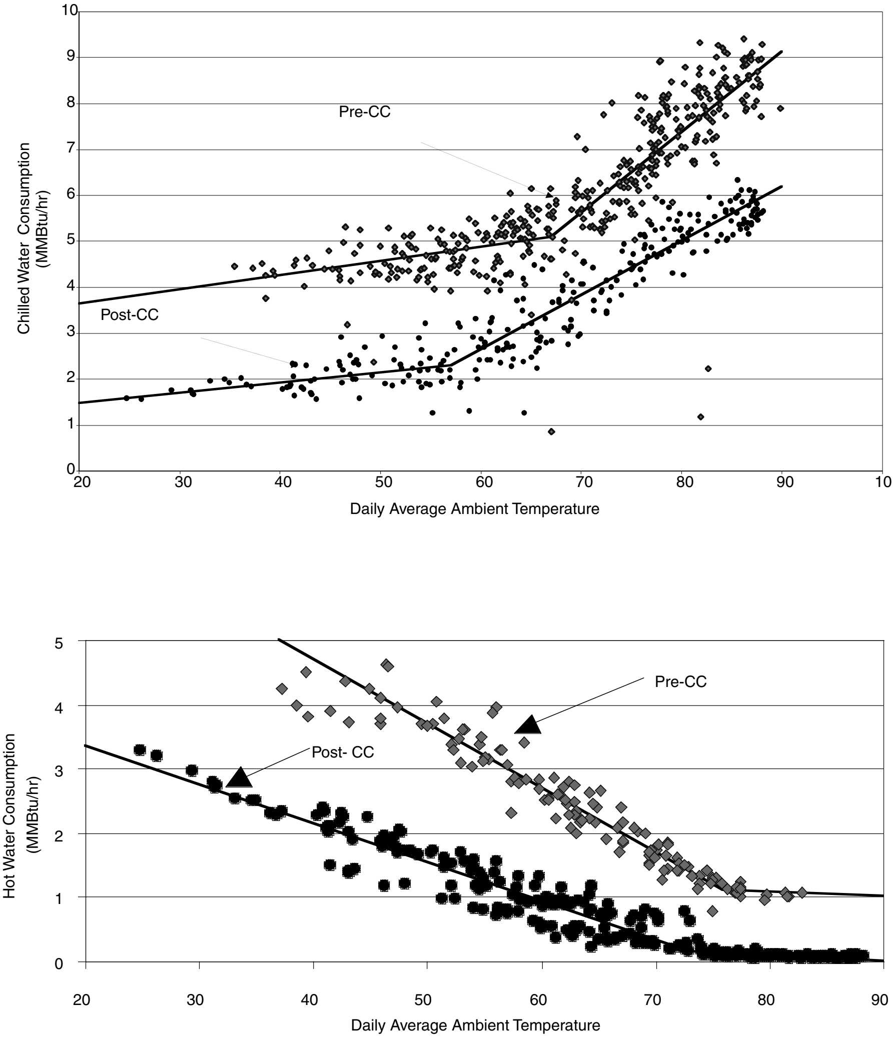

FIGURE 7.1.3 Comparison of chilled water and hot water consumption for the pre-CC and post-CC period.

The measured savings reached $102,700 during the first 8.5 months following completion of the commissioning. This corresponds to an annualized savings rate of 27%, or $144,700 relative to 1994.

7.1.5 Monitoring, Verification, and Commissioning

The need to analyze the energy performance of commercial buildings, to measure savings from energy efficiency retrofits, and to provide information for use in commissioning activities has increased dramatically in recent years. Energy Service Companies (ESCOs) are providing capital retrofits to save energy, with billions of dollars in contract volume. Many of these contracts guarantee a certain level of operating savings, with provision for rebates or penalties for savings not realized. This makes the determination of the savings resulting from these projects a very serious concern for ESCOs and building owners alike. The U.S. Department of Energy (DOE) began developing interim protocols in 1995 which led to the *North American Energy Measurement and Verification Protocol*, and the *International Performance Measurement and Verification Protocol* for measuring savings in contracts between ESCOs and building owners. ASHRAE is currently developing Guideline 14 for this purpose.

Importance of M&V for Commissioning

Monitoring and Verification (M&V) of energy savings for energy efficiency retrofits is growing rapidly. The major impetus for growth has been the tremendous increase in volume of energy service company business where large financial payments hinge on the determination of energy savings in specific buildings. However, a major factor in the willingness of many building owners to commission, particularly in existing buildings, is the expectation that the project will produce energy savings that will at least pay for the cost of the commissioning. A plot clearly showing that cooling costs for a building dropped by 30% following a commissioning project can quickly convince an owner of the value of the project. Likewise, plots which show a facility operator that changing a cold deck setpoint resulted in savings of $10/hour (nearly $90,000 per year in a continuously operated facility), can enlist his enthusiastic support for a commissioning program.

The second major application of measured energy use data is its use as a tool for diagnosis of building operating problems. Both of these applications are described below.

M&V Methods

What is needed to determine savings for a commissioning project? Early energy savings projects were typically evaluated by simple comparison of utility bills before and after measures were implemented. This works fine when the savings from the measures implemented result in obvious large savings. However, savings from commissioning efforts are probably most often in the range of 5%–20%, and at this level, there are many factors that can obscure the savings. This requires employing more sophisticated M&V methods that can normalize for changes in occupancy, schedule, and weather. Over the last five years, two major efforts have been implemented to develop standard methods for savings determination. The DOE initiated an effort which has since involved dozens of domestic and international organizations and resulted in publication of the *International Performance Measurement and Verification Protocol* (IPMVP, 1997). ASHRAE is currently developing a guideline for savings measurement through the ASHRAE consensus process (not completed at press time).

The process for determining savings as adopted in the IPMVP defines:

Energy Savings = Baseline Energy Use – Post-Installation Energy Use

where the *baseline energy use* is determined from a model of the building operation before the retrofit (or commissioning) which uses post-installation operating conditions (e.g., weather, occupancy, etc.). *Post-installation energy use* is simply the measured energy use, but it may be determined from a model, though we would seldom recommend this approach.

The IPMVP includes four different M&V techniques or options. These options may be summarized as Option A: stipulated savings, Option B: measurement at the system or device level, Option C: measurement at the whole building or facility level, and Option D: determination from calibrated simulation. Each option is described in more detail next.

Option A

This option focuses on a physical determination of equipment changes to ensure that the installation meets contract specifications. It determines savings by measuring the capacity or the efficiency of a system before and after retrofit, and then multiplies the difference by an agreed upon or "stipulated" factor such as the hours of operation, or the load on the system. Key performance factors (e.g., lighting wattage) are determined with spot or short-term measurements and operational factors (e.g., lighting operating hours) are stipulated based on historical data or spot measurement. Performance factors are measured or checked yearly. The accuracy of this method is generally inversely proportional to the complexity of the measures being evaluated. As such, it may be quite suitable for lighting retrofits, or replacement of motors operated at constant load with high efficiency motors. However, it is not suitable for the more complex changes typically implemented in the process of commissioning an existing building or applying the continuous commissioning process.

Option B

This option normally determines savings by continuous measurements taken throughout the project term at the device or system level. Individual loads or end uses are monitored continuously to determine performance and the long-term persistence of the measures installed. The data collected can be used to improve or optimize the system operation, and as such is particularly valuable for continuous commissioning projects. This option includes procedures for verifying that the proper equipment or systems were installed and that proper operating procedures have been implemented. Since measurements are taken throughout the project term, the savings determination is normally more accurate than with Option A, but cost is higher.

Option C

Option C determines savings by analysis of "whole building" or facility level data measured during the baseline period and the post-installation period. This option is required when it is desired to measure interaction effects, for example, the impact of a lighting retrofit on the cooling consumption as well as savings in lighting energy. The data used may be utility data, or sub-metered data, and may be recorded at monthly or shorter intervals.

Option C requires that installation of the proper systems/equipment and proper operating practices are confirmed. It determines savings from metered data taken throughout the project term. The major limitation in the use of Option C for savings determination is that the size of the savings must be larger than the error in the baseline model. The major challenge is accounting for changes other than those associated with the ECMs or commissioning changes implemented.

The following points should be carefully considered when using Option C, especially when using utility billing data. Many of these points are applicable to Option B as well.

1. All explanatory variables that affect energy consumption as well as possible interactive terms (i.e., combination of variables) need to be specified, whether or not they are accounted for in the model. Critical variables can include weather, occupancy patterns, setpoints, and operating schedules.
2. Independent variable data need to correspond to the time periods of the billing meter reading dates and intervals.
3. If the energy savings model discussed above incorporates weather in the form of heating degree-days and cooling degree-days, the following issues should be considered:
   (a) Use of the building "temperature balance point" for defining degree-days vs. an arbitrary degree-day temperature base.
   (b) The relationship between temperature and energy use tends to vary depending upon the time of year. For example, an ambient temperature of 55°F in January has a different implication for energy usage than the same temperature in August. Thus, season should be addressed in the model.
   (c) The nonlinear response to weather. For example, a 10°F change in temperature results in a very different energy use impact if that change is from 75°F to 85°F, rather than 35°F to 45°F.
   (d) Matching degree-day data with billing start and end dates.
4. The criteria used for identifying and eliminating outliers need to be documented. Outliers are data beyond the expected range of values (or 2–3 standard deviation away from the average of the data). Outliers should be defined using common sense as well as common statistical practice.
5. Statistical validity of the final regression model needs to be demonstrated. Validation checks make sure:
   (a) The model makes intuitive sense, e.g., the explanatory variables are reasonable and the coefficients have the expected sign (positive or negative) and are within an expected range (magnitude).
   (b) Modeled data is representative of the population.
   (c) Model form conforms to standard statistical practice.

(d) The number of coefficients is appropriate for the number of observations (approximately no more than one explanatory variable for every five data observations).
(e) All model data is thoroughly documented, and model limits (range of independent variables for which the model is valid) are specified. (IPMVP, 1997.)

Accurate determination of savings using Option C normally requires 12 months of continuous data before a retrofit and continuous data after a retrofit. However, for commissioning applications, a shorter period of data during which daily average ambient conditions cover a large fraction of normal yearly variation is generally adequate.

Option D

Savings are determined through simulation of the facility components and/or the whole facility. The most powerful application of this approach calibrates a simulation model to baseline consumption data. For commissioning applications, it is recommended that calibration be to daily or hourly data. This type of calibration may be done most rapidly if simulated data is compared to measured data as a function of ambient temperature.

Just as for the other options, the implementation of proper operating practices should be confirmed. It is particularly important that personnel experienced in the use of the particular simulation tool conduct the analysis. The simulation analysis needs to be well documented, with electronic and hard copies of the input and output decks preserved.

Measurement Channels

The minimum number of measurement channels recommended for evaluation of a commissioning project will be the number needed to separate heating, cooling, and other electric uses. The actual number of channels will vary, depending on whether pulses are taken from utility meters, or if two or three current transformers are installed to measure the three-phase power going into a chiller. Other channels may be added, depending on the specific measures being evaluated.

Use of M&V Data for Diagnostics

Most whole-building diagnostic procedures can be split into two major categories: examination of time series data, and use of physical or empirical models in the analysis of whole-building data streams.

Diagnostics with Time Series Data — the simplest form of diagnostics with whole-building data is manual or automated examination of the data to determine whether prescribed operational schedules are followed. The normal minimum set of whole-building data required for diagnostics are separate channels for heating, cooling, and other electrical uses. With these data streams, it is possible to identify probable opportunities for HVAC system shut-offs, excessive lighting operation, etc.

Shut-Off Opportunities — this is often the most intuitive of all diagnostic procedures. However, the use of whole-building data, even with heating and cooling removed, can cause some confusion since nighttime electric use in many buildings is 30%–70% of daytime use. If nighttime and weekend use seems high, then the connected load must be investigated to determine whether observed consumption patterns correspond to reasonable operating practices. Our experience indicates that while many, if not most, opportunities for equipment shut-off by an EMCS or other system-level action may have been already implemented, time series data analysis can still find opportunities in 10%–20% of buildings.

While these opportunities can be observed using plots that show several days of hourly data, it is often helpful to superimpose several days or weeks of hourly data on a single 24-hour plot to observe typical operating hours and the frequency of variations from the typical schedule.

Operating Anomalies — a slightly different category of opportunities can be identified using the same techniques. Mistakes in implementing changes in thermostat setup/setback schedules sometimes result in short-time simultaneous heating and cooling which show up as large spikes in consumption lasting only an hour or two. Time series plots of motor control centers often show that VAV systems seldom operate above their minimum box settings — and hence are essentially operating CAV systems. Comparisons between typical weather-independent operating profiles from one year to the next will often reveal "creep" in consumption which is often due to addition of new computers or other office equipment.

Blink Tests — a valuable way in which whole-building data can be used to identify the size of various equipment loads such as switchable connected lighting load, AHU consumption, etc., is the use of a short-term "blink test" such as that described in the example of the state office building discussed earlier.

Diagnostics with Models and Data

The description of the process used to diagnose opportunities for improved operation at the BSB building made heavy use of a physical simulation model. Calibration of simulation models has been regarded as time consuming making it appropriate only for research projects. However, this approach has been systematized by the authors using a series of energy "signatures" which have enabled the performance of calibrated simulation as a classroom assignment. Signatures have been developed for constant volume dual-duct AHUs, dual-duct VAV systems, single-duct CAV systems, and single-duct VAV systems.

These model-based approaches can readily be used in conjunction with limited field measurements to diagnose and determine the potential savings from correcting a large variety of systems problems which include:

- VAV behavior as CAV systems
- Simultaneous heating and cooling
- Excess supply air
- Excess OA
- Sub-optimal cold deck schedule
- Sub-optimal hot deck schedule
- High duct static pressure
- Others

Conclusions

Whole-building data for heating, cooling, and non-weather dependent electricity consumption can be used to identify a range of shut-off opportunities, scheduling changes, and operating anomalies due to improper control settings and other factors. It can also be used in conjunction with appropriate simulation tools and energy signatures to identify an entire range of nonoptimum system operating parameters. It is then very straightforward to reliably predict the energy savings which will be realized from correcting these problems.

It should be recognized that the systems diagnostics available from whole-building data and modeling are indications of probable cause. Additional field measurements are generally needed to confirm the probable cause.

References

ASHRAE, 1996, *ASHRAE Guideline 1-1996: The HVAC Commissioning Process*, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, GA.

Claridge, D.E., Liu, M., Turner, W.D., Zhu, Y., Abbas, M., and Haberl, J.S., Energy and Comfort Benefits of Continuous Commissioning in Buildings, *Proceedings of the International Conference Improving Electricity Efficiency in Commercial Buildings*, September 21–23, 1998, Amsterdam, The Netherlands, pp. 12.5.1–12.5.17.

Davenny, M., Doering, D., and McGuire, T., Case Study: Commissioning the Boeing Commercial Airplane Group Headquarters Office Building, *Proceedings of the 7th National Conference on Building Commissioning*, May 3–5, 1999, Portland, OR.

Haasl, T. and Sharp, T., *A Practical Guide for Commissioning Existing Buildings*, Portland Energy Conservation, Inc., and Oak Ridge National Laboratory for U.S. DOE, ORNL/TM-1999/34, 1999.

Haasl, T. and Wilkinson, R., Using Building Commissioning to Improve Performance in State Buildings, *Proceedings of the 11th Symposium on Improving Building Systems in Hot and Humid Climates*, June 1–2, 1998, Fort Worth, TX, pp. 166–175.
IPMVP, 1997, *International Performance Measurement and Verification Protocol*, U.S. Department of Energy, DOE/EE-0157.
Odom, J.D. and Parsons, S., The Evolution of Building Commissioning at Walt Disney World, 6th National Conference on Building Commissioning, Lake Buena Vista, FL, May 18–20, 1998.
PECI, 1999, *National Strategy for Building Commissioning*, PECI, Inc., Portland, OR.

7.2 Building Systems Diagnostics and Predictive Maintenance

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There has been an increasing interest in the development of methods and tools for automated fault detection and diagnostics (FDD) of building systems and components in the 1990s. This chapter will describe the status of these methods and methodologies as applied to heating, ventilation, air conditioning, and refrigeration (HVAC&R) and building systems and present illustrative case studies.

Building Systems Diagnostics

Operation problems associated with degraded equipment, failed sensors, improper installation, poor maintenance, and improperly implemented controls plague many commercial buildings. Today, most problems with building systems are detected as a result of occupant complaints or alarms provided by building automation systems (BASs). Building operators often respond by checking space temperatures or adjusting thermostat settings or other setpoints. The root cause of an operation problem often goes undiagnosed, so problems recur, and the operator responds again by making an adjustment. When the operator diagnoses problems more carefully by inspecting equipment, controls, or control algorithms, the process is time consuming and often based on rudimentary or incorrect physical reasoning and rules of thumb built on personal experience. Often a properly operating automatic control is overridden or turned off, when it *appears* to be the cause of a problem. Moreover, some "latent" problems do not manifest themselves in conditions that directly affect occupants in obvious ways and, as a result, go undetected — such as simultaneous heating and cooling. These undetected problems may affect energy costs or indoor air quality.

Operating problems lead to inefficient operation (energy costs), a loss in cooling/heating capacity (comfort), discomfort (loss of productivity and loss of tenants), and increased wear of components (reliability). However, too much maintenance leads to excessive maintenance costs. Automated diagnostics for building systems and equipment promise to help remedy these problems and improve building operation by automatically and continuously detecting performance problems and maintenance requirements and bringing them to the attention of building operators. In addition, early diagnosis of equipment problems using remote monitoring techniques can reduce the costs associated with repairs by improving scheduling and reducing on-site labor time. Furthermore, as performance contracting for services becomes more prevalent, the need for tools that ensure performance will increase.

Automation and data visualization are key elements of FDD systems. Because the building industry is cost sensitive and lacks a sufficient number of well-trained building operators, fully automated tools can help alleviate the problem. Data visualization is the key link between the building system and building operators in fully automated systems. Clear data presentation will help the building operator avoid scanning, sorting, and interpreting raw data, thus performing metrics, allowing time for correcting the problems identified by the FDD system, and improving equipment performance and efficiency.

Predictive Maintenance

Many buildings today use sophisticated BASs to manage a wide and varied range of building systems. Although the capabilities of BASs have increased, many buildings still are improperly operated and maintained. Lack of or improper commissioning, the inability of the building operators to grasp the complex controls, and lack of proper maintenance are some of the reasons for improper operations. A study of 60 commercial buildings found that more than half of them suffered from control problems. In addition, 40% had problems with the HVAC&R equipment, and a third had sensors that were not operating properly (PECI, 1997).

Effective maintenance extends equipment life, maintains comfort, improves equipment availability, and results in fewer complaints from building occupants; whereas, poorly maintained equipment will have a shorter life and will experience more frequent equipment failure, leading to low levels of equipment availability and occupant dissatisfaction. If regularly scheduled maintenance practices are adopted, they can be expensive. However, if there were a way to decide whether maintenance is required for a particular piece of equipment, it would certainly cut down on the cost of maintenance. The art of predicting when building systems need maintenance is generally referred to as predictive maintenance or condition-based maintenance.

There are many similarities between the FDD and the predictive maintenance methods because both require monitoring of building systems to detect abnormal conditions; therefore, a significant portion of this chapter is devoted to building systems diagnostics.

In the following section, we define the scope for the entire chapter, provide definitions of terms used, and present a generic overview of an FDD system.

7.2.1 Objectives and Scope

The primary objective of this chapter is to provide the HVAC&R engineer and researcher with a fundamental knowledge of (a) the methods and methodologies used in the detection and diagnosis of faults in building systems and components, and (b) predictive maintenance. The chapter contains

- A description of a generic FDD system
- The benefits of automated FDD and predictive maintenance applications
- Results of a detailed review of the literature to identify the methods and the methodologies used
- A discussion on cost vs. benefits, and how to select methods for FDD
- Detailed description of the FDD application on a few building systems
- A brief description of the FDD tools that are currently being used in the field, and application of the automated FDD methods to continuous commissioning of building systems
- Infrastructure requirements to deploy the automated FDD tools in the field
- The future of building systems diagnostics

Definition of Terms

Until recently most of the research and development in the areas of FDD have been limited to nuclear power plants, aircraft, process plants, and the automobile industry. A survey of the FDD literature indicates a lack of consistent terminology. Issermann and Ballé (1997) provide a set of definitions, used in this chapter with minor modifications, as given below.

Cause: A primary reason or explanation of the current fault or problem in the system.

Error: A deviation between a measured or computed value (of an output variable) and the true (actual) specified or theoretically correct value.

Disturbance: An uncontrolled (and possibly sometimes unknown) input acting on a system.

Failure: A permanent interruption of a system's ability to perform a required function under specified operating conditions.

Fault or problem: A deviation of at least one characteristic property or parameter of the system from the acceptable, usual, and/or standard state or condition.

Malfunction: An intermittent irregularity in a system's ability to perform a desired function.

Perturbation: Input acting on a system, which results in a temporary departure from the current state.

Residual or error: A fault indicator, based on a deviation between measurements and model- or equation-based computations.

Symptom: A deviation of an observable quantity from normal behavior.

Fault detection: Detection and time of detection of a fault or faults in the system.

Fault diagnosis: Determination of the kind, magnitude (size), location, time variant behavior, and time of detection of a fault. Follows fault detection. Includes fault isolation and identification.

Fault isolation: Determination of the kind, location, and time of detection of a fault. This usually follows fault detection.

Fault identification (*evaluation*): Determination of the magnitude (size) and time-variant behavior of a fault. Follows fault isolation.

Monitoring: A continuous real-time task of determining the conditions of a physical system by recording information, and recognizing and indicating anomalies in the behavior.

Supervision: Monitoring a physical system and taking appropriate actions to refine diagnoses and maintain the operation in case of faults.

Protective or proactive control: Means by which a potentially dangerous behavior of the system is suppressed or the consequences of a dangerous behavior are avoided or mitigated.

Commissioning: A systematic process by which proper installation and operation of building systems and equipment are checked and adjusted when necessary to improve performance.

Analytical redundancy: Analytical redundancy implies that values computed analytically can be compared with measured sensors, in contrast to physical redundancy where measurements from multiple sensors are compared to each other.

7.2.2 An Introduction to the FDD Process

There are several different ways to represent an FDD process depending on the methods used and the intended application. In this section, a generic FDD process that can be applied to many building systems is described. A similar process has been used widely in both critical and noncritical systems (Issermann, 1984). There are many similarities between the FDD system and a predictive maintenance system. In the next section, these similarities will be identified. The primary objective of an FDD system is early detection of the fault and diagnosis of the causes before the entire system fails. It is accomplished by continuously monitoring the operations of a system or process to detect, diagnose, evaluate, and respond to the faults arising from abnormal conditions. Therefore, a typical FDD system can be viewed as having four distinct functional processes, as shown in Figure 7.2.1. The first step in the FDD process is to monitor the building systems or subsystems and detect any abnormal (problem) conditions. This step is generally referred to as the fault detection phase. If an abnormal condition is detected, then the fault diagnosis process evaluates the fault and diagnoses the cause of the abnormal condition. Following diagnosis, fault evaluation assesses the size of the impact (energy and/or cost or availability of the plant) on system performance. Finally, a decision is made on how to react to the fault. In most cases, detection of faults is relatively easier than diagnosing the cause of the fault, or evaluating the size or impact arising from the fault.

Fault Detection

In the fault detection stage, the building system or component is continuously monitored and abnormal conditions are detected. There are several methods by which faults can be detected including comparison of the raw outputs that are directly measured from the components, or estimated characteristic quantities based on the available measurements with the expected values. A fault is indicated if the comparison residual (difference between actual value and expected value) exceeds a predefined threshold. The char-

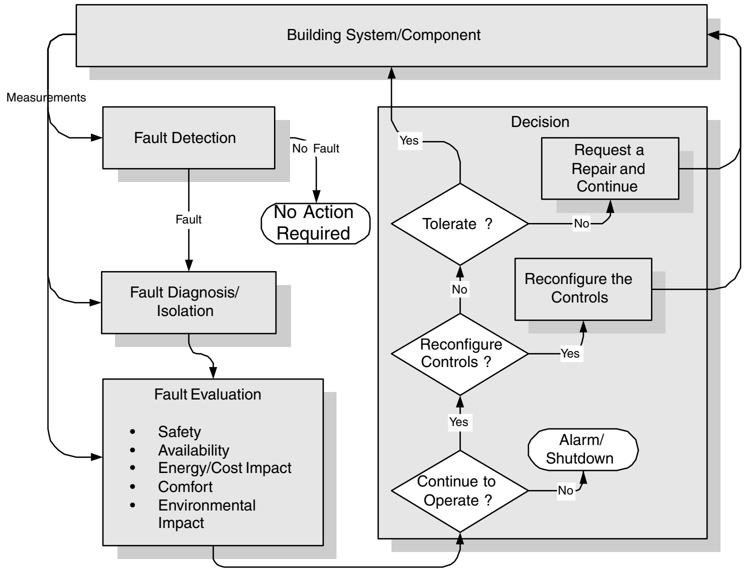

FIGURE 7.2.1 Generic fault detection and diagnostic system with proactive control/diagnostic test capability.

acteristic quantities are features that cannot be directly measured but can be computed from other measured quantities, for example, the outdoor-air fraction for the air-handling unit (AHU) or the coefficient of performance of an air conditioner. In addition to using the raw measured data and characteristic quantities, detailed mathematical models are also widely used in estimating the expected values (Gertler, 1988; Issermann, 1984) for comparison with the measured values accounting for data uncertainties.

In most cases, a model of some kind is essential to detect a fault because most building systems are dynamic in nature. For example, a characteristic quantity such as efficiency can be used to detect a fault in an air conditioner. In the absence of a model, the efficiency calculated from the measured values is compared to a fixed threshold. However, because the efficiency varies with the indoor and outdoor conditions, the threshold will have to be at the minimum efficiency value associated with the normal operation. With a model-based approach, the efficiency threshold can be dynamically calculated based on the other measured inputs.

Several different types of models are used for detection including detailed physical models, empirical models based on first principles, and black-box models. These models can be steady state, linear dynamic, or nonlinear dynamic. A brief discussion of different models is provided later in the chapter.

Fault Diagnosis

At the fault diagnosis stage, the residuals and other data are analyzed, and the cause of the fault is determined. Unlike fault detection, fault diagnosis is not a binary outcome (fault, no fault). A fault is diagnosed as soon as it is detected for FDD implementations at the subsystem or the component level with adequate measured data. Fault diagnosis is generally difficult when implemented at the system level, with multiple components, for example, air conditioner, chiller, and air handler, or at the component level with multiple subsystems. For example, if a fault with the air handler's air filter is detected because the pressured drop across the filter is excessive, the cause of the fault is a dirty or clogged filter. Therefore, additional diagnosis is not necessary in this case. However, if a deviation of the efficiency of the air conditioners is detected, a fault diagnosis is essential to isolate the actual cause because there is more than one possible cause for the deviation. In some cases, because of the lack of analytical redundancy, the fault diagnosis may yield more than one possible cause for a fault. Most buildings systems have limited sensors making the fault diagnosis step inevitable.

Most methods used for detection can also be used for diagnosis, but the criteria used are different. Generally, black-box approaches and statistical pattern recognition methods are well suited for the diagnostic step. A brief discussion of the different modeling techniques is provided later in the chapter.

Fault Evaluation

Following fault detection and diagnosis, the impact of the fault has to be evaluated. For most latent faults, the impacts have to be evaluated before a decision is made to stop, continue, or reconfigure the controls. The evaluation criteria depend on the application and severity of the fault. For critical processes, safety is the primary evaluation criterion. For FDD applied in a process industry, availability of the plant is important because it dictates the profit margin. Although for most building systems the cost of operations is the primary criterion, productivity impacts from lack of proper ventilation and comfort conditioning should not be neglected. Safety and environmental issues can also play an important role for building systems.

Fault evaluation is particularly important when the performance of a component is degrading slowly over time, such as heat exchanger fouling (Rossi and Braun, 1996). In this case, it is possible to detect and diagnose a fault well before it is severe enough to justify the service expense.

Decision on Course of Action

Finally, after the fault has been detected, diagnosed, and evaluated, a decision is needed on the course of action to be taken. The first step in the decision making process is to stop the system or send an alarm to shut it down if the fault is severe and the controls cannot be reconfigured to accommodate the fault. In some FDD applications, such as aeronautics and nuclear power plants where safety is critical, there is redundancy in controllers, actuators, and sensors. In such situations, corrective action can be taken to ensure continued safe operations using redundant fault-free components. For example, if a failure of one sensor of a redundant pair of sensors is diagnosed, then the supervisory system can reconfigure the controls such that the failed sensor is not used in making control decisions until it is replaced or fixed. This type of FDD system, which can enable corrective action to counteract the fault or make recommendations for altering the system operation, is referred to as fault-tolerant control system or an FDD supervisory system. In most cases, fault-tolerant control applications reconfigure the programmable parts of the control loop such that the system operates in a fault-free environment. In some cases, reconfiguration in the control loop may slightly degrade the reliability or the performance of the system. Operating the system in a degraded state, in some cases, is better than shutting it down. However, in other cases, the system can operate without any degradation in performance. For example, if the FDD system detects a sensor bias, it can reconfigure the controls to compensate for the bias.

If the fault is not severe (i.e., it is not a safety issue and will not damage the system or equipment) and the system controls cannot be reconfigured to accommodate it, the fault has to be tolerated or a request for repair needs to be made. Unlike critical systems, most building systems do not pose an immediate safety problem because of faulty operation; therefore, they lack redundancy and extensive instrumentation. For building systems, if the cost impact is small compared to the cost of correcting the fault, the fault can be tolerated. However, if the cost impact is large, the FDD system must provide a message leading to correction of the problem along with the impact it has on the operations.

Advanced supervisory systems can also have the capability to perform nonintrusive tests to refine a fault diagnosis. For example, if the FDD system detects a sensor failure but is able to pinpoint the failed sensor from among three sensors (e.g., return-, outdoor-, and mixed-air temperature) of an air-handling unit, the supervisory control system can perform additional nonintrusive tests during the unoccupied hours of the day to refine the diagnosis. For example, the air-handling unit can be operated at 100% outdoor-air and comparing the outdoor-air and mixed-air temperature signals, then operating the air-handling unit at 100% return-air and comparing the return-air and mixed-air temperature signals.

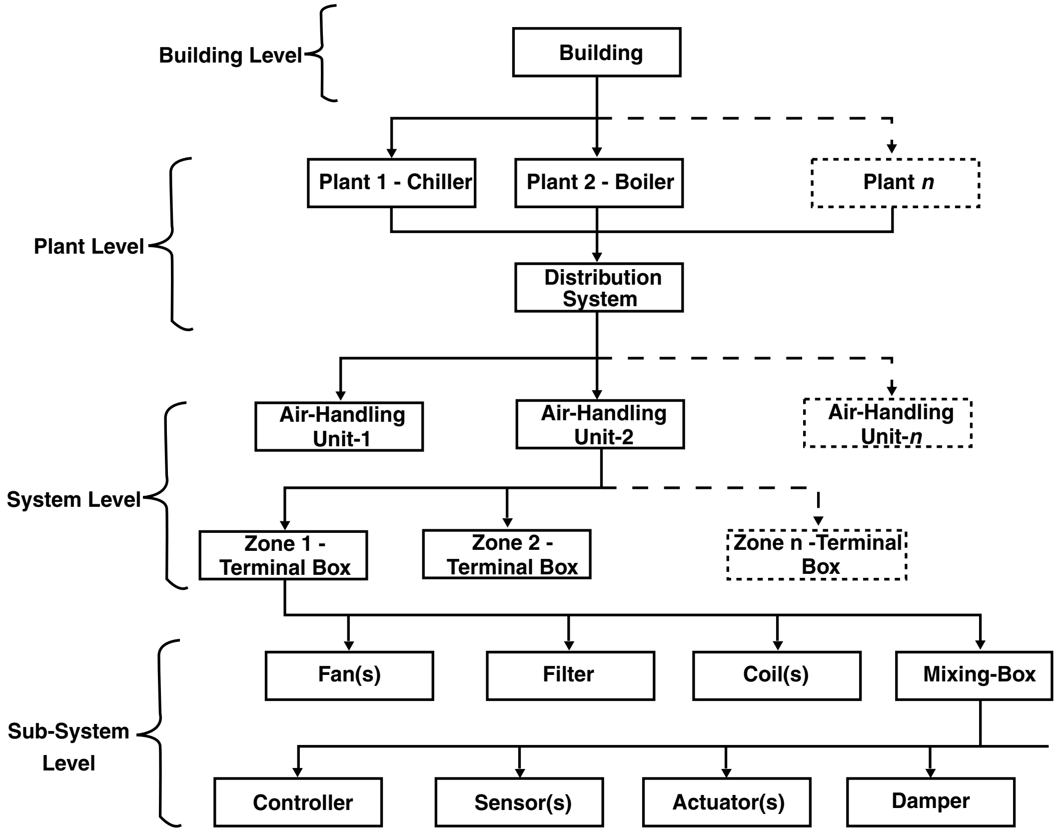

FIGURE 7.2.2 Hierarchical relationships of the various HVAC&R systems and subsystems in a building.

7.2.3 Hierarchical Relationships of the Various HVAC&R Systems and Subsystems in a Building

An FDD system can be deployed at several different levels in the building hierarchy, as shown in Figure 7.2.2. There are several different types of HVAC&R systems and subsystems in a building; some are independent while most are linked hierarchically to other systems in the building. An FDD system deployed at the building level can use the whole-building energy use (electric or thermal) to detect abnormal energy use (Dodier and Kreider, 1999). Although abnormal conditions can be detected at the whole-building level, their cause cannot be easily diagnosed because of insufficient resolution in the data.

Additional monitoring at lower levels is generally required for fault diagnosis. Almost any FDD method can be deployed at the building level. Regression and neural network models are probably a good choice for detection at this level. In contrast, for most implementations at the subsystem level, no fault diagnosis is needed. At that level, when a fault is detected, the cause of the fault is already known. FDD systems deployed at the intermediate plant and systems levels need methods for both detection and diagnosis.

7.2.4 Predictive Maintenance

Maintenance can be defined broadly as having three components: service, inspection, and repair (Patel and Kamrani, 1996). Service includes all steps taken to preserve the nominal state of the equipment and to prevent equipment failure. Inspection involves measuring and evaluating the current state of the equipment to detect the malfunction early and to prevent failure. Repair involves all steps taken to restore the nominal state of the equipment (Patel and Kamrani, 1996).

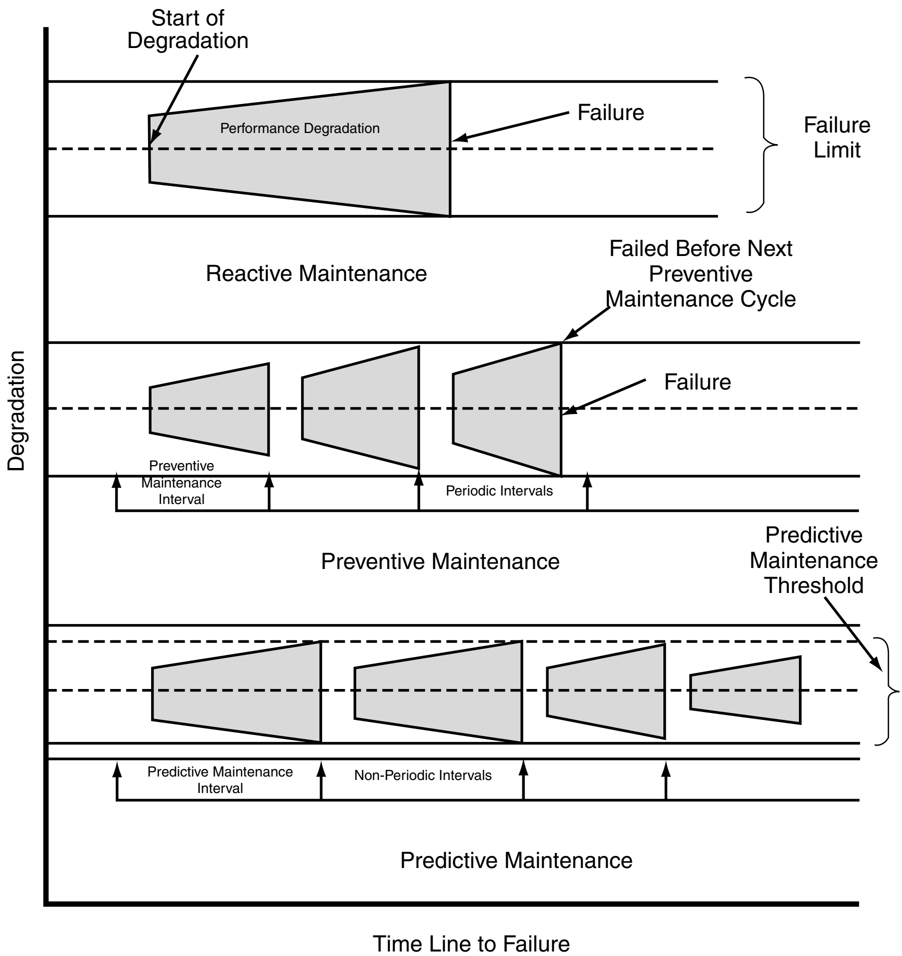

FIGURE 7.2.3 Comparison of the various maintenance practices.

Improper maintenance of building systems can lead to inefficiency, unreliable operations, and safety hazards. Maintenance costs are substantially determined by the chosen maintenance strategy. There are three commonly used maintenance practices: corrective or reactive maintenance, preventive maintenance, and predictive maintenance (Figure 7.2.3). In the corrective or reactive maintenance mode, the equipment is operated without maintenance until it breaks down. No attention is paid to ensuring that operating conditions are within the design envelope; consequently, the actual service performance and life span of the equipment may be substantially below the estimates of the manufacturer. While reactive maintenance may make sense in some instances (for example, replacing a light bulb), in the vast majority of building systems it is the most expensive option (Jarrell and Meador, 1997).

Corrective maintenance results in unscheduled downtime and may lead to unpredicted fatal failures. To avoid this problem, engineers started to maintain equipment at scheduled intervals throughout the life span of the equipment. This preventive maintenance method is the art of periodically checking the performance or condition of a piece of equipment to determine if the operating conditions and resulting degradation rate are within the expected limits. Statistics of past failures are used to define the periods for checking (for example, every 1000 working hours). If the periodic inspection reveals degradation in a part of the equipment, that part is replaced and no root cause analysis is usually undertaken. While good failure statistics allow the test interval to be optimized, catastrophic failures are still likely to occur. This method is labor intensive and, sometimes, parts are replaced unnecessarily and unjustifiably because no root cause analysis is performed. Preventive maintenance can be a cost-effective strategy when the life span of the equipment is consistent and well understood. Studies in the utility industry (power plants) have reported savings of 12 to 18% with preventive maintenance compared to reactive maintenance (Jarrell and Meador, 1997). Savings for the building systems have not been documented yet.

Although preventive maintenance leads to fewer unscheduled interruptions and extends the life span of the equipment, it increases the maintenance cost because it is conducted whether it is necessary or not. Instead of periodic maintenance, if the failure of a component can be predicted, the performance of the equipment can be optimized and enhanced while the maintenance expenditure is reduced (Patel and Kamrani, 1996). In the early 1990s, the concept of predictive maintenance was widely introduced. Predictive maintenance advocates measurements and procedures aimed at the detection of degradation mechanisms, thereby allowing the degradation to be understood, eliminated, or controlled prior to a complete failure (Jarrell and Meador, 1997). To predict the failure, the equipment must be constantly monitored for fault symptoms, symptoms must be analyzed for trends, and decisions must be made regarding the existence, location, cause, and severity of the fault.

Predictive maintenance strategy requires information about the state of wear and the remaining life span or rate of performance degradation of a system, and how long the system will be able to meet the design intent of the monitored device. Predictive maintenance can result in marked increase in equipment life, earlier corrective actions, decreased downtime, decreased maintenance, better quality product, decreased environmental impact, and reduced operational and energy costs. It is estimated that predictive maintenance can save between 8 and 12% over a good preventive maintenance program (Jarrell and Meador, 1997). However, there is an up-front cost in installation of additional sensors and the development of procedures to detect degradation.

Methods for Detecting Degradation

The basic requirements (Patel and Kamrani, 1996) for developing methods of predictive maintenance are

1. The system must identify abnormal conditions accurately.
2. The system must not give false alarms of abnormal conditions.
3. The system must report the level of confidence associated with each diagnosis.
4. The system must rank the conclusions.
5. The system must be able to handle insufficient data and uncertain situations.

These requirements are almost identical to the requirements of the FDD systems; therefore, many of the methods used in the FDD applications can also be used in detection of equipment degradation. However, most FDD applications detect faults at discrete time intervals and do not keep track of any discernable trends. Furthermore, most current FDD systems for building applications do not implement or discuss the fault evaluation and decision steps described previously (Figure 7.2.1). Fault evaluation is particularly important when the performance of a component is degrading slowly over time.

Predictive maintenance tools have been deployed in the telecommunications, automobile, aircraft, process, nuclear, and computer networks industries. In building applications, most research has focused on detection and diagnosis of faults (but not evaluating them) with the exception of Rossi and Braun (1996), Katipamula et al. (1999), and Dodier and Kreider (1999). Patel and Kamrani (1996) have tabulated more than 75 predictive maintenance research projects developed around the world. These projects are mostly related to manufacturing and process control and are based on some form of expert system.

Because many of the methods developed for FDD systems can also be used for predictive maintenance, the rest of the chapter will be devoted to FDD systems without discussion of their application to predictive maintenance.

7.2.5 Benefits from FDD Applications and Predictive Maintenance

Commercial buildings are increasingly using sophisticated BASs that have tremendous capabilities to monitor and control the building systems. Nonetheless, building systems routinely fail to perform as designed (Brambley et al., 1998; Katipamula et al., 1999). Although the BASs are sophisticated, they lack the tools necessary to detect and diagnose faults arising in the building systems. Furthermore, building operators generally overlook the symptoms because they lack a proper understanding of the control strategy and the failure symptoms. This leads to manual override of control strategies.

Faults that cause discomfort to the occupants are reported as complaints, while "latent" faults (such as simultaneous heating and cooling) go undetected. Such faults can have a significant impact on the operations of the building. Use of FDD applications has great potential to alleviate the problems associated with both the latent faults and the time needed to detect and correct conspicuous faults in building systems. FDD applications can improve energy efficiency, extend equipment life, reduce maintenance costs, reduce unscheduled equipment downtime, improve occupant comfort, health, and productivity, and reduce liability. Operating cost savings are the result of lower service and utility costs and extended equipment life. Productivity gains come from reduced equipment downtime and better overall comfort for the occupants.

Some of these benefits are tangible, i.e., the cost impact or the benefit from correcting existing problems can be quantified. On the other hand, the costs associated with poor indoor-air quality, lost productivity, and impact on equipment life are very difficult to quantify. Although difficult in most cases, energy and cost savings associated with the faults identified by the FDD applications in a building's equipment can be estimated. An example is given later in the chapter. One of the major barriers to widespread adoption of automated diagnostic tools is quantifying the impact of both tangible and intangible benefits.

Published reports indicate 3 to 50% of HVAC&R energy is wasted because of improper operations in existing buildings. The wide variation is primarily caused by the types of problems uncovered during the commissioning process and is, in part, the result of the various methods employed in the estimation of savings. Typical savings are expected to be between 5 and 15%. (Gregerson, 1997).

Published reports also indicate that many of the problems identified during the recommissioning process are related to controls. Unless the building is periodically recommissioned, these problems resurface. Fortunately, a number of problems related to improper controls can be detected and diagnosed in a continuous manner using automated tools.

7.2.6 Literature Review

While FDD was well established in the process, nuclear, aircraft, and automotive industries, it did not enter the building and HVAC&R industries until the mid 1990s (Braun, 1999). High reliability and safety were relatively less critical in building operations; therefore, FDD did not receive the same level of interest among building researchers, owners, and operators. The primary driver of building operations is still the operating cost and capital investment. Although FDD has been an active area of research among the buildings and HVAC&R community for several years, it is not widely used in the field. The primary reasons for slow adoption of FDD in buildings and HVAC&R areas include a relatively high cost-to-benefit ratio for an FDD implementation, partly caused by the lack of extensive instrumentation in the building and HVAC&R systems, and lack of data to quantify the benefits.

Because critical processes require high reliability and operational safety, the FDD system was an essential element of the plant operation. Early fault detection methods were generally limited to detecting values of measurable output when the signals had already exceeded the limit. Widespread use of microcomputers in the early 1980s led to advanced mathematical process models, which provided the ability to detect the fault earlier and to locate the fault by use of additional measurable signals (Isserman, 1984). Because reliability and safety are a primary concern, these plants have extensive and redundant sensors. Therefore, the FDD methods evolved around the data-rich environment. In the late 1970s, fault detection and diagnosis began to be applied to mass-produced consumer equipment such as automobiles and household appliances (Willsky, 1976).

Aeronautics, Nuclear, and Process Industry

Over the last 3 decades, several survey papers have summarized the FDD research in the aeronautics, nuclear, and process industries. The first major survey was written by Willsky (1976). Isserman (1984) surveyed various modeling and estimation methods for process fault detection. Gertler (1988) published a survey of model-based FDD in complex plants. Frank (1990) surveyed methods based on analytical and knowledge-based redundancy for fault diagnosis in dynamic systems. Issermann and Ballé (1997) published trends in applications of model-based FDD of technical processes. Frank (1997) published new developments using artificial intelligence in fault diagnosis. The developments in fault-detection methods up to the respective times are also summarized in books by Himmelblau (1978), Pau (1981), Patton et al. (1989), Mangoubi (1998), Gertler (1998), and Chen and Patton (1999).

The literature review shows a wide array of approaches used to detect and diagnose faults. The sequencing of the detection and diagnosis varies. In some cases, the detection system ran continuously, while the diagnostic system was triggered only upon the detection of a fault. In other applications, the detection and diagnostic systems ran in parallel and, in some instances, the detection and diagnostics were performed in a single step. The methods of detection and diagnosis can be broadly classified into two groups: model-based methods and model-free methods. In some cases, similar models were used for detection and diagnosis and, in others cases, different models were used.

Since the advent of computers in the process control industry, most practical FDD systems have used some form of fault detection and diagnosis (Gertler, 1988). Earlier deployments relied on simple limit checking for detection and diagnostic functions. Even the early fault detection systems for the space shuttles' main engines, while on the ground, primarily used limit checking with fixed thresholds on each measured variable (Cikanek, 1986). As the complexity of the control systems and use of computers increased, model-based FDD systems were developed. These systems rely on analytical redundancy by using an explicit mathematical model of the monitored plant to detect and diagnose faults. In contrast to physical redundancy (where measurements from multiple sensors are compared to each other), with analytical redundancy sensor measurements are compared to values computed analytically, with other measured variables serving as model inputs (Gertler, 1998).

The commonly used model-based methods for fault detection included observer, parity space, parameter estimation, frequency spectral analysis, and neural networks. The methods used for fault classification included neural nets, fuzzy logic, Bayes classification, and hypothesis testing (Issermann and Ballé, 1997). These methods were used mostly to detect and diagnose the faults with sensors, actuators, process, and control loop or controller. Details about the individual methods and how they are used in an FDD system can be found in the various survey papers and books written over the past two decades (Willsky, 1976; Issermann, 1984; Gertler, 1988; Frank, 1987; Frank, 1990; Issermann and Ballé, 1997; Frank, 1997; Himmelblau, 1978; Pau, 1981; Patton et al., 1989; Mangoubi, 1998; Gertler, 1998; and Chen and Patton, 1999).

Building Systems

Unlike process control systems, FDD research for building systems did not begin until the early 1990s. In the 1990s, several FDD applications for building systems were developed and tested in the laboratory, and were related to vapor compression equipment (refrigerators, air conditioners, heat pumps, and chillers) followed by the application of AHU. The methods used measured pressure and/or temperatures at various locations and the thermodynamic relationships to detect and diagnose common faults.

It is clear from the literature review that there is a lack of standard definitions of terms. For example, the term FDD is loosely used even when the described approach only detects faults. Furthermore, the words "fault" and "failure" are loosely used to mean the same thing — the fault. However, in the following literature review, the definitions provided earlier in the chapter are used in order to be consistent.

The available literature relating to building systems includes refrigerators, air conditioners and heat pumps, air-handling units, HVAC&R control systems, heating systems, pumps, thermal plant, several FDD applications for motors, and whole-building systems. In the following section, the FDD methods for refrigerators, air conditioners and heat pumps, chillers, and AHUs are summarized. For details on other building systems, refer to the relevant literature: HVAC&R plants (Pape et al., 1990; Dexter and Benouarets, 1996; Georgescu et al., 1993; Jiang et al., 1995; Han et al., 1999); HVAC&R control systems (Fasolo and Seborg, 1995); heating systems (Li et al., 1996; Li et al., 1997); pumps (Isserman and Nold, 1988; Dalton et al., 1995); thermal plant (Noura et al., 1993); several FDD applications for motors (Isserman and Ballé, 1997); and whole-building systems (Dodier and Kreider, 1999). In one of the earliest automated FDD systems used in industry, Kreider and Reinert (private communication, July 1999) deployed a diagnostic system using an expert system in a large computer manufacturing plant; the system detected and diagnosed the imminent failure of a large, centrifugal chiller.

In the early 1990s, the International Energy Agency (IEA) commissioned the Annex 25 collaborative research project on real-time simulation of HVAC&R systems for building optimization, fault detection, and diagnostics (Hyvärinen and Kärki, 1996). The Annex 25 study identified common faults for various types of HVAC&R systems, and investigated a wide variety of detection and diagnosis methods including physical models of HVAC&R systems and black-box models. The black-box models use classification techniques such as artificial neural networks, fuzzy models, and rule-based expert systems. The selected methods proved to be successful in detecting and diagnosing faults with simulated data; however, the effectiveness of the FDD systems in real building systems was not assessed.

Summary of Methods Used in Building Systems

The FDD literature related to the building systems is summarized in Table 7.2.1, and a more detailed review of the individual building system follows this section. In addition to the methods used to detect and diagnose faults, it summarizes whether or not the fault evaluation is addressed, whether the study included any discussion of the sensitivity of detection/diagnosis of faults vs. false alarms, and whether the FDD system was tested in the field.

In the 1990s, there was a significant contribution to FDD from a theoretical point of view; however, the practical aspects of implementing FDD systems in the field have not yet been thoroughly analyzed (sensitivity of diagnosis vs. false alarm and data gathering). Simplified physical models were mostly used for fault detection followed by rule-based methods and neural networks. Many studies did not address fault diagnosis, and some developed methods that combined fault detection and diagnosis into a single step. Most studies that addressed fault diagnosis used some type of classification approach, especially based on neural networks, rule-based knowledge systems, or fuzzy logic. Fault evaluation and sensitivity of the methods to detect and diagnose faults vs. false alarms were rarely addressed. With the exception of a couple of studies, detailed field tests were not conducted.

Review of Literature Related to Building Systems Applications

In this section, we briefly describe methods used in development of FDD applications for building systems. As the summary in Table 7.2.1 indicates, many researchers did not address the tradeoffs between the sensitivity of the methods to detect and diagnose faults vs. the false alarms and, with the exception of a couple of studies, none of the FDD systems were tested in the field. Because most of the studies did not discuss these issues unless otherwise mentioned, it should be assumed that the studies lacked such information.

Refrigerators — One of the early applications of FDD was to a vapor compression cycle based refrigerator (McKellar, 1987; Stallard, 1989). Although McKellar (1987) did not develop an FDD system, he identified common faults for a refrigerator based on the vapor compression cycle, and investigated the effects of the faults on the thermodynamic states of various points in the cycle. He concluded that the suction pressure (or temperature), discharge pressure (or temperature), and the discharge-to-suction pressure ratio were sufficient for developing an FDD system. The faults considered were compressor valve leakage, fan faults (condenser and evaporator), evaporator frosting, partially blocked capillary tube, and improper refrigerant charge (under- and over-charge).

Building upon McKellar's work, Stallard (1989) developed an automated FDD system for refrigerators. A rule-based expert system was used with simple limit checks for both detection and diagnosis. Condensing temperature, evaporating temperature, condenser inlet temperature, and the ratio of discharge-to-suction pressure were used directly as classification features. Faults were detected and diagnosed by comparing the change in the direction of the measured quantities with the expected values, and matching the changes to expected directional changes associated with each fault.

TABLE 7.2.1 Summary of FDD Literature Related to Building Systems

Reference	Method: Detection	Method: Diagnosis	Evaluation	Sensitivity/False Alarm	Field Testing
		Refrigerator			
McKellar (1987)	TM	None	No	No	No
Stallard (1989)	RB	PM	No	No	No
		Air Conditioner			
Yoshimura and Ito (1989)	RB with FC[a]		No	No	No
Kumamaru et al. (1991)	RB[a]		No	No	No
Wagner and Shoureshi (1992)	Li/Tr and SPM[a]		No	Yes	No
Rossi and Braun (1996)	SPM	SRB	Yes	No	No[b]
Breuker and Braun (1999a, 1999b)	SPM	SRB	Yes	Yes	No
		Chiller			
Grimmelius et al. (1995)	Empirical regression model with pattern matching[a]		No	No	No
Gordon and Ng (1995)	SPM	None	No	No	No
Stylianou and Nikanpour (1996)	SPM	PM	No	No	No
Tutsui and Kamimura (1996)	TCBM	None	No	Yes	No
Bailey et al. (2000)	NN[a]		No	Yes	Yes
		Air Handling Unit			
Norford and Little (1993)	EM	Inferred	No	No	No
Glass et al. (1995)	QM	Inferred	No	No	No
Yoshida et al. (1996)	ARX & Kalman filter	None	No	No	No
Haves et al. (1996)	RBF/SPM	None	No	No	No
Lee et al. (1996a)	Li/ARX/ARMX[a]		No	No	No
Lee et al. (1996b)	NN[a]		No	No	No
Lee et al. (1997)	NN	NN	No	No	No
Peitsman and Soethout (1997)	ARX	ARX	No	No	No
Brambley et al. (1998), Katipamula et al. (1999)	SPM	KB and MI	Yes	Yes	Widely
Ngo and Dexter (1999)	FMB[a]		No	Yes	No
House et al. (1999)	NN, RB, Bayes, NNC, NPC	NN, RB, Bayes, NNC, NPC	No	—	No
Yoshida and Kumar (1999)	ARX/AFMM	None	No	No	No
Seem et al. (1999)	CQ	None	No	No	No
Kreider and Reinert (1997)	NN, TM	KB	No	No	Yes
		HVAC&R Plants			
Pape et al. (1990)	SPM	SPM	No	No	No
Dexter and Benouarets (1996)	FMB[a]		No	No	No
Georgescu et al. (1993)	SPM	KB	No	No	No
Jiang et al. (1995)	CQ[a]		No	Yes	Yes
Han et al. (1999)	KB/RB[a]		No	No	No
		HVAC&R Controls			
Fasolo and Seborg (1995)	CQ	None	No	Yes	No

TABLE 7.2.1 (continued) Summary of FDD Literature Related to Building Systems

Reference	Method: Detection	Method: Diagnosis	Evaluation	Sensitivity/False Alarm	Field Testing
		Heating Systems			
Li et al. (1996)	NN[a]		No	No	No
Li et al. (1997)	NN[a]		No	No	No
		Pumps			
Issermann and Nold (1988)					
Dalton et al. (1995)					
		Thermal Plants			
Noura et al. (1993)	EM	PM	No	No	No
Issermann and Ballé (1997)					
		Whole Building			
Dodier and Kreider (1999)	NN	No	Yes	Yes	No

AFMM	Adaptive Forgetting through Multiple Models	NN	Neural Network
ARMX	Autoregressive Moving Average with Exogenous Input	NNC	Nearest Neighbor Classifier
		NPC	Nearest Prototype Classifier
ARX	Autoregressive Exogenous	PM	Pattern Matching
CQ	Characteristic Quantities	QM	Qualitative Model
EM	Empirical Model	RB	Rule Based Expert System
FC	Fuzzy Classification	RBF	Radial Basis Function
FMB	Fuzzy Model Based	SPM	Simplified Physical Models
KB	Knowledge Based	SRB	Statistical Rule Based System
Li	Limits	TCBM	Topological Case Based Modeling
MI	Mathematical Inference	TM	Thermodynamic Model
		Tr	Trends

[a] Fault detection and diagnosis was performed as a single step.
[b] A slightly modified version of the FDD system has been widely tested and is currently commercially available.

Air-Conditioners and Heat Pumps — There are many applications of FDD to air conditioners and heat pumps based on a vapor compression cycle; some of the studies are discussed below (Yoshimura and Ito, 1989; Kumamaru et al., 1991; Wagner and Shoureshi, 1992; Rossi, 1995; Rossi and Braun, 1996; Rossi and Braun, 1997; Breuker, 1997; Breuker and Braun, 1999a, 1999b).

Yoshimura and Ito (1989) used pressure and temperature measurements to detect problems with condenser, evaporator, compressor, expansion valve, and refrigerant charge on a packaged air conditioner. The difference between the measured values and the expected values was used to detect a fault. The expected value for comparison was estimated from the manufacturers' data, and the thresholds for fault detection were experimentally determined in the laboratory. The detection and diagnosis was conducted in a single step. No details were provided on how the thresholds for detection were selected.

Wagner and Shoureshi (1992) developed two different fault detection methods and compared their ability to detect five different faults in a small heat pump system in the laboratory. The five faults included condenser and evaporator fan fault, capillary tube blockage, compressor piston leakage, and seal system leakage. The first method was based on limit and trend checking, and the second method was a model-based approach in which the difference between the prediction from a simplified physical model and the monitored observations are transformed (or normalized) into useful statistical quantities. The transformed statistical quantities are then compared to predetermined thresholds to detect a fault.

The two fault detection strategies were operated in parallel on a heat pump in a psychrometric room. The model-free method was able to detect four of the five faults that were introduced abruptly, while the model-based method was successful in detecting only two faults. The selection of the thresholds for both methods is critical in avoiding false alarms and reduced sensitivity. Wagner and Shoureshi (1992) provide a brief discussion of how to trade off between sensitivity to diagnosis and false alarm. The implementation is only capable of detecting faults but lacks diagnosis, evaluation, and decision stages described in the previous section.

Rossi (1995) described the development of a statistical rule based fault detection and diagnostic method for air conditioning equipment with nine temperature measurements and one humidity measurement. The FDD method is capable of detecting and diagnosing condenser fouling, evaporator fouling, liquid-line restriction, compressor valve leakage, and refrigerant leakage. In addition to the detection and diagnosis, Rossi and Braun (1996) also described an implementation of the fault evaluation method. A detailed explanation of the fault evaluation method can be found in Rossi and Braun (1997). The methods were demonstrated in limited testing with a rooftop air conditioner in a laboratory.

Breuker (1997) performed a more detailed evaluation of the methods developed by Rossi (1995). The methods and results of the evaluation on a rooftop air conditioner in a laboratory environment (Breuker and Braun, 1999a, 1999b) are discussed in more detail later in the chapter.

Chillers — Several researchers have applied FDD methods to detect and diagnose faults in vapor compression based chillers; some of the studies are summarized below (Grimmelius et al, 1995; Gordon and Ng, 1995; Stylianou and Nikanpour, 1996; Tutsui and Kamimura, 1996; Peitsman and Bakker, 1996; Stylianou, 1997; Bailey et al., 2000; Gordon and Ng, 2000).

Grimmelius et al. (1995) developed a fault diagnostic system for a chiller. A reference model is used in parallel with the measured variables for fault detection and diagnosis. While the fault detection and diagnostics are carried out in a single step, their approach lacks the evaluation and decision steps. Twenty different measurements were used including temperature, pressure, power consumption, and compressor oil level. In addition to the measured variables, some derived variables were used, such as liquid subcooling, superheat, and pressure drop. The reference model is a multivariate linear regression model developed with the data from a properly operating chiller to estimate the process variables. These estimates were subsequently used to generate residuals by comparing the actual measured values with those estimated by the reference model. The inputs to the reference model included the environmental inputs and load conditions. The residuals were then used to score each fault symptom.

The chiller operation was classified into seven regions. Fault modes were associated with any component that was serviceable, which led to 58 different fault modes. The cause and effect study of the 58 fault modes helped establish the expected influence on the components and subsequent chiller behavior. The symptoms associated with the 58 fault modes on the measured and derived variables were generated. In the resulting symptom matrix, some fault modes were indistinguishable in terms of their respective symptoms because they either had identical or empty patterns. As a result, the symptom matrix was reduced from 58 to 37 fault modes and symptom patterns.

To diagnose a fault, scores are assigned to each known fault mode in the matrix. The score for a given symptom is not a constant, but is determined based on knowledge about the particular fault symptoms. A variable that shows a very distinct reaction to a fault mode becomes a higher score than a variable that shows only a limited reaction to the fault mode. For example, if there is increased resistance to flow of the evaporator on the chilled water side, the score associated with the decrease in suction pressure becomes higher than the decrease in the cooling water temperature difference. A symptom matrix for selected faults is shown in Table 7.2.2 (arrow pointing up, ↑, indicates increasing value as a result of the fault; likewise, arrow pointing down, ↓, indicates decreasing value as a result of the fault; a horizontal arrow, →, indicates the fault has no effect on the variable).

TABLE 7.2.2 Symptom Patterns for Selected Faults in a Chiller

Fault	Compressor Suction Pressure	Compressor Suction Temperature	Compressor Discharge Pressure	Compressor Discharge Temperature	Compressor Pressure Ratio	Oil Pressure	Oil Temperature	Oil Level	Crankcase Pressure	Compressor Electric Power	Subcooling of Refrigerant	ΔT Refrigerant and Cooling Water	ΔT Cooling Water	Inlet Temperature at Expansion Valve	Filter Pressure Drop	Evaporator Outlet Pressure	Superheat	ΔT Chilled Water	Evaporator Outlet Temperature	Number of Active Cylinders
Compressor, suction side, increase in flow resistance	↓	→	→	→	→	↓	→	→	↓	↓	→	→	→	→	→	↑	↑	↓	→	→
Compressor, discharge side, increase in flow resistance	↑	→	↑	→	→	↑	→	→	↑	→	→	→	→	→	→	↑	↑	↓	→	→
Condenser, cooling water side, increase in flow resistance	→	→	↑	→	→	→	→	→	→	↑	↓	→	↑	→	→	→	→	→	→	→
Fluid line increase in flow resistance	→	→	→	→	→	→	→	→	→	↓	→	→	→	↓	→	→	↑	↑	→	→
Expansion valve, control unit, power element loose from pipe	↑	→	→	→	→	↑	→	→	↑	↑	→	→	→	→	→	↑	↓	↑	→	→
Evaporator, chilled water side, increase in flow resistance	↓	→	→	→	→	↓	→	→	↓	↓	→	→	→	→	→	↓	↑	↑	→	→

Source: Grimmelius et al., 1995.

Using the symptom matrix, a total score is generated by adding the individual scores of all expected symptoms that match the measured symptoms. A normalized score is calculated by dividing the total score by the total number of points per pattern. A normalized score of 0.9 or higher is used to indicate a probable fault, and a score between 0.5 and 0.9 is used to indicate a possible fault. Although the method proved effective in identifying faults in the systems before the system failed completely, faults with only a few symptoms got high scores more often. Because the reference model is a simple regression model developed with the data from the test chiller, the same model may not work on another chiller.

Gordon and Ng (1995, 2000) developed thermodynamic models for three commonly used chillers: reciprocating, centrifugal, and absorption. In addition, they also developed thermodynamic models for thermoacoustic and thermoelectric refrigerators. These models may not work to develop characteristic quantities for use within an FDD system. Although the models were used to demonstrate both the predictive and diagnostic capabilities, no full FDD system was developed.

Stylianou and Nikanpour (1996) used the reciprocating chiller model developed by Gordon and Ng (1995) and the pattern matching approach outlined by Grimmelius et al. (1995) as part of their FDD system. Like Grimmelius et al. (1995), they also perform the detection and diagnosis in a single step, and their approach lacks the evaluation and decision steps. The methods used in the FDD system included a thermodynamic model for fault detection, and pattern recognition from expert knowledge for diagnosis of selected faults. The diagnoses of the faults are performed by an approach similar to that outlined by Grimmelius et al. (1995). Seventeen different measurements were used, including pressures, temperatures, and flow rates, to detect four different faults: refrigerant leak, refrigerant line flow restriction, condenser water side flow resistance, and evaporator water side flow resistance.

The FDD system is subdivided into three parts: one used to detect problems when the chiller is off, one used during the start-up, and one used at the steady state condition. The off-cycle module is deployed when the chiller is turned off, and is primarily used to detect faults in the temperature sensors. The temperature sensor readings are compared to one another after the chiller is shut down. The differences are then compared to the values established during commissioning.

TABLE 7.2.3 Fault Patterns Used in the Diagnostic Module

Fault	Discharge Temperature	High Pressure Liquid Line Temperature	Discharge Pressure	Low Pressure Liquid Line Temperature	Suction Line Temperature	Suction Pressure	ΔT_{cond}	ΔT_{Evap}
Restriction in refrigerant line	↑	↓	↓	↓	↑	↓	↓	↑
Refrigerant leak	↑	↓	↓	↓	↑	↓	↓	↑
Restriction in cooling water	↑	↑	↑	↓	↓	↓	↑	↓
Restriction in chilled water	↑	↓	↓	↓	↓	↓	↓	↓

Source: Stylianou and Nikanpour, 1996.

The start-up module is deployed once the chiller is started and is left deployed for 15 minutes. The module used four measured inputs — discharge temperature, the crankcase oil temperature, and refrigerant temperature entering and leaving the evaporator — scanned at 5 sec intervals to detect refrigerant flow faults that are easier to detect before the system reaches steady state. To detect faults, the responses of the measured variables are compared to the baseline responses. For example, a shift (in time or magnitude) in the peak of the discharge temperature may indicate liquid refrigerant floodback, refrigerant loss, or refrigerant line restriction. Because the ambient conditions affect the baseline response, the response may have to be normalized before a comparison is made.

The steady state module is deployed after the chiller reaches steady state and stays deployed until the chiller is turned off. In this mode, it performs two functions: (1) to verify performance of the system, and (2) to detect and diagnose selected faults. Performance is verified using the thermodynamic models developed by Gordon and Ng (1995). For the fault diagnostics, linear regression models are used to generate estimates of pressure and temperature variables, similar to the approach outlined by Grimmelius et al. (1995). To diagnose faults, the estimated variables are compared to the measured values, and the residuals are matched using a rule-base to the patterns shown in Table 7.2.3.

Although Stylianou and Nikanpour (1996) extended the previous work of Gordon and Ng (1995) and Grimmelius et al. (1995), the evaluation of the FDD systems was not comprehensive and lacked several key elements including sensitivity and false alarm. In addition, it is not clear whether the start-up module can be easily generalized.

Tutsui and Kamimura (1996) developed a model based on a topological case based reasoning technique, and applied it to an absorption chiller. They showed that although the linear model had a better overall modeling error (mean error) than the topological case based model, the latter was better at identifying abnormal conditions.

Peitsman and Bakker (1996) used two types of black-box models, neural networks (NNs) and auto-regressive with exogenous inputs (ARX), to detect faults at the system, as well as at the component level of a reciprocating chiller system. The inputs to the system models included condenser supply water temperature, evaporator supply glycol temperature, instantaneous power of compressor, and flow rate of cooling water entering the condenser (for NN only). The choice of the inputs was only limited to those that are commonly available in the field. Using the inputs with both the NN and ARX models, 14 outputs were estimated. For the NN models, inputs from the current and the previous time step and outputs from two previous time steps were used.

Peitsman and Bakker (1996) state that 14 system level models and 16 component level models were developed to detect faults in a chiller; however, only one example is described in their research. The intent was to use system level models to detect the fault at the system level and then use the component level models to isolate the fault. NN models appeared to have a slightly better performance than the ARX models in detecting faults at both the system and the component level. The evaluation and decision steps were not implemented.

Stylianou (1997) replaced the rule-based model used to match the pattern shown in Table 7.2.3 with a statistical pattern recognition algorithm. This algorithm uses the residuals generated from comparison of predicted (using linear regression) models, and measured pressures and temperatures to generate patterns that identify faults. Because this approach relies on the availability of training data for normal and faulty operation, it may be difficult to implement it in the field. There was only limited testing of the method.

Bailey, Kreider, and Curtiss (2000) also used the NN model to detect and diagnose faults in an air-cooled chiller with a screw compressor. The detection and diagnosis was carried out in a single step. The faults evaluated included: refrigerant under- and over-charge, oil under- and over-charge, condenser fan loss, and condenser fouling. The measured data included: superheat for circuits 1 and 2, subcooling from circuits 1 and 2, power consumption, suction pressure for circuits 1 and 2, discharge pressures for circuits 1 and 2, chilled water inlet and outlet temperatures from the evaporator, and chiller capacity.

***Air-Handling Unit* —** There are several studies relating to the FDD method for the air-handling units (both the air side and the water side) and some of these are summarized in this section (Norford and Little, 1993; Glass et al., 1995; Yoshida et al., 1996; Haves et al., 1996, 1996a, 1996b, and 1997; Peitsman and Soethout, 1997; Brambley et al., 1998; Katipamula et al., 1999; House et al., 1999; Ngo and Dexter, 1999; Yoshida and Kumar, 1999; Seem et al., 1999).

Norford and Little (1993) classify faults in ventilating systems consisting of fans, ducts, dampers, heat exchangers, and controls. They review two forms of steady state parametric models for the electric power used by ventilation system fans and propose a third, that of correlating power with a variable speed drive control signal. The models are compared based on prediction accuracy, sensor requirements, and their ability to detect faults.

Using the three proposed models, four different types of faults associated with fan systems are detected: (1) failure to maintain supply-air temperature, (2) failure to maintain supply air pressure setpoint, (3) increased pressure drop, and (4) malfunction of fan motor coupling to fan and fan controls. Although Norford and Little's study lacked details on how the faults were evaluated, error analysis and associated model fits were discussed. The results indicate that all three models were able to identify at least three of the four faults. The diagnosis of the faults is inferred after the fault is detected.

Glass et al. (1995) used a qualitative model-based approach to detect faults in an air-handling unit. The method uses outdoor-, return-, and supply-air temperatures and control signals for the cooling coil, heating coil, and the damper system. Although Glass et al. (1995) mentioned that the diagnosis is inferred from the fault conditions, no clear explanation or examples were provided.

Detection starts by analyzing the measured variables to verify whether steady state conditions exist. Then, the controller values are converted to qualitative signal data and, using a model and the measured temperature data expected, qualitative signals are estimated. Faults are detected based on discrepancies between measured qualitative controller outputs and corresponding model predictions based on temperature measurements. Examples of qualitative states for the damper signal include: "maximum position," "minimum position," "closed," and "in between." When the quantitative value of the damper signal approaches maximum value, the corresponding qualitative value of "maximum" is assigned to the measured controller output.

The results of testing the method on a laboratory AHU were mixed because it requires steady state conditions to be achieved before fault detection is undertaken. Fault detection sensitivity and ability to deal with false alarms were not discussed.

Yoshida et al. (1996) used ARX and the extended Kalman filter approach to detect abrupt faults with simulated test data of an AHU. Although the fault diagnosis approach was clearly described, the authors noted that diagnosis is not feasible with the ARX method, but the Kalman filter approach could be used for diagnosis. Fault detection sensitivity and ability to deal with false alarms were not discussed.

Haves et al. (1996) used a combination of two models to detect coil fouling and valve leakage in the cooling coil of an AHU. The methodology was tested with data produced by the HVACSIM+ simulation

TABLE 7.2.4 Normalized Pattern for AHU Fault Diagnosis Used in NN Training

	Network Inputs — Residuals															
Fault Diagnosis	Supply Pressure	Difference in Air Flow Supply and Return	Supply-Air Temperature	Control Signal to Cooling Coil	Supply Fan Speed	Return Fan Speed	Cooling Coil Valve Position	Network Outputs								
Normal	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Supply Fan	–1	–1	0	1	–1	0	0	0	1	0	0	0	0	0	0	0
Return Fan	0	1	0	0	0	–1	0	0	0	1	0	0	0	0	0	0
Pump	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
Cooling Coil Valve	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0
Temperature Sensor	0	0	–1	–1	0	0	0	0	0	0	0	0	1	0	0	0
Pressure Transducer	–1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Supply Fan Flow Station	0	–1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Return Fan Flow Station	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Source: From Lee et al., 1996b.

tool (Clark, 1985). A radial bias function (RBF) models the local behavior of the HVAC&R system and is updated using a recursive gradient-based estimator. The data generated by exercising the RBF over the operating range of the system are used in the estimation of the parameters of the physical model (UA and percent leakage) using a direct search method. Detection is accomplished by comparing estimated parameters to fault-free parameters.

Lee et al. (1996a) used two methods to detect eight different faults (mostly abrupt) in a laboratory test AHU. The first method used discrepancies between measured and expected variables (residuals) to detect the presence of a fault. The expected values were estimated at nominal operating conditions. The second method compared parameters that were estimated using autoregressive moving average with exogenous input (ARMX) and ARX models with the normal (or expected) parameters to detect faults. The faults evaluated included: complete failure of the supply and return fan, complete failure of the chilled water circulation pump, stuck cooling coil valve, complete failure of temperature sensor, complete failure of static pressure sensor, and failure of supply and return air fan flow station. Because each of the eight faults had a unique signature, no diagnosis was necessary.

Lee at al. (1996b) used an NN model to detect the same faults described previously (Lee et al., 1996a). NN was trained using the normal data and data representing each of the eight faults. Seven normalized residual values were used as inputs to the NN model and the nine output values consitute a pattern that represents normal operation or one of the eight fault modes. Instead of generating the training data with faults, idealized training patterns were specified by considering the dominant symptoms of each fault. For example, supply fan failure implies: supply fan speed of zero, supply-air pressure of zero, supply fan control signal of maximum, flow difference between the supply, and return ducts of zero.

Using similar reasoning, a pattern of dominant training residuals for each fault was generated and is shown in Table 7.2.4. The NN was trained using the pattern shown in Table 7.2.4. Normalized residuals were calculated for the faults that were artificially generated in the laboratory AHU. The normalized residuals vector at each time step was then used with the trained NN to identify the fault. Although the NN was successful in detecting the faults from laboratory data, it is not clear how successful this method will be, in general, because the faults generated in the laboratory setting were severe and without noise.

Lee et al. (1997) extended the previous work described in Lee et al. (1996b). In the 1997 analysis, two NN models were used to detect and diagnose the faults. The AHU was broken down into various subsystems such as: the pressure control subsystem, the flow control subsystem, the cooling coil subsystem, and the mixing damper subsystem. The first NN model is trained to identify the subsystem in which a fault occurs, while the second NN model is trained to diagnose the specific cause of a fault at the subsystem level. An approach similar to the one described previously (Lee et al., 1996b) is used to train both NN models.

Lee et al. (1997) noted that this two-stage approach simplifies generalization by replacing a single NN that encompasses all considered faults with a number of less complex NNs, each one dealing with a subset of the residuals and symptoms. Although 11 faults are identified for detection and diagnosis, fault detection and diagnosis for only one fault are presented in their study.

Peitsman and Soethout (1997) used several different ARX models to predict the performance of the AHU and compared the prediction to the measured values to detect faults in the AHU. The training data for the ARX models were generated using HVACSIM+. The AHU is modeled at two levels: (1) the system level where the complete AHU is modeled with one ARX model, and (2) the component level where the AHU is subdivided into several subsystems such as return fan, the mixing box, and the cooling coil. Each component is modeled with a separate ARX model. The first level ARX model is used to detect a problem, and the second level ARX models are used to diagnose the problem.

Most abrupt faults were correctly identified and diagnosed, while the slow evolving faults were not detected. In addition, there is a potential for conflict between the two levels; for example, the top level ARX model could detect a fault with the AHU, and the second level ARX models may not indicate any faults. Furthermore, there is a potential for multiple diagnoses at the second level. Peitsman and Soethout (1997) indicated that some of the multiple diagnoses could be discriminated by ranking them according to their improbability; however, no details were provided on how to implement such a scheme.

As part of its mission in commercial buildings research and development, the U.S. Department of Energy (DOE), in collaboration with industry, has developed a tool that automates detection and diagnosis of problems associated with outdoor-air ventilation and economizer operation. The tool, known as the outdoor-air/economizer (OAE) diagnostician, monitors the performance of AHUs and detects problems with outdoor-air control and economizer operation, using sensors that are commonly installed for control purposes (Brambley et al., 1998; Katipamula et al., 1999).

The tool diagnoses the operating conditions of AHUs using rules derived from engineering models of proper and improper air-handler performance. These rules are implemented in a decision tree structure in software. The diagnostician uses data collected periodically (e.g., from a BAS) to navigate the decision tree and reach conclusions regarding the operating state of the AHU. At each point in the tree, a rule is evaluated based on the data, and the result determines which branch the diagnosis follows. When the end of a branch is reached, a conclusion is reached regarding the current condition of the AHU. A detailed description of the methodology used is described later in the chapter.

House et al. (1999) compared several classification techniques for fault detection and diagnosis of seven different faults in an AHU. The data for the comparison were generated using a HVACSIM+ simulation model. Using the residuals, as defined in Lee et al. (1996a, 1996b), five different classification methods were evaluated and compared for their ability to detect and diagnose faults. The five classification methods include: NN classifier, nearest neighbor classifier, nearest prototype classifier, a rule-based classifier, and a Bayes classifier.

Based on the performance of classification methods, the Bayes classifier appeared to be a good choice for fault detection. For diagnosis, the rule-based method proved to be a better choice for the classification problems considered, where the various classes of faulty operations were well separated and could be distinguished by a single dominant symptom or feature.

Ngo and Dexter (1999) developed a semiqualitative analysis of the measured data using generic fuzzy reference models to diagnose faults with the cooling coil of an AHU. The method uses sets of training data with and without faults to develop generic fuzzy reference models for diagnosing faults in the cooling coil, including leaky valve, water side fouling, valve stuck closed, valve stuck midway, and valve stuck open. The fuzzy reference models describe in qualitative terms the steady state behavior of a particular class of equipment with no faults present and when each of the faults has occurred. The measured data are used to identify a partial fuzzy model that describes the steady state behavior of the equipment at a particular operating point. The partial fuzzy model is then compared to each of the reference models using a fuzzy matching scheme to determine the degree of similarity between the partial model and the reference models. The Ngo and Dexter (1999) study provides a detailed description of fault detection sensitive and false alarm rates.

Yoshida and Kumar (1999) evaluated two model-based methods to identify abrupt/sudden faults in an AHU. They reported that both ARX and adaptive forgetting through multiple models (AFMM) seem promising for use in on-line fault detection of the AHU. They report that ARX models require only a minimal knowledge of the system, and the potential limitation of the technique is that it requires long periods to stabilize its parameters. On the other hand, Yoshida and Kumar (1999) report that the AFMM method requires long moving averages to suppress false alarms. By doing so, faults of lesser magnitude cannot be easily detected. Implementation details were lacking, and only one example of fault detection was provided.

Seem et al. (1999) developed a method based on estimating performance indices that can be used for fault detection; however, no details were provided.

7.2.7 Costs and Benefits of Diagnostics and Predictive Maintenance

The cost of FDD implementation depends on several factors including the type of diagnostic method used, type of faults to be evaluated, number of sensors required (including any redundancy), and level of automation. The benefits from FDD can be classified into three categories: (1) improved health and safety, (2) improved reliability and availability, and (3) reduced cost of operations and maintenance.

Because safety is the overriding factor in the critical process, FDD applications with high cost can be easily justified. High availability of plant equipment is critical in the chemical or food process plants, where equipment failures and inefficiencies can have a significant impact on production costs. The economic impact of abnormal operations in the petrochemical process operations is about $20 billion per year in the U.S. (Mylaraswamy and Venkatsubramanian, 1997). Therefore, automated FDD systems are almost essential in reducing downtime and improving productivity. Most FDD research and applications development so far have been for critical and process industries because these industries can afford applications with a high cost, or because the benefits are so large that the cost of the FDD can be correspondingly high.

Cost vs. Benefits in Building Systems

In general, the health and safety benefits for building systems are lower than for critical or process plants and are generally limited to detection of problems relating to indoor-air quality, operations of fire systems, and elevator operations. Generally, FDD benefits must be derived entirely from reduction in operation and maintenance cost, and improved occupant comfort and health to offset the development and implementation costs. In comparison to critical or process plants, the cost savings are undoubtedly a smaller portion of the costs of operating the businesses that they serve. This means that FDD applications for noncritical building applications must have lower installed costs to achieve the same cost-to-benefit ratio (Braun, 1999).

Clearly, low installed costs are critical to wider adoption of FDD applications in building systems. Interest in FDD has grown as the costs of sensors and control hardware have gone down. In addition, there is increased emphasis on using information technology within the HVAC&R industry for scheduling, parts tracking, billing, and personnel management. This has provided an infrastructure and a higher expectation for the use of quantifiable information for better decision making. Finally, the structure of the industry that provides services for the operation and maintenance of buildings is changing. Companies are consolidating and offering whole-building operation and maintenance packages. In addition, utilities are in the process of being deregulated and are beginning to offer new services, which could ultimately include complete facility management. The cost-to-benefit ratio for FDD improves as the industry moves toward large organizations managing the operations and maintenance of many buildings. In particular, the cost of developing and managing the necessary software tools can be spread out over a larger revenue base.

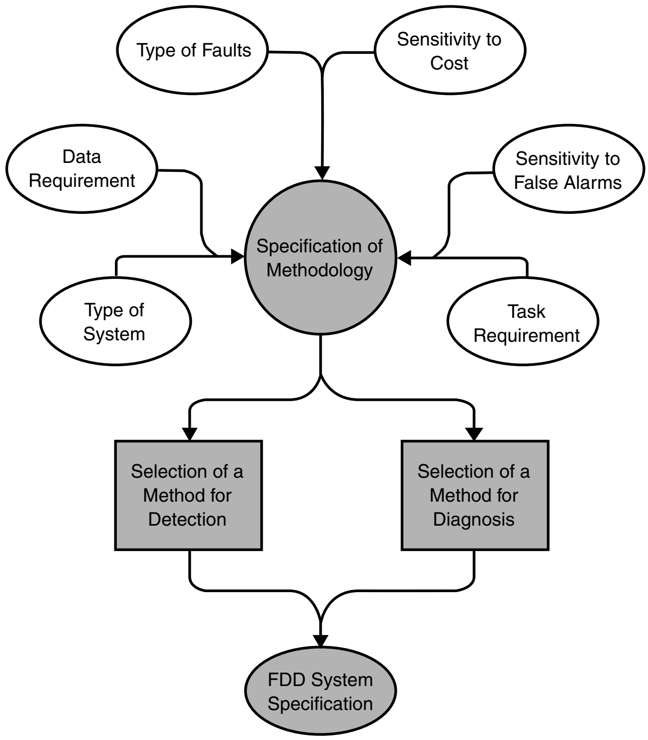

FIGURE 7.2.4 Schematic of a methodology specification.

7.2.8 Selection of Methods for FDD Applications

Selection of methods for FDD plays a critical part in the development of FDD systems. There is a wide range of methods available for FDD; most of them perform adequately in the laboratory or test setting, but many of them may not be suitable for field implementation. Some methods have fewer data requirements, while others require extensive data. This section provides a brief discussion on how to properly select a method for FDD.

There are several approaches to detecting and diagnosing faults in building systems. They differ widely depending on the type of system they are applied to, the necessary degree of knowledge about the diagnosed object, cost-to-benefit ratio (including monetary, as well as life safety related issues), the degree of automation, and the input data required. Most classical methods use alarm limits as fault criteria, whereas the advanced methods apply accurate mathematical models of the process. Between the two groups are various simplified empirical and heuristic knowledge-based methods of fault detection and diagnostics. Development of detailed physical models is expensive and impractical in most instances; therefore, either a simplified model based on first principles, or a heuristic knowledge base is widely used for FDD.

The success of the FDD system depends on proper selection of methods for both detection and diagnosis. Often methods are selected because of the interest of the developer or the availability of an existing tool. While this approach may yield satisfactory results for small-scale laboratory applications, it often leads to problems in full-scale real applications. For some FDD applications, fault diagnosis may not be needed because detection isolates the fault. On the other hand, fault diagnosis may not be possible because resolution of the data is not sufficient for diagnosis. Selection of the best method for detection and diagnosis depends on several factors, as shown in Figure 7.2.4.

The methods used for detection are often different from the methods used for diagnosis. During detection, the actual measurements (or estimated actual state/parameter) are compared to the expected measurements to identify an abnormal condition. Diagnosis is more involved and requires sophisticated methods to isolate the fault and the cause. From the survey of the literature both in critical processes and in the HVAC&R area, model-based approaches were widely used in detecting faults. Model-based approaches relied on mathematical models to predict the state or the output variables and compare them to the measured variables. For diagnosis, classification methods such as NNs, fuzzy clustering, and rule-based reasoning methods were widely used in the literature.

As mentioned earlier, almost any type of FDD method can be used at the building level (Figure 7.2.2); however, diagnosis at that level is limited. FDD systems deployed at the subsystems level, or component level, many not need a diagnosis method because when a fault is detected, the cause is already known. FDD systems deployed at the intermediate levels will most likely need both detection and diagnosis methods.

The amount of measured data plays a critical role in the selection of a method for both detection and diagnosis. A limited set of information will lead to selection of a detailed or moderately detailed physical model for detection. For diagnosis, it will then be necessary to have a set of fault models and a technique for selecting the fault models for a given set of inputs and outputs. In general, most building HVAC&R systems will have limited sensors — sensors that are required for controls purposes only. Additional sensor costs should be considered when selecting methods that require data beyond those that are normally provided for controls. On the other hand, methods that rely on a limited set of data may generate more false alarms.

Statistical pattern recognition techniques are often used to identifying the best matching model. If the system is extensively instrumented, classical limit checks and simplified empirical models are sufficient for detection, while rule-based or knowledge-based models are needed for diagnosing the cause.

Before selecting methods for detection and diagnosis, a good understanding of the anticipated faults is essential. Some faults influence the selection of the diagnostics method more than the detection. Examples of faults that make diagnosis difficult include faults that exhibit different symptoms at different times, faults that are intermittent, and multiple simultaneous faults. Not many methods can diagnose the fault that exhibits different symptoms at different times depending on the operational dynamics. For example, if the outdoor-air damper is stuck wide open and the outdoor-air conditions are favorable for economizing, there is no fault. However, if the outdoor-air conditions are unfavorable for economizing, it is a fault. In addition, multiple simultaneous faults make determining the cause of the fault difficult.

To a lesser extent, the cost of development and deployment of an FDD system influences the methods selected. Because the building industry is cost sensitive and safety is not an issue with the building systems, the methods used for detection and diagnosis have to rely on a limited set of measured data.

For noncritical applications, the methods used for detection and diagnosis should minimize the number of false positives (false alarms). If a number of false positive faults are detected and diagnosed, the operators may disable the FDD system completely. FDD methods applied to critical systems are tuned to be sensitive to fault detection; therefore, these applications may generate false alarms more often. On the other hand, FDD methods applied to noncritical systems (most building systems) are tuned to generate fewer false alarms.

The task requirement of the FDD system also plays a crucial role in the selection of the methods. If the FDD system is deployed in a decision support role, simple detection and diagnostic methods such as knowledge-based models are sufficient. On the other hand, if the FDD system is deployed as a fault-tolerant control system, more accurate and robust detection and diagnostics methods are required.

7.2.9 Detailed Descriptions of Three FDD Systems

In the next section, detailed descriptions of three FDD systems are presented: (1) a whole-building energy diagnostician, (2) an outdoor-air/economizer diagnostician, and (3) an automated FDD system for vapor compression systems. These three FDD applications were selected because they use different detection and diagnosis methods.

Whole-Building Energy Diagnostician

Energy consumption levels and patterns in buildings, when properly understood, can be indicators of building systems operation. Malfunctions of costly equipment can be identified by comparing "nominal" equipment behavior to that measured in real time during ongoing building operation. A statistically rigorous method was developed to detect problems in the whole-building energy consumption by organizing NNs into a higher-level model called a belief network, which can be viewed as a probabilistic database containing what is known about a system (Pearl, 1988). The whole-building energy (WBE) module described here is one module of a larger system for whole-building diagnostics developed by a team of private sector, national laboratory, and university researchers (Brambley et al., 1998). A summary of the WBE follows; for more information refer to Dodier and Kreider (1999).

Detection Variables in WBE

The WBE diagnostician determines the ratio of measured energy use to expected energy use accounting for the weather, time of day, day of week, and other features of building energy use that are time and day dependent. Specifically, WBE detections are based on the energy consumption index (ECI), which is defined as

$$\text{ECI} = \frac{(\text{Actual energy use})}{(\text{Expected energy use})}$$

A separate ECI is computed for each for the four major energy end uses: building total electric, building total thermal, HVAC&R electric other than chiller/packaged units, and chiller/packaged units. Therefore, the data required for the FDD systems include: outdoor-air temperature and humidity, whole-building electricity and thermal, electricity consumption of the chiller or packaged units, and other HVAC&R electricity consumption (less chiller or packaged units). If any of the consumption data are not available, detection for that end use is not performed.

The actual energy use is measured, while the expected energy use is computed as a function of time of day, day of year, day of week, outdoor-air dry-bulb temperature and relative humidity, and other optional weather and load predictors may be used as well (such as wind speed, production, historical or sales). NNs are used to predict each energy end use given the values of these weather and calendar variables. These predictor networks are calibrated by training them on data from the same building. The amount of training data depend on the end use; an end use that varies by outdoor conditions may need as much as 6 to 9 months, while others many need as little as 4 weeks.

The actual and expected energy use variables of interest are totals computed from hourly values recorded over a 24-hour period from midnight on one day to midnight the next day. Each of the four ECI values is calculated once a day. Installing the WBE in a new building requires that it be tuned (by training the neural network predictor models) especially for that building. Because energy use varies widely from one building to another, tuning the WBE for each building gives much more accurate energy use predictions than are possible with models that do not consider a building's particular characteristics.

Problem Detection Approach

The flow of data within WBE is shown schematically in Figure 7.2.5. In summary, the current belief network, current end use consumption data, current weather variables (dry-bulb temperature and relative humidity), and calendar variables (time of day, day of year, and a weekday/weekend flag) are the inputs. The time of day and day of year are represented as sine and cosine functions. The weekday/weekend flag is "1" if the day is a weekday, and "0" if it is a weekend. Detected problems and their costs are output. Essentially a belief network embodies, in a quantitative way, the relationships between known or measured influencing parameters (e.g., weather, schedule, occupancy in a building) and the energy end uses of interest. The WBE module compares the measured data with predicted data to detect problems. If a problem is detected, it estimates energy cost impacts.

Specifically, the WBE module uses probabilistic inference in the form of a belief network with continuous and discrete variables for problem detection. Problems to be detected are represented as variables

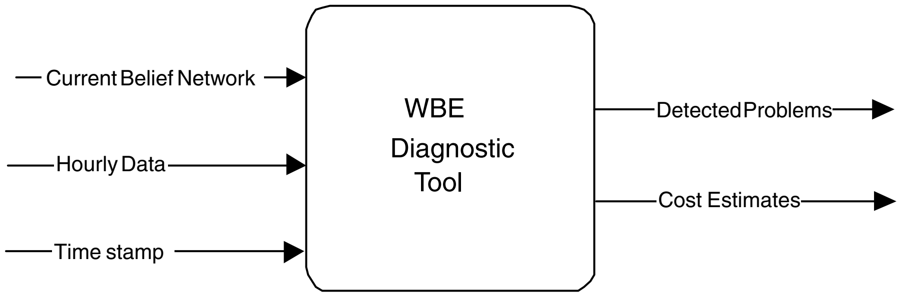

FIGURE 7.2.5 Data flow in WBE diagnostician (from Dodier and Kreider, 1999).

in the network. Metered data and other known values are also variables in the network. Some intermediate quantities (such as daily energy use totals and estimated values for missing sensor readings) are variables as well. Probability distributions are propagated through the belief network. The result of the propagation algorithm is the probability distribution over each variable conditional on observed values.

The probability distribution over each detection variable is used to compute the risk associated with each possible diagnostic message. A cost matrix for each detection variable is stored with the associated messages. The message with least risk is output from the WBE.

Belief Networks

A belief network is a probabilistic model composed of a number of submodels that compute the probability of a dependent variable x, given the values of the variables that have a cause or influence relation to x. These influential variables are called "parent" variables, and x is called a "child" variable. The model is called a "belief" network because it computes probabilities, representing degrees of belief. Although slightly dated from a technical point of view, Pearl (1988) remains the best general introduction to belief networks because of clarity and breadth; it discusses the interpretation of belief networks and how they represent the world.

Because the belief network summarizes what is known about a system, discussion of the fault detection system is centered on the belief network. A belief network allows heterogeneous data to be organized into a single structure; therefore, all relevant data is stored within the network.

Summary of WBE Diagnostician

The belief networks offer a workable approach to including both physical and statistical knowledge for detecting energy use problems. A strictly probabilistic approach supersedes the use of ad hoc "certainty factors" commonly used in expert systems. Neural networks can be used to predict whole-building energy use quickly and with sufficient accuracy to form the basis of WBE detection process.

Testing on field data indicates that the WBE approach is able to identify changes in HVAC&R systems (Dodier and Kreider, 1999) and to estimate the difference in energy use. Data from a large building have been analyzed using the WBE, with encouraging results. In practice, the most significant hurdle is to automatically train accurate prediction models for energy end uses, when only short data streams are available. The other important practical obstacle is baseline data. The WBE diagnostician automatically determines when there is sufficient data to make accurate predictions. Furthermore, the WBE automatically determines if it is not making sufficiently accurate predictions and if additional training data need to be collected.

Outdoor-Air/Economizer Diagnostician

The outdoor-air/economizer (OAE) diagnostician is part of a larger tool developed by the DOE (Brambley et al., 1998; Katipamula et al., 1999). It monitors the performance of AHUs and automatically detects problems with outdoor-air control and economizer operation using sensors that are commonly installed for control purposes. The OAE diagnostician can be used with most major types of economizer and

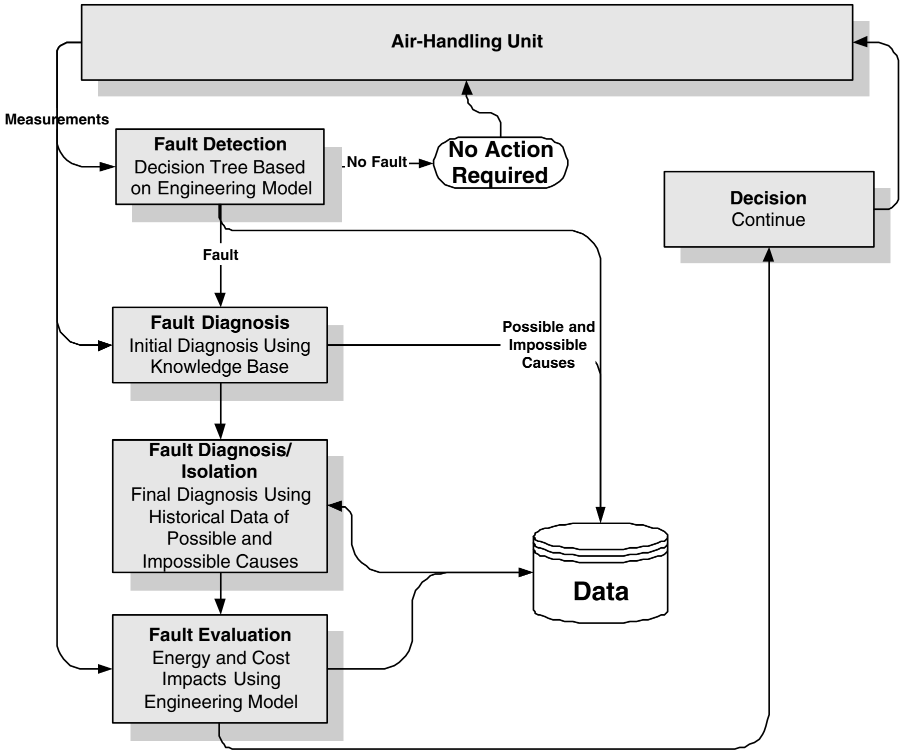

FIGURE 7.2.6 Overview of OAE diagnostician.

ventilation systems. It detects both over- and under-supply of outdoor air; thus, it can be used to ensure adequate outdoor-air supply for the occupants and eliminate excess heating or cooling.

Detection and Diagnostic Methods

As with any mechanical system, faults that diminish or eliminate an economizer's usefulness can occur. However, unlike the primary (mechanical) cooling system, a failure of the economizer may go completely unnoticed. Any failure, for example, that prevents outdoor air from being used for cooling when outdoor conditions are favorable may go unnoticed because the mechanical cooling system will pick up the load and maintain occupant comfort. Similarly, a failure that results in too much outdoor air may not be apparent in a reheat system. Reheating will ensure that the air supplied to the space is at a comfortable temperature. In both of these examples, however, the system would be using much more energy (and costing much more to operate) than necessary.

The OAE diagnostician is designed to monitor conditions of the system not normally observable by occupants, and to alert the building operator when there is evidence of an operational fault. The common types of outdoor-air ventilation and economizer problems handled by the DAE diagnostician include: stuck outdoor-air dampers, failures of temperature and humidity sensors, economizer and ventilation controller failures, supply-air controller problems, and air flow restrictions that cause unanticipated changes in overall system circulation. The diagnostician also performs some self-diagnosis to identify errors introduced by users in setup and configuration of the software tool.

An overview of the fault detection and diagnostic process is shown in Figure 7.2.6. The first step in the FDD process for the OAE diagnostician is fault detection. The diagnoses of the faults are carried out in two steps: (1) initial diagnosis of the fault is accomplished by using a knowledge base, and (2) the final diagnosis that refines the initial diagnosis is accomplished by reviewing the historical results. The initial and the final diagnoses are carried out for each time step. After the fault is detected and the cause of the fault is diagnosed, the fault is evaluated, and the energy and cost impact arising from the fault are estimated. Although the current version of the OAE diagnostician provides the user with information about the fault that is necessary to make a decision on whether to continue to run the system in the faulty mode or shut it down for repair, it does not take any corrective actions by itself. Details of the fault detection, diagnosis, and evaluation methods are described in the following subsections.

Fault Detection Approach

An overview of the logic tree used to identify operational states and to build the lists of possible failures is illustrated in Figure 7.2.7. The boxes represent major subprocesses necessary to determine the operating state of the air handler; diamonds represent tests (decisions), and ovals represent end states and contain brief descriptions of "OK" and "not OK" states. Only selected end states are shown in this overview.

The OAE diagnostician uses a logic tree to discern the operational "state" of outdoor-air ventilation and economizer systems at each point in time for which measured data are available. The tool uses rules derived from engineering models of proper and improper air-handler performance to diagnose operating conditions. The rules are implemented in a decision tree structure in the software. The diagnostician uses periodically measured conditions (temperature or enthalpy) of the various air flow streams, measured outdoor conditions, and status information to navigate the decision tree and reach conclusions regarding the operating state of the AHU. At each point in the tree, a rule is evaluated based on the data, and the result determines which branch the diagnosis follows. A conclusion is reached regarding the operational state of the AHU when the end of a branch is reached.

Many of the states that correspond to normal operation are dubbed "OK states." For example, one OK state is described as "ventilation and economizer OK; the economizer is correctly operating (fully open), and ventilation is more than adequate." Other states correspond to something operationally wrong with the system and are referred to as "problem states." An example problem state might be described as "economizer should not be off; cooling energy is being wasted because the economizer is not operating; it should be fully open to utilize cool outside air; ventilation is adequate." Other states may be tagged as incomplete diagnoses if the measured information is insufficient.

Fault Diagnosis Approach

The OAE diagnostician performs fault diagnosis in two steps. After a fault is detected, using a knowledge base, a list of possible and impossible causes is identified for the fault state. The knowledge base is populated *a priori* with possible causes and impossible causes for every problem state in the decision tree. In the example above, a bad or biased temperature sensor, stuck outdoor-air damper, an economizer controller failure, an actuator failure, a broken linkage, or perhaps an error in setting up the diagnostician could cause an economizer malfunction to be reported. Thus, at each measured time period, a list of possible and impossible causes is generated.

The list of possible causes can be rather long and often different at different time steps because the same fault can manifest itself in different problem states depending on the current operating conditions. For example, if the outdoor-air conditions are favorable for economizing and if the outdoor-air damper is stuck fully open, it is not a fault; but if the conditions are not favorable for economizing, then it is a fault. Thus, each set of observations leads to a different end branch in the decision tree. In the second stage diagnosis, the number of possible causes is reduced. The methodology uses a historical list of possible and impossible causes and reduces the list of possible causes. It does this by jointly considering the faults, possible causes, and impossible causes along with metrics of their statistical certainties over time to determine a reduced set (subset) of causes that are more likely to have caused the fault during that timespan.

Data Requirements

The OAE diagnostician uses two primary types of data — measured and setup. The measured data include information on mixed-air, return-air, and outdoor-air temperatures (and enthalpies for enthalpy-controlled economizers), supply fan on/off status, and heating/cooling on/off status. These data are typically available from BASs as trend logs or at requested intervals. Alternatively, measured data could be collected using custom metering and data collection systems, or the diagnostician could be used to process an

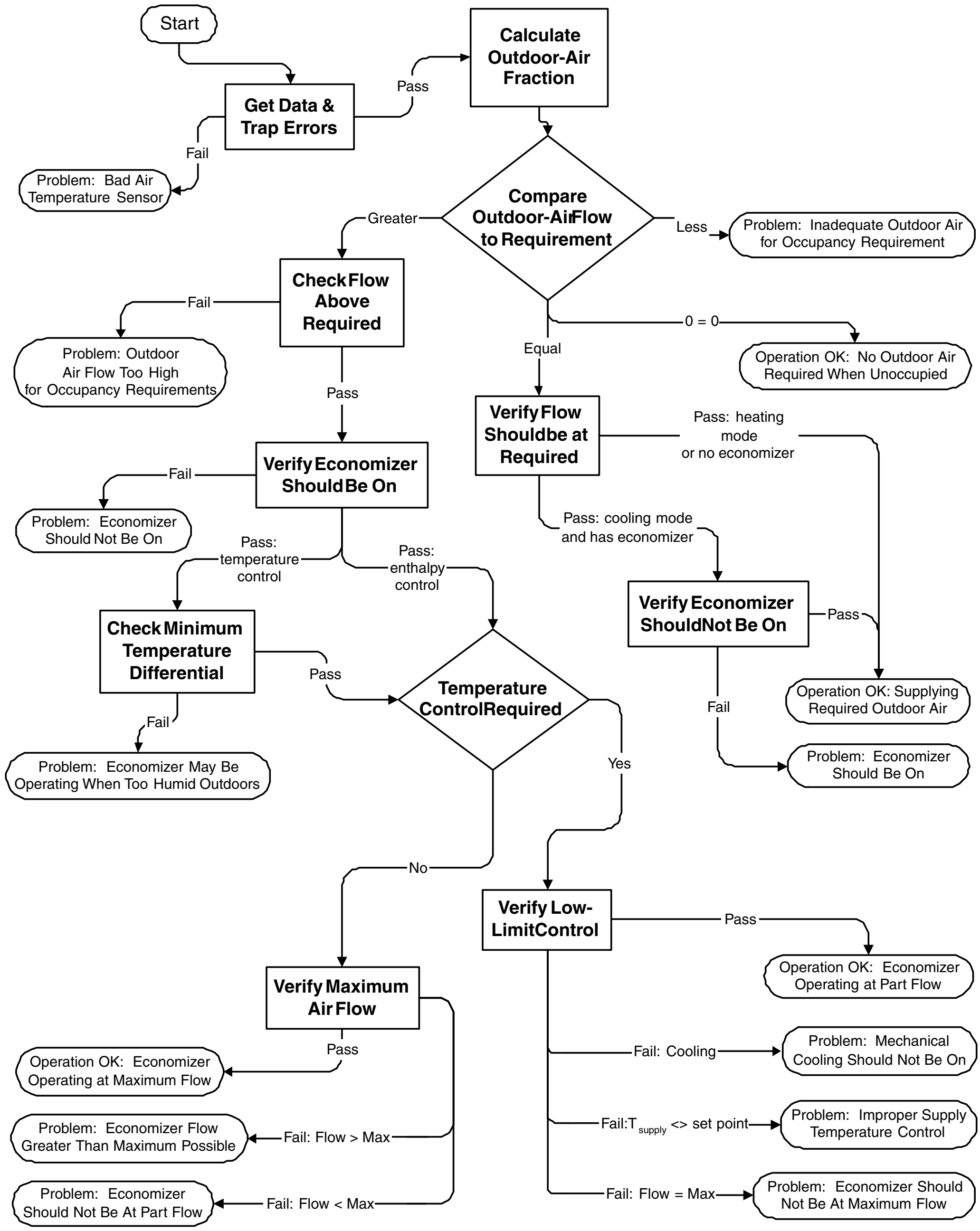

FIGURE 7.2.7 Overview of the diagnostic logic tree showing key operating states.

existing database containing the required data. The setup data, obtained by querying the user (building operator or installer), include information describing the type of economizer, its control strategies, setpoints, and building occupancy (and hence, ventilation) schedules.

Basic OAE Functionality

The OAE diagnostician detects about 25 different basic operational problems using the methodology described earlier. The results are presented using a color code to alert the building operator when a fault occurs and then provides assistance in identifying (diagnosing) the causes of the fault and correcting

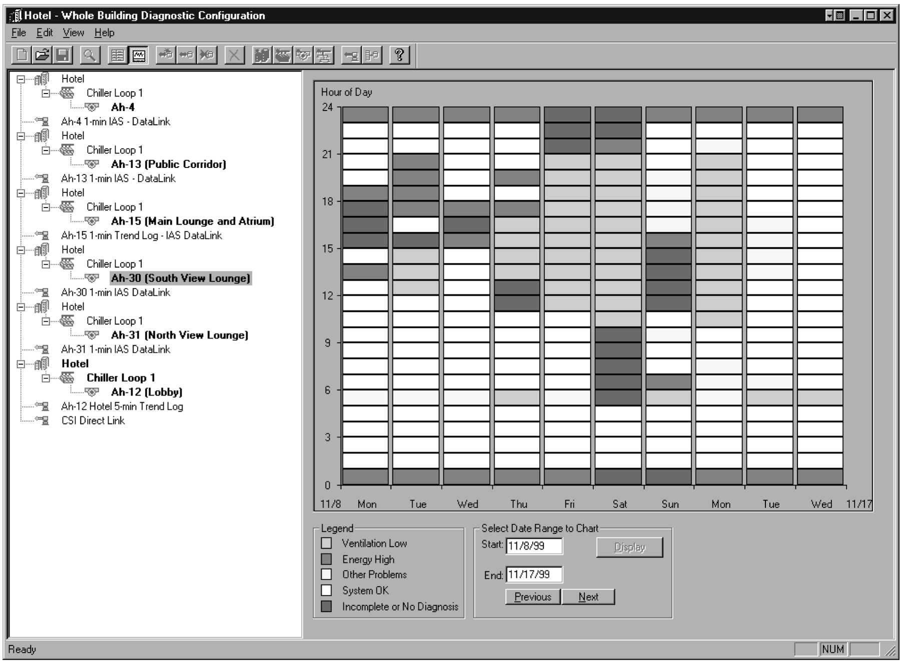

FIGURE 7.2.8 Diagnostic results showing proper and faulty operation with a data set having a faulty outdoor-air sensor.

them. Figure 7.2.8, for example, shows a representative OAE diagnostician window. Each cell in the diagram represents an hour. The color of the cell indicates the type of state. White cells identify "OK states," for which no faults were detected. Other colors represent problem states. "Clicking" the computer mouse on any colored cell brings up the specific detailed diagnostic results for that hour as shown in Figures 7.2.9 and 7.2.10.

Sensitivity vs. False Alarm

Adjustment of the sensitivity of the methods to detect and diagnose faults vs. generating false alarms is critical because the measured data in the field has both noise and bias. In the OAE, tolerances for each measured and static input variable are used to generate uncertainties that are propagated through all calculations and tests. For example, to test if the outdoor-air temperature is greater than the return-air temperature, not only should the outdoor-air temperature value be greater than the return-air temperature, the uncertainty of the test should also be less than a specified threshold. The uncertainty thresholds and tolerances on each variable are user specified. By specifying the tolerance and adjusting the uncertainty thresholds, false alarms can be reduced or sensitivity of detector increased.

Although field testing is ultimately required, simulations provide an effective way of generating data that would be more costly to generate in a laboratory or through field tests. The results are also valuable for illustrating the success of the diagnostician in detecting operation problems and their underlying causes. The general approach involves generating sets of data by simulation, where each set corresponds to an air handler with a specific underlying fault. These data sets are then processed by the OAE diagnostician to determine whether it detected problems and identified the correct cause (i.e., underlying problem). Although there are over 25 problem states defined in the OAE algorithm, only a few common fault states (problems) were tested with annual hourly simulated data sets. They include: bad sensors (outdoor-air sensor biased to read 10°F higher), outdoor-air damper stuck fully closed, outdoor-air damper stuck fully open, outdoor-air damper stuck at required ventilation position, outdoor-air damper stuck between fully closed and fully open.

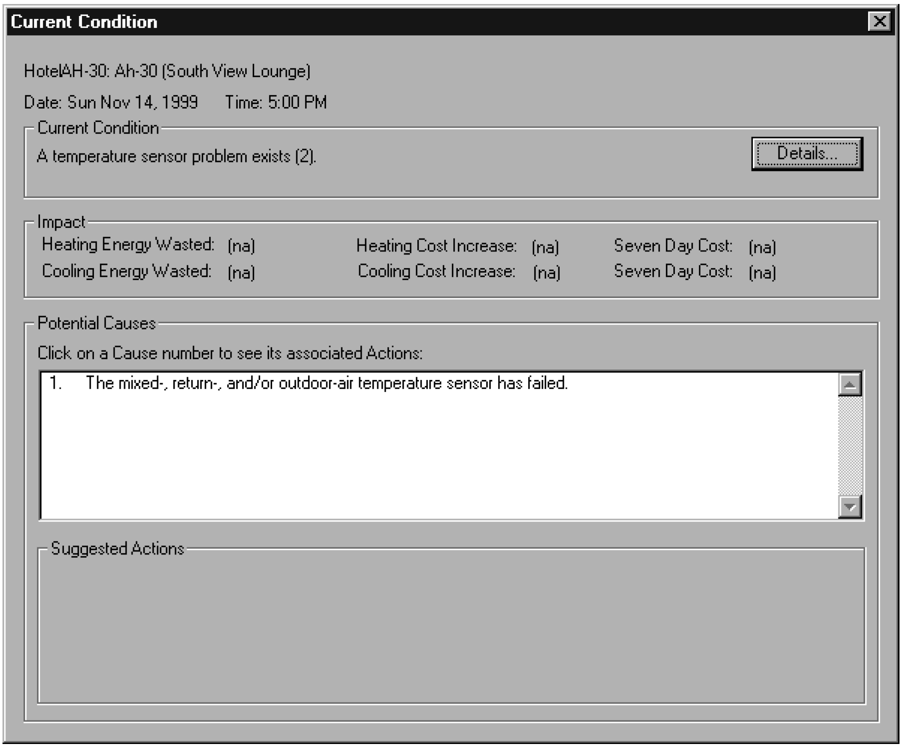

FIGURE 7.2.9 Pop-up windows providing a description of a problem, a list of reduced causes, and suggested actions to correct that cause.

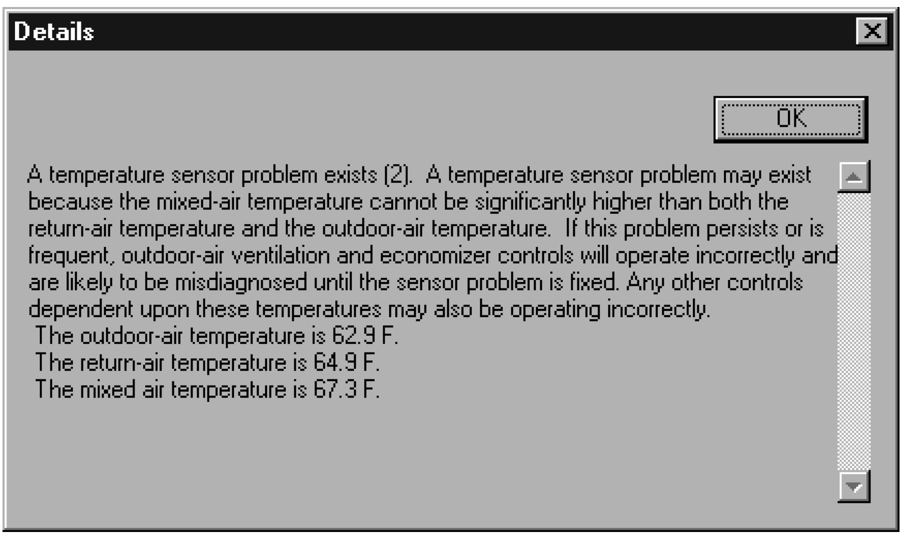

FIGURE 7.2.10 Details of diagnostic results.

Field Test Results

The OAE diagnostician was installed in three buildings for initial field testing. Field testing provides opportunities to investigate unanticipated practical problems and test usefulness in practice. The results obtained suggest that the OAE diagnostician will provide significant benefits.

Of the 18 air handlers monitored, more than half were found to have problems shortly after initial processing of data. The problems found included: sensor problems, return-air dampers not closing fully when outdoor-air dampers were fully open, and a chilled water controller problem. All problems have been confirmed by inspection of the AHUs.

Elements of an Automated FDD for Vapor Compression Systems

This section describes some of the methods being developed for automated FDD as applied to vapor compression equipment. In general, HVAC&R applications will not tolerate the use of expensive sensors. As a result, many of the methods being developed rely on the use of temperature, and in some cases, pressure measurements. As discussed earlier, contributions in the development of FDD methods for vapor compression equipment have been made by McKellar (1987), Stallard (1989), Yoshimura and Ito (1989), Kumamaru et al. (1991), Wagner and Shoureshi (1992), Inatsu et al. (1992), Grimmelius et al. (1995), Gordon and Ng (1995), Stylianou and Nikanpour (1996), Peitsman and Bakker (1996), Stylianou (1997), Rossi and Braun (1996, 1997), Breuker and Braun (1998a,b), and Bailey et al. (2000). The faults considered include: compressor valve leakage, heat exchanger fan failures, evaporator frosting, condenser fouling, evaporator air filter fouling, liquid line restrictions, and refrigerant leakage. The following subsections provide background and details on some of the more promising and well-documented methods. The presentation is organized according to the major elements of an FDD system.

Faults for vapor compression systems can be divided into two categories: (1) "hard" failures that occur abruptly and either cause the system to stop functioning or fail to meet comfort conditions, and (2) "soft" faults that cause a degradation in performance but allow continued operation of the system. Many of the most frequently occurring and expensive faults are associated with service in response to hard failures, such as compressor and electrical faults. Certainly, an automated FDD system should be able to diagnose "hard" faults. However, these faults are typically easy to detect and diagnose using inexpensive measurements. For instance, a compressor failure leads to a complete loss of refrigerant flow and can be easily diagnosed by monitoring the temperatures or pressures at the inlet and outlet of the compressor. Similarly, a fan motor failure could be diagnosed by measuring temperatures or pressures at the inlets and outlets of the heat exchangers (evaporator or condenser) that they serve. Other hard faults that should probably be included within an FDD system include common controls failures, blown fuses, and malfunctioning electrical components such as contactors. It would also be important to detect dangerous operating conditions, such as the possibility of a flooded start, which lead to "hard" failures. "Soft" faults, such as a slow loss of refrigerant or fouling of a heat exchanger, are more difficult to detect and diagnose. Furthermore, they often lead to premature failure of components, a loss in comfort, or excessive energy consumption.

The techniques developed for diagnosing "soft" faults in vapor compression cooling equipment can be described in terms of a series of steps, presented in Figure 7.2.11 (for discussion of the various steps refer to Section 7.2.2).

Fault Detection

Fault detection is accomplished by comparing measurements with some expectations for normal behavior, where the expectations are determined from a model. In the simplest system, the expectations could be that the measurements (e.g., suction and discharge pressure) should fall within acceptable ranges (low and high limits). Generally, the measurements vary with the operating conditions so the acceptable ranges need to be relatively large to avoid false alarms. In this case, only relatively large faults can be detected. Much better resolution can be obtained if an on-line model is utilized that relates expectations for measurements under normal operation to measurements of the operating conditions (e.g., ambient temperature). Because no model is perfect, the deviations of measurements from expected values need to be greater than some threshold that depends upon the uncertainty in the model and measurements.

COP as a Performance Expectation — If the only goal is to detect faults (without diagnosis), then one or two measurements are probably sufficient. In particular, cooling capacity and power consumption (or COP) are excellent performance indices, because it probably is not necessary to perform service unless

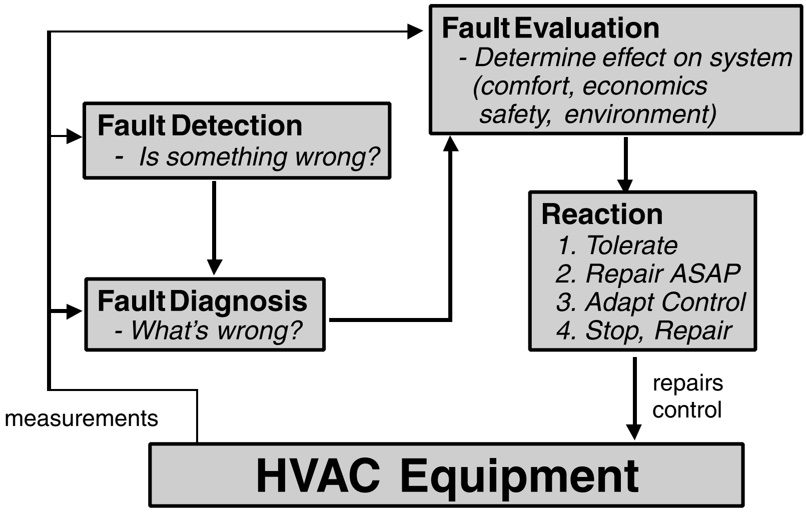

FIGURE 7.2.11 Diagnostics for vapor compression cooling equipment.

these indices change by a significant amount. Gordon and Ng (1995, 2000) presented a semiempirical model for predicting the COP of chillers during steady state operation that is useful for fault detection. Stylianou and Nikanpour (1996) used the model of Gordon and Ng for fault detection during steady state operation. This was one element of an overall FDD approach that was developed for a reciprocating chiller.

The model of Gordon and Ng (1995, 2000) was derived from a simple first and second law analysis using empirical relations for the irreversibilities associated with the heat exchangers. For a given chiller, COP is correlated using the following form.

$$\frac{1}{COP} = -1 + \frac{T_{c,i}}{T_{e,o}} + \frac{-a_0 + a_1 T_{c,i} - a_2 \dfrac{T_{c,i}}{T_{e,o}}}{\dot{Q}_e} \tag{7.2.1}$$

where $T_{c,i}$ is the temperature of the secondary working fluid (air or water) entering the condenser, $T_{e,o}$ is the temperature of the secondary working fluid leaving the evaporator (air, water, or water/glycol), $\dot{Q}_e$ is the rate of heat addition to the evaporator (cooling load), and a_0, a_1, and a_2 are empirical constants. The constants are determined using linear regression applied to a set of training data obtained from the equipment manufacturer, from laboratory tests, or from the field when the unit is operating normally. There are some advantages in using the model of Equation 7.2.1 as compared with polynomial correlations that are typically employed. In particular, less data are required to obtain an acceptable fit, and there is better confidence that the model extrapolates well to operating conditions outside of the range used to obtain the correlations.

It is necessary to establish thresholds for the identification of faults. Stylianou and Nikanpour (1996) did not directly address the issue of fault detection thresholds for their proposed method. However, it is not difficult to establish reasonable thresholds for deviations in COP. One criterion is that the thresholds should be significantly larger than the uncertainty of the models in predicting the expected values of the measurements to avoid false alarms. The semiempirical model of Gordon and Ng can predict cooling COP to within about 4%. Expert knowledge could be used to set larger thresholds that would guarantee that the detected faults are important and should be repaired. In this case, the fault evaluation step in Figure 7.2.11 could be skipped. For instance, a 10% loss in efficiency represents a significant fault and should probably be repaired as soon as possible.

Thermodynamic States as Expectations — Many diagnostic approaches utilize thermodynamic state measurements as inputs (see next section) for differentiating between faults. Because several measurements are necessary for diagnostics, these measurements can also be used for fault detection. Rossi and Braun (1997) and Breuker and Braun (1998a,b) developed and evaluated a complete FDD system for packaged air conditioning equipment that utilizes steady state models for both fault detection and diagnosis. All of the measurements required for fault diagnosis are used in the fault detection step (i.e., any measurement can trigger the detection of a fault). The output state measurements used by the technique are

1. Evaporating temperature (T_{evap})
2. Suction line superheat (T_{sh})
3. Condensing temperature (T_{cond}),
4. Liquid line subcooling (T_{sc})
5. Hot gas line or compressor outlet temperature (T_{hg})
6. Secondary fluid (air or water) temperature rise across the condenser (ΔT_c)
7. Secondary fluid (air or water) temperature drop across the evaporator (ΔT_e)

Seven steady state models are used to describe the relationship between the driving conditions and the expected output states in a normally operating system. In a normally operating, simple packaged air conditioning unit (on/off compressor control, fixed speed fans), all the output states (**Y**) in the system are assumed to be functions of only three driving conditions (**U**) that affect the operating states of the unit: the temperature of the ambient air into the condenser coil (T_{amb}), the temperature of the return air into the evaporator coil (T_{ra}), and the relative humidity (Φ_{ra}) or wet-bulb temperature (T_{wo}) of the return air into the evaporator coil.

Polynomial models were fit using steady state training data obtained in the laboratory and compared with a separate set of steady state test data. The form of the polynomial models are

$$\begin{aligned} y_i = {} & a_1 + a_2 T_{wb} + a_3 T_{ra} + a_4 T_{amb} + a_5 T_{wb}^2 + a_6 T_{ra}^2 + a_7 T_{amb}^2 \\ & + a_8 T_{wb} T_{ra} + a_9 T_{ra} T_{amb} + a_{10} T_{wb} T_{amb} + a_{11} T_{wb}^3 + a_{12} T_{ra}^3 + a_{13} T_{amb}^3 \\ & + a_{14} T_{wb} T_{ra}^2 + a_{15} T_{wb} T_{amb}^2 + a_{16} T_{ra} T_{wb}^2 + a_{17} T_{ra} T_{amb}^2 + a_{18} T_{amb} T_{wb}^2 \\ & + a_{19} T_{amb} T_{ra}^2 + a_{20} T_{wb} T_{ra} T_{amb} + \dots \end{aligned} \tag{7.2.2}$$

where i_i is the ith output variable prediction and the As are coefficients determined using linear regression.

Table 7.2.5 gives the model orders used by Breuker and Braun (1998a,b) and model accuracy for the test data considered. Stylianou and Nikanpour (1996) used similar polynomial forms for thermodynamic states of a small water-cooled reciprocating chiller. In this case, the driving conditions were the temperatures of the secondary fluid for the condenser and evaporator.

TABLE 7.2.5 Example Model Evaluations

Variable	Best Model to Use	RMS Error (F)	Maximum Error (F)
T_{evap}	1st order	0.49	0.99
T_{sh}	3rd order with cross terms	1.39	3.03
T_{hg}	3rd order with cross terms	1.00	3.24
T_{cond}	1st order	0.31	0.61
T_{sc}	2nd order with cross terms	0.46	1.39
ΔT_c	1st order	0.18	0.48
ΔT_e	2nd order with cross terms	0.23	0.56

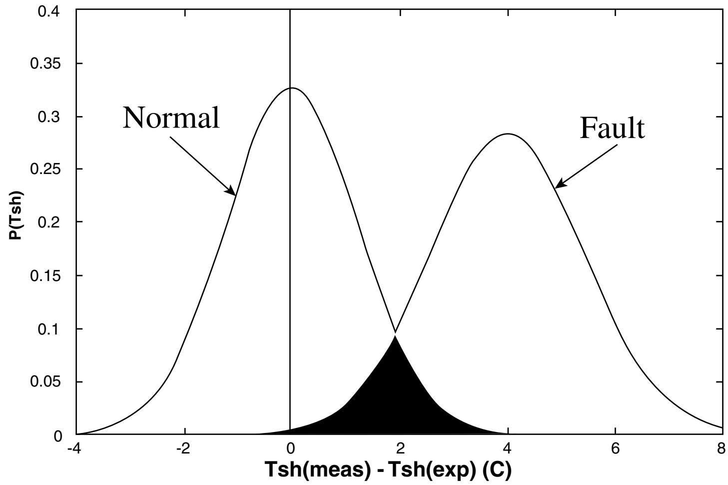

FIGURE 7.2.12 One-dimensional example of the fault detection classifier.

In the fault detection method described by Rossi and Braun (1997) and Breuker and Braun (1998a,b), a fault is identified whenever the current measurements are statistically different than the expected values. The detection algorithm uses the differences between the measurements and expected values (termed residuals) as features for a classifier. Figure 7.2.12 illustrates how this method works for a one-dimensional example. A probability distribution of the residual of the suction line superheat for both normal and faulty operation is shown. Under normal operation, there is a distribution of residuals that results from measurement noise and modeling errors. In the absence of modeling errors and with random noise, the distribution for normal operation would have zero mean. The introduction of a fault changes both the mean and/or standard deviation of the residuals. A fault is indicated whenever the overlap between the two distributions is less than a fixed threshold. The overlap is termed the fault detection error and the threshold is called the fault detection threshold. The overlap is related to the probability of erroneously classifying the current operation as faulty and decreases with the severity of the fault.

In the general case of *m* output measurements, the statistical fault detection method estimates the overlap between *m*-dimensional probability distributions of residuals for current and normal operation. The method assumes that residual distributions are Gaussian and can be characterized using a mean vector and covariance matrix and that the separation between the distributions for current and normal operation is dominated by mean vector differences as opposed to covariance matrix differences. The resulting classifier is termed an optimal linear classifier (Fukunaga, 1990). A fault is identified whenever the following inequality holds.

$$\left(\mathbf{M}_C - \mathbf{M}_N\right)^T \Sigma^{-1} Y - \frac{1}{2}\left(\mathbf{M}_N^T \Sigma^{-1} \mathbf{M}_N - \mathbf{M}_C^T \Sigma^{-1} \mathbf{M}_C\right) \geq 0 \tag{7.2.3}$$

where

$$\Sigma = s\Sigma_n + \left(1 - s\right)\Sigma_C \tag{7.2.4}$$

and where **Y** is a vector of current residuals, $\mathbf{M}_N$ is the mean vector and Σ_N is the covariance matrix that describes the distribution of residuals in the absence of any faults (i.e., normal operation), and $\mathbf{M}_C$ and Σ_C are the mean vector and covariance matrix that describe the current distribution of residuals determined using recent measurements. The average covariance matrix, Σ, is determined as the weighted average of Σ_N and Σ_C with Equation 7.2.3 where the weighting factor *s* is determined by minimizing the classification error (i.e., probability of making an erroneous decision). The classification error, ε, is determined by integrating the overlapping areas associated with the multidimensional normal and fault distributions using Fukunaga (1990).

$$\varepsilon = erfc\left(\frac{-\mathbf{V}^T\mathbf{M}_N - v_o}{\sqrt{2\sigma_N^2}}\right) + erfc\left(\frac{-\mathbf{V}^T\mathbf{M}_C - v_o}{\sqrt{2\sigma_C^2}}\right) \tag{7.2.5}$$

where

$$V = \left(s\Sigma_N + (1-s)\Sigma_C\right)^{-1}\left(\mathbf{M}_C - \mathbf{M}_N\right)$$

$$v_o = -\frac{s\sigma_N^2\mathbf{V}^T\mathbf{M}_C + (1-s)\sigma_C^2\mathbf{V}^T\mathbf{M}_N}{s\sigma_N^2 + (1-s)\sigma_C^2}$$

$$\sigma_N^2 = \mathbf{V}^T\Sigma_N\mathbf{V}$$

$$\sigma_C^2 = \mathbf{V}^T\Sigma_C\mathbf{V}$$

The mean vector is determined by averaging differences between measured and model predictions of outputs over a specified measurement window. The uncertainty of the residuals characterized with the covariance matrix depends upon both measurement and modeling errors. Measurement errors impact output measurements directly and output model predictions indirectly through their effect on input measurements. Modeling errors can result from neglecting inputs that affect the output states, using a steady state model to characterize transient operation, and an imperfect mapping between the inputs and outputs.

The covariance matrix is determined if the modeling and measurement errors are independent and normally distributed. The measurement errors associated with the inputs are propagated through the steady state model using a first-order Taylor series about the known operating point, so that the elements of the covariance matrix for the model form of Equation 7.2.2 are

$$\Sigma_{ij} \approx \sigma_T^2 + \sigma_{M,i}^2 + \left(\frac{\partial y_i}{\partial T_{amb}}\right)^2\sigma_T^2 + \left(\frac{\partial y_i}{\partial T_{ra}}\right)^2\sigma_T^2 + \left(\frac{\partial y_i}{\partial T_{wb}}\right)^2\sigma_{wb}^2, \qquad \mathrm{i=j} \tag{7.2.6}$$

$$\Sigma_{ij} \approx \left(\frac{\partial y_i}{\partial T_{amb}}\right)\left(\frac{\partial y_j}{\partial T_{amb}}\right)\sigma_T^2 + \left(\frac{\partial y_i}{\partial T_{ra}}\right)\left(\frac{\partial y_j}{\partial T_{ra}}\right)\sigma_T^2 + \left(\frac{\partial y_i}{\partial T_{wb}}\right)\left(\frac{\partial y_j}{\partial T_{wb}}\right)\sigma_{wb}^2, \qquad \mathrm{i \neq j} \tag{7.2.7}$$

where

- Σ_{ij} is the element in the *i*th row and *j*th column of the covariance matrix
- y_i is the steady state model prediction for output i
- σ_T^2 $E(w_T^2)$, where w_T is zero mean noise added to the dry-bulb temperature measurements (uncertainty in temperature measurement)
- $\sigma_{M,i}^2$ $E(w_{M,i}^2)$, where $w_{M,i}$ is zero mean noise added to the model predictions (modeling uncertainty) for output i
- σ_{wb}^2 $E(w_{wb}^2)$, where w_{wb} is zero mean noise added to the wet-bulb temperature measurements (uncertainty in wet-bulb measurement)
- E( ) is the expected value operator

The modeling uncertainty for the ith output model can be estimated as the variance associated with the fit to the training data (approximated by the sum of the squares of the errors). In general, measurement uncertainty is caused by both random and systematic errors. Random errors are associated with noise in the instrumentation system and can be characterized using specifications from the sensor manufacturer. Systematic errors refer to measurements that are biased in one direction (i.e., higher or lower than the actual value). Systematic measurement errors may be caused by miscalibration or drift in sensors. If the models are trained using the installed sensors, miscalibration is not an issue. However, if systematic errors are not considered as part of the measurement uncertainty, the fault detection method will identify a fault condition when sensors drift. Generally, it is prudent to assign a measurement uncertainty that allows for some sensor drift. Reasonable values for the standard deviations of the temperature and wet-bulb measurements are $\sigma_T = 0.5$ C and $\sigma_{wb} = 1.0$ C.

Method Comparisons — There are some advantages and disadvantages associated with each of the two approaches for fault detection presented in this section. The use of COP as a performance index is very straightforward to implement, but requires costly measurements of cooling capacity and power. The use of temperature measurements as performance indices has lower sensor cost but is more complicated to implement. Either of these methods could be utilized for packaged air conditioning or chiller equipment. However, the model forms and driving conditions are different for the two applications and may depend upon the method used for capacity control.

Fault Diagnosis

Once a fault has been detected, it is necessary to identify its cause. This may involve sending a technician to the site to perform additional testing and analysis. However, a fully automated FDD would perform some diagnoses using the available measurements. Several investigators have proposed the use of thermodynamic impact to diagnose faults which will be illustrated using the following example.

Consider a packaged air conditioner with a fixed orifice as the expansion device, a reciprocating compressor with on/off control, fixed condenser, and evaporator air flows, with R22 as the refrigerant. Figure 7.2.13 shows a P-h diagram for three cases of steady state operation at a given set of secondary fluid inlet conditions to the evaporator and condenser: normal, fouled condenser, and low refrigerant charge. Condenser fouling is equivalent to having a smaller condenser and leads to higher condensing temperatures and pressures than for the normal (no fault) case. For a system with a fixed orifice, the higher condensing pressures lead to a greater condenser-to-evaporator pressure differential that tends to increase the refrigerant flow rate. Furthermore, the increased flow rate tends to reduce the amount of condenser subcooling and evaporator superheat and increase the evaporating temperature. In contrast, the loss of refrigerant tends to lower the pressure throughout the system leading to reductions in both evaporating and condensing temperatures. The lower evaporating pressure and corresponding vapor density leads to a lower refrigerant flow rate, which results in higher evaporator superheat and a higher refrigerant discharge temperature from the compressor. This example illustrates that condenser fouling and low refrigerant can be distinguished by their unique effects on thermodynamic measurements.

Rule-Based Classifiers — Some of the proposed diagnostic methods for vapor compression cooling equipment use differences between measurements and normal expectations of thermodynamic states at steady state for diagnoses of faults. Fault diagnosis is then performed using a set of rules that relate each fault to the direction that each measurement changes when the fault occurs. Table 7.2.6 gives the diagnostic rules for the five faults and seven output measurements developed by Breuker and Braun (1998a,b) for a rooftop air conditioner. The arrows in Table 7.2.6 indicate whether a particular measurement increases (↑) or decreases (↓) in response to a particular fault at steady state conditions. For instance, as previously shown, the loss of refrigerant generally causes the superheat of the refrigerant entering the compressor to increase above its "normal" value at any steady state condition. Each of the faults results in a different combination of increasing or decreasing measurements with respect to their normal values. The rules of Table 7.2.6 are effectively fault models that are generic for this type of air conditioner and

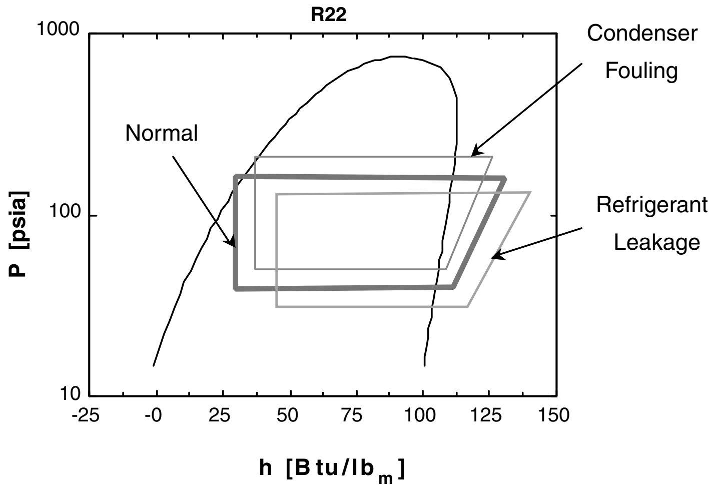

FIGURE 7.2.13 Effect of faults on thermodynamic states.

TABLE 7.2.6 Rules for the Diagnostic Classifier

Fault	T_{evap}	T_{sh}	T_{cond}	T_{sc}	T_{hg}	ΔT_{ca}	ΔT_{ea}
Refrigerant Leak	↓	↑	↓	↓	↑	↓	↓
Compressor Valve Leakage	↑	↓	↓	↓	↑	↓	↓
Liquid-Line Restriction	↓	↑	↓	↑	↑	↓	↓
Condenser Fouling	↑	↓	↑	↓	↑	↑	↓
Evaporator Fouling	↓	↓	↓	↓	↓	↓	↑

do not require any on-line learning. Similar rules were developed by Grimmelius et al. (1995) and Stylianou and Nikanpour (1996) for chillers (see Section 7.2.6).

Similar to the fault detection problem, it is necessary to have thresholds for diagnostics. The diagnostic classifier should evaluate the probability that each fault applies to the current operation, and the evidence should be high for a particular fault before any recommendations are made. Rossi and Braun (1997) addressed the issue of diagnostic thresholds in the development of their statistical rule-based FDD method. The diagnostic classifier evaluates the probability that each fault applies to the current operation. It estimates the degree to which the probability distribution characterizing the current residuals overlaps the region of the m-dimensional space defined by the set of rules corresponding to that fault.

Figure 7.2.14 illustrates the fault diagnostic classification method for two possible faults (refrigerant leakage and liquid-line restriction) with two input features (superheat and subcooling residuals). The progression of changes in the contours of two-dimensional probability distributions are shown as the two different faults are slowly introduced. Normal operation is shown as the distribution centered at the zero point. As a fault develops, the contour moves along a curve. When the overlap between the normal performance distribution and the current distribution (as indicated by the classification error, ε), is small enough for the false alarm rate to be acceptable (e.g., $\varepsilon < 0.001$), a fault is signaled by the fault detector. The different diagnostic classes are separated by the axis. The overlap of the current distribution with each of the modeled classes is calculated and represents the probability that the fault class is the correct diagnosis. A diagnosis is indicated when the probability (overlap) of the most likely class is larger than the second most likely class by a specified threshold (e.g., factor of 2). As the fault becomes more severe, confidence in the fault detection and diagnosis increases as the current distribution moves further from the normal distribution, and from the axis separating the classes. The choice of a diagnostic threshold results from a tradeoff between diagnostic sensitivity and the rate of false diagnoses.

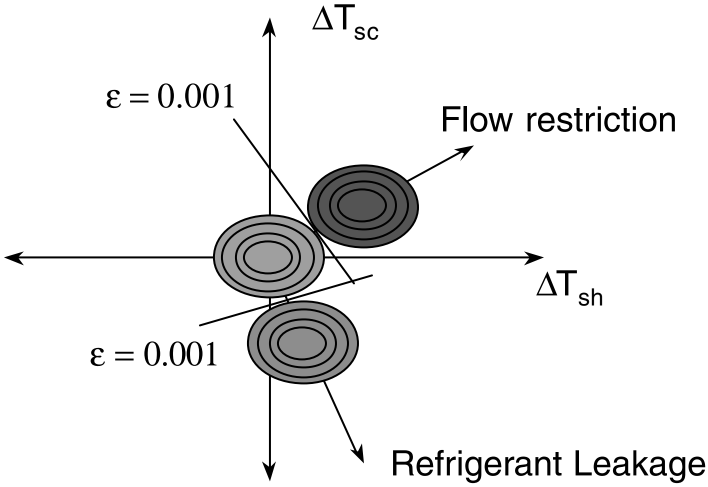

FIGURE 7.2.14 Fault diagnostic classifier (two-dimensional example).

To perform the classification for diagnostics, the probability that each rule applies to the current operation is evaluated. The probability of each hypothesis is determined by the degree to which the distribution characterizing the current residuals overlaps each class. The overlap is evaluated by integrating the area under the m-dimensional Gaussian probability distribution that falls within each class's region of the domain. Assuming that each dimension is independent, then the probabilities in each dimension can be "ANDed" together such that:

$$w_j = \prod_{k=1}^{m} \frac{1}{2}\left[1 + C_{jk} erf\left(\frac{\mathbf{M}_C(k) - \mathbf{M}_N(k)}{\sqrt{2\Sigma_C(k,k)}}\right)\right] \tag{7.2.8}$$

where $C_{jk} = +1$ if ($\mathbf{M}_c(k) - \mathbf{M}_N(k)$) falls within the domain for the jth fault (i.e., ($\mathbf{M}_c(k) - \mathbf{M}_N(k)$) has the same sign as defined in Table 7.2.6 for the appropriate fault) and $C_{jk} = -1$, otherwise. For diagnoses, the current distribution has been shifted to give zero mean for normal operation. A nonzero residual mean could occur for normal operation with an imperfect model.

Fault Evaluation

It is possible to design an FDD system that can detect and diagnose faults well before there would be a need to repair the unit. In general, an FDD system should evaluate the impact of the fault before recommending a course of action. These recommendations should be based upon the severity of the fault with respect to four criteria:

1. Impact on equipment safety
2. Environmental impact
3. Loss of comfort
4. Economics

Equipment safety primarily relates to the compressor and motor. The compressor/motor should not operate under conditions that will lead it to fail prematurely. These conditions include liquid entering the compressor, high compressor superheat, high pressure ratio, high discharge pressure, high motor temperatures, low oil, etc. Existing controllers generally have safeties that will shut down the unit in case of operation at adverse conditions. Under these circumstances, the FDD system could add an explanation regarding the probable fault that led to the shutdown. In addition, lower level warning limits should be established for these variables. When these limits are exceeded, the evaluator might recommend that service be performed when convenient.

The environmental criterion primarily relates to refrigerant leakage. Refrigerant leakage is an environmental hazard and should be repaired quickly. This is particularly true if the refrigerant is toxic (ammonia). However, when a refrigerant leak is detected and diagnosed, the actual output of the evaluator might depend on the rate of refrigerant leakage and type of refrigerant. For a small leak, it may be acceptable to keep the unit running and schedule repairs for the near future. Conversely, for a large leak, it may be appropriate to shut down the unit and call for immediate repairs.

Ideally, the evaluator should be able to identify if the current "health" of the equipment is such that it will not have sufficient cooling capacity to maintain comfort in the future. Once a fault has been identified, this feature would allow scheduling of service to address this need rather than requiring immediate service in response to a loss of comfort (i.e., complaints). This could involve the use of online models for predicting cooling capacity and cooling needs.

If a fault has been identified, but the current operation is not adversely affecting the equipment life or the environment and the system can maintain comfort both now and in the future, then service should be performed only if it is economical to do so. In this case, the best decision results from a tradeoff between service and energy costs. Service costs money but reduces energy costs. Rossi and Braun (1996) developed a simple method for optimal maintenance scheduling for cleaning heat exchangers and replacing air-side filters. The method relies on measurements of power consumption, estimates of cost per service, and utility rates, but does not require any forecasting. At any time, *t*, a decision to recommend service is based upon evaluation of the following inequality.

$$\int_0^t \gamma_{on} h(\tau) d\tau + \frac{C_s}{C_e} > t \cdot h(t) \tag{7.2.9}$$

where C_s is the cost for performing the service (\$), C_e is the cost per unit energy (\$/kW), γ_{on} is an on/off indicator (one if the unit is on and zero otherwise), and $h(\tau)$ is the extra power required to provide the necessary cooling caused by the performance degradation. At any time,

$$h(t) = P(t) - P^*(t) \tag{7.2.10}$$

where $P(t)$ is a measurement of the current power and $P^*(t)$ is a prediction of the power at the current operating conditions if the unit was operating normally (no fouling).

Equation (7.2.9) was derived by applying optimization theory with simplifying assumptions to a cost function that combines energy and service costs. This simplified method gave nearly identical results as a detailed optimization when tested through simulation for a range of situations. The combined energy and cost savings were found to between 5 and 15% for optimal vs. regular maintenance scheduling. The savings primarily depend upon the ratio of service to energy costs, the rate of fouling, and the baseline regular service interval.

Steady State Detectors

Many vapor compression cooling systems utilize "on/off" control and spend a significant amount of time in a transient condition. When a steady state model is used to predict normal operating states, a steady state detector must be used to distinguish between transient and steady state operation. The FDD system should only indicate a fault and provide a diagnosis when the system is in steady state.

Steady state detection can be implemented using the time rate of change in measurements during a moving window. Steady state is indicated whenever the "smoothed" time derivatives are less than a fixed threshold (e.g., 0.1 F/h for temperature measurements). Another approach is the exponentially weighted variance method of Glass et al. (1995). This algorithm estimates the sample variance about the mean of output measurements over a moving exponentially weighted window. In general, the variance decreases

TABLE 7.2.7 Performance of FDD Prototype (3 Input, 10 Output Temperatures)

Performance Index	Refrigerant Leakage (% Leakage)		Liquid-Line Restriction (% ΔP)		Compressor Valve Leak (% $\Delta\eta_v$)		Condenser Fouling (% lost area)		Evaporator Fouling (% lost flow)	
	1st	All	1st	All	1st	All	1st	All	1st	All
Fault Level (%)	5.4	Max	2.1	4.1	3.6	7.0	11.2	17.4	9.7	20.3
% Loss Capacity	3.4	>8	1.8	3.4	3.7	7.3	2.5	3.5	5.4	11.5
% Loss COP	2.8	>4.6	1.3	2.5	3.9	7.9	3.4	5.1	4.9	10.3
ΔT_{sh}	5.4	>11	2.3	4.8	–1.8	–3.6	–0.6	–1.6	–1.7	–2.7
ΔT_{hg}	4.8	>10	2.4	4.8	0.0	0.0	1.8	2.3	–1.2	–2.7

as the system approaches steady state. Two parameters of the steady state detector that impact FDD performance are the forgetting factor, and the threshold for steady state detection. The forgetting factor varies between zero and one and dictates the weighting of previous measurements (one for equal weighting, and zero for zero weighting of all previous measurements). The steady state detector threshold is the output variance below which an output is considered to be at steady state. As the threshold is decreased, the residuals of the steady state operating points should decrease, and FDD sensitivity should be improved. However, fewer operating points are available for FDD. In general, all of the output measurements could be used in testing for steady state behavior. However, it is also possible to select measurements having slower transients, such as compressor shell temperatures.

FDD System Performance

Only limited testing has been performed on complete FDD systems for vapor compression cooling equipment. To adequately test an FDD system in the field, it would be necessary to install several systems and collect data for several years before enough faults could develop and experience could be collected to make general assessments. Laboratory testing allows a more thorough evaluation of FDD performance in a shorter time frame, but may not include some important effects that occur in the field. Grimmelius et al. (1995), Stylianou and Nikanpour (1996), and Bailey et al. (2000) performed laboratory evaluations of FDD systems for chillers. In these tests, a limited number of faults were simulated in the laboratory and the performance of the methods was evaluated in terms of whether the method could correctly identify the fault. In some cases, the misclassification (or false alarm) rate was estimated.

Breuker and Braun (1998a,b) performed an extensive evaluation of the FDD technique developed by Rossi and Braun (1997). Steady state and transient tests were performed on a simple rooftop air conditioner in a laboratory over a range of conditions and fault levels. The data without faults were used to train the models for normal operation and determine statistical thresholds for fault detection, while the transient data with faults were used to evaluate FDD performance.

Table 7.2.7 shows results that characterize the sensitivity of the FDD method for detecting and diagnosing faults. The levels at which each fault could be detected at one point ("First Detected") and at all steady state points ("All Detected") from the database of transient test results are presented for the five faults along with the corresponding percent loss in capacity and COP, and the change in superheat and subcooling at these detectable levels. These results show that the faults can generally be detected and diagnosed before a decrease in capacity or efficiency of 5% is reached. In terms of the effect on performance, the technique is less sensitive to compressor valve leakage and evaporator fouling. At these levels, the changes in compressor superheat and hot gas temperature were probably not large enough to have an impact on the life of the compressor.

7.2.10 Application of Diagnostics Methods and Tools for Continuous Commissioning of Building Systems

In most cases, FDD systems installed on-line can also be used to continuously commission a building system. Commissioning is a systematic process by which proper installation and operation of building systems and equipment are checked and adjusted as necessary to improve performance (adjustment is virtually always required; only the degree of correction and performance impact differ among buildings). Proper commissioning begins during design, continues through construction (remodeling or retrofit), and includes establishment of a good preventive maintenance program (PECI, 1997; US DOE/PECI, 1997). Although a distinction is made between commissioning of new buildings (Cx) and commissioning of existing buildings (retro-commissioning or Rx), in this chapter we will refer to both generically as Cx. Cx is active, i.e., test and analyze, while Rx is passive, i.e., observe and analyze.

Despite the benefits, the commercial buildings market has been slow to widely adopt Cx. One reason is the first cost associated with performing Cx. Although Cx has been shown in many cases to be cost-effective on a life-cycle basis, the importance of first cost still dominates many decisions in the buildings industry.

Automation is already used for some commissioning tasks. Spreadsheets, for example, are used for processing, tabulating, and graphing input data and results. Handheld personal computers are used for such tasks as inputting data directly into a database in the field. Cx and Rx are discussed in detail in Chapter 7.1.

Prospects for Improvement

Automation provides several opportunities for improving the process of commissioning. Generic improvements that automated tools can provide include:

- Speeding up the process of preparing a commissioning plan
- Ensuring compliance with standards/guidelines, and providing consistency across projects
- Speeding up the process of detecting and diagnosing problems with operation of heating, ventilating, and air conditioning equipment and systems
- Eliminating errors that occur during manual data entry
- Disseminating expert knowledge by embedding it in software tools
- Ensuring consistency in fault detection and diagnosis across buildings, projects, and different commissioning agents through the use of that embedded knowledge
- Archiving data electronically for future reference or use

The promise of automation is higher quality commissioning at lower cost. Higher quality results from better quality control (in data management and analysis) and from making expert knowledge readily available in an easy-to-use form. Lower costs are the result of reducing use of expensive labor for mundane tasks such as recording data.

Tools and methodologies that implement some of these generic capabilities are available today. In some cases, tools have been implemented by individual commissioning agents or companies in spreadsheets or specialty programs. In other cases, software that assists with data management, analysis, or diagnosis is available commercially, from professional organizations, or from government agencies. Some examples are identified later in this chapter.

A Tool for Commissioning Outdoor-Air Handling

This section describes in some detail how the OAE software tool developed for detecting and diagnosing problems with outdoor-air control can be used to facilitate and potentially improve commissioning of air-handling units.

As mentioned earlier, the OAE diagnostician monitors the performance of the air-handling units and can detect more than 25 different basic operation problems with outdoor-air control and economizer operation.

OAE Application in Commissioning

The OAE diagnostician can be used to commission AHUs. Data can be collected over a short term, and batch processed or continuously collected and processed on-line. The first of these is easier and, therefore, less costly to implement. It requires no installation of the OAE diagnostician onsite, no direct connection to data sources, such as a BAS, and no operator training. Data are typically collected by establishing trend logs in a BAS to collect the necessary data. Alternatively, temporarily installed data loggers can be used to collect some or all of the required data. Data should be collected for approximately 2 weeks. If the data are already available from historical trend logs, these logs can be used in place of collecting new data.

When available, data are processed by the OAE diagnostician, which identifies problems, possible causes, and corresponding corrective actions, and estimates energy and cost impacts caused by improper operations during the observation period. The energy and cost impacts can be used to prioritize actions to address the problems found. When problems are found, further investigation may be required and actions should be taken to correct them. After implementing corrective actions, the commissioning team should collect metered data for another week or two to confirm correct operation. In some cases, the OAE diagnostician may detect new and previously undetected problems during this follow-up period. These problems should be corrected and proper operation verified by an additional week of metering and processing by the OAE. Problems not ordinarily found during commissioning may be detected this way.

As with commissioning in general, there is a set of operational problems that cannot be detected easily during normal operation unless commissioning tests are performed over the full range of weather and occupancy conditions. Tests must be performed for these during other seasons, or systems artificially tested in these modes. Because the OAE diagnostician is a passive diagnostician, it can only examine system performance for conditions that exist during data collection. To commission the outdoor-air handling system completely, testing by the OAE diagnostician must be conducted during other times of the year. Ideally, a complete check would require testing under occupied and unoccupied conditions for each of the following operation modes:

- Heating
- Economizer cooling with throttling: outdoor-air temperature (or enthalpy) lower than supply-air temperature (or enthalpy)
- Economizer with outdoor-air damper fully open: outdoor conditions lower than return-air conditions, but higher than the supply-air conditions
- Mechanical cooling with economizer locked out (closed to the minimum required ventilation position) because outdoor-air conditions are warm and/or humid

The commissioning plan should specify the full range of tests to be conducted, for how long, and at what times of the year. Partial testing is far better than no testing at all; however, retesting at various times of the year (and operating modes) is necessary to be reasonably assured that all problems have been identified. Having set up the necessary BAS trend logs for initial use of the OAE, collection of data during various times of year and processing by the OAE should be relatively simple. Furthermore, periodic testing in the long term (i.e., periodic recommissioning) can help ensure that good performance persists.

The OAE also provides a continuous record of attempts to meet the standard of best practice to provide adequate outdoor-air ventilation. This record can be used to help establish due diligence on the part of the building owner or operators in the event of a lawsuit related to indoor-air quality (IAQ). The importance of maintaining proper outdoor-air ventilation is emphasized by a recent EPA study (Daisey and Angell, 1998) which found that the leading cause of IAQ problems in schools is simply inadequate outdoor-air supply.

Significant energy and money savings, associated productivity improvements, and carbon emission reductions are possible from proper Cx followed by steps that help ensure the persistence of the Cx improvements. Productivity savings are the most significant of these. However, the penetration of commissioning in the building stock is very low. Steps are underway to promote greater use of commissioning, including demonstration projects, publication of case studies, documentation of savings, and government programs that encourage Cx. Improving and reducing the cost of the Cx process is also an important component of a multifaceted approach to bringing the benefits of Cx to the entire building stock. Automation shows promise as a tool for improving the process. Automating parts of the commissioning process will reduce cost, improve effectiveness, and ensure persistence of the benefits of Cx.

7.2.11 Infrastructure Requirements for Deploying FDD Systems in Buildings

Networked software applications, which can harness the vast potential of integrating control networks with the Internet, require access to data from control panels or sensing devices that may be distributed across buildings. Being able to exchange data and information between field devices and software applications is the key to successful implementation of the networked software applications (Bayne, 1999). Although software applications are independent from the process of gathering data, the capability to gather data is dependent on the functions provided by the BAS and the type of interface (gateway) and communications protocols it uses.

An infrastructure supporting the next generation of software tools that owners and operators will use to manage distributed facilities requires

- A control network with a BAS or network of intelligent devices (in each building)
- A mechanism or a transport layer that ties field panels and other devices on the control networks to the Internet
- The "killer software applications" that enhance facility management

Networking Developments

BASs have evolved over the past two decades from pneumatic and mechanical devices to direct digital controls (DDC). Today's BASs consist of electronic devices with microprocessors and communication capabilities. Widespread use of powerful, low-cost microprocessors, use of standard cabling, and adoption of standard protocols (such as BACnet, LonWorks) have led to today's improved BASs. Most modern BASs have powerful microprocessors in the field panels and controllers, and the prevalence of microprocessors embedded in the sensors is growing as well. Therefore, in addition to providing better functionality at a lower cost, these BASs also allow for distributing the processing and control functions including FDD within the field panels and controllers without having to rely on a central supervisory controller.

Many BAS manufacturers support either BACnet or LonWorks protocols; some support both (EUN, 1999). Recently, ASHRAE has approved a BACnet/IP addendum that makes it easier to monitor and control building systems from remote locations over the Internet. LonWorks is also heading in the same direction.

The manufacturers of BASs are developing gateways to connect modern proprietary control networks to the Internet, making it easy for distributed software applications to share information. However, there are many legacy BASs in the field for which gateways are needed but do not exist or will never be developed. In such situations, there are three options to connect these systems to the Internet: (1) DDE (dynamic data exchange), (2) OLE (object link and embedding), and (3) developing a custom interface between the BAS and the Internet for legacy systems that do not support either DDE or OLE.

Data-Gathering Tools

Without easy access to data from meters, controllers, and equipment that are distributed throughout the facility, it would be difficult to realize all the benefits of distributed facilities management. Although the details of data gathering depend on the type of BAS and the protocols it supports, integrated networks provide some standard methods to access data from geographically distributed facilities.

As part of a larger U.S. Department of Energy project to develop an automated diagnostician (whole building diagnostician (WBD)), prototype tools were developed to collect data from BASs locally or over the Internet. These tools allow building-generated data to be collected at any frequency and stored in a database.

Many BAS manufacturers provide DDE/OLE servers to facilitate data exchange between controllers/devices and software application programs. The WBD data collection tools, running in the background, initiate a DDE "conversation" between the manufacturer's DDE server (provided by the BAS manufacturer) and the WBD database, and collect data at time intervals set by the operator. Relationships defined during setup of the software for the building are used to map data from the sensors for each of the AHUs and building end-use meters into the WBD database. The data-gathering tools are independent of the WBD diagnostic modules; therefore, any application can use the data-gathering infrastructure. By querying the database, raw data can be retrieved for use by other software applications, such as programs used to reconcile metered data with utility bills and charge tenants for energy use.

7.2.12 Estimating Cost and Energy Impacts from Use of Diagnostic and Predictive Maintenance Tools

It is very important that FDD systems evaluate the cost impacts of faults detected in building systems for two basic reasons: (1) justifying the expense of developing and/or purchasing the FDD system by quantifying its benefits, and (2) providing perspective on the magnitude of the fault to prompt the user to fix the faults with high cost impacts, prioritize correction of faults with moderate impact, and neglect faults with low impacts. This section will discuss how *energy* cost impacts of faults can be estimated. Other impacts, such as comfort, health, and damage or shortened lifetimes for equipment are also very important, but are difficult to quantify and often very specific to the buildings and systems involved. We will not attempt to provide guidance on estimating these impacts here, although their importance and the added value to an FDD system of providing this information cannot be overemphasized.

We express the energy cost at any instant of time (t) as the product of the demand for power, its price, and the interval being analyzed (Δt)

$$\mathrm{Cost}(t) = \mathrm{Demand}(t)\ \mathrm{Price}(t)\ \Delta t \tag{7.2.11}$$

Denoting quantities under faulted conditions with a prime (′), the cost increment of a fault is

$$\begin{aligned}\Delta\mathrm{Cost}(t) &= \mathrm{Cost}'(t) - \mathrm{Cost}(t) = \mathrm{Demand}'(t)\ \mathrm{Price}'(t)\Delta t - \mathrm{Demand}(t)\ \mathrm{Price}(t)\Delta t \\ &= \left[\Delta\mathrm{Demand}(t)\ \mathrm{Price}(t) + \mathrm{Demand}'(t)\Delta\mathrm{Price}(t)\right]\Delta t \end{aligned} \tag{7.2.12}$$

where, for any general property, X

$$\Delta X(t) = X'(t) - X(t) \tag{7.2.13}$$

Equation 7.2.12 includes the general case where the price of power, usually electricity, is dependent upon time (real-time pricing or time-of-day rates), or the demand itself (either at the current time or during some time period used by a utility to define peak demand). If the price is not a function of demand, as is often the case (at least for the fault's impact), then the second term drops out and Equation 7.2.12 reduces to

$$\Delta\mathrm{Cost}(t) = \Delta\mathrm{Demand}(t)\ \mathrm{Price}(t)\Delta t \tag{7.2.14}$$

Often a building system uses more than one fuel to supply the services it is designed to provide. An example is an AHU supplying both heating and cooling services in a gas or steam heated building. In such cases Equations 7.2.11 and 7.2.13 must be applied twice, once for each fuel affected by a given fault.

Direct Estimation of Impacts Based on Measured Consumption

In cases where the FDD technique directly measures the demand for energy and compares it against some expected value (see the whole-building energy diagnostician, described earlier), the change in demand caused by the fault at any given time can be directly estimated as the difference between the actual and expected consumption. Estimating the impact of the fault then reduces to integrating ΔCost over time (more on this later).

In such methods, the expected consumption is typically based on some type of model of *average* consumption for the time-of-day, and/or time-of-week, weather, and other conditions. These models are either empirical (regression, neural network, bin method, etc.), or engineering-based (presumably calibrated to fit historical consumption patterns). At best, random deviations of the actual consumption from the average for the time and conditions are to be expected, with the size of the deviations proportional to the accuracy of the model. Nonrandom deviations can also be expected when, as is usually the case, the input data or the mathematical form of the model imperfectly captures important effects, including nonlinearity.

Even for very accurate models, these errors tend to become larger as the time interval for the FDD cost analysis (Δt) gets smaller, i.e., weekly models are more stable than daily models, and daily models are more stable than hourly models. Subhourly models exhibit even more "noise," including that from such tangible effects as the cycle time of equipment in a building. Cost impacts, therefore, will generally be more accurate when integrated over a number of time intervals (Katipamula et al., 1996).

The advantage of this approach to estimating cost impacts is its simplicity and directness. This advantage is strong enough that it is worthwhile considering directly measuring and modeling the demand of the system or subsystem, which is the focus of the FDD system. This will become clearer when an alternative approach to estimating energy cost impacts is described below. However, there are two primary limitations to this approach related to the need to measure and model demand. The first limitation is cost; if it is not used as an inherent part of the FDD method, extra instrumentation and analysis capability is added to it solely for the purpose of estimating energy cost impacts.

The second limitation is complexity. While obvious at the whole building and boiler/chiller plant levels, the demand caused by other systems is often indirect and hard to quantify. A good example of this is an AHU in a built-up HVAC system; it consumes energy in the form of hot and chilled water from the plant, some electricity for fan power, and its operation impacts the subsequent need for terminal reheat in the zones it serves. In principal, it might be possible to measure and model each of these three modes of consumption separately. This may be less expensive if some proxy measurements are used. Examples are valve positions or temperature differences across coils instead of Btu meters, for estimating the energy in constant volume flows. The complexities of such an approach become evident, however, when considering how to handle faults that may lie in other systems (the terminal boxes, or the hot and chilled water reset schedule, for example) but that reflect themselves in the consumption patterns of the AHU.

Estimation of Impacts from First Principles

An alternative means of estimating energy cost impacts of faults in buildings is to base them on a first principles analysis. This approach is useful when

- Impacts are expected to be a small fraction of a measured consumption total
- Attribution of impacts among multiple faults is desired
- The expected impacts are about the same as the expected accuracy (i.e., the "noise") of an empirical model of the measured consumption.

An example is failure of a lighting occupancy sensor in one office of a zone encompassing many offices. Here the expected impacts may be much less than 5%, but are virtually certain to exist. In such cases, it may be preferable to estimate the impact based on first principles, for accuracy, simplicity or both. If the lights involved do not impact heating or cooling loads, because they are not in a conditioned space, for example, then the impact could be estimated simply as the product of the lighting power density and the floor area per occupancy sensor.

The principal complicating factor in using this approach is when the fault impacts the heating or cooling loads, directly through the energy conversion efficiency or the outdoor-air ventilation of the system, or indirectly because it changes the internal heat gains of the space. This discussion will focus on cases where there are direct effects on heating and cooling loads, or there are enough indirect effects that it is necessary or desirable to consider them.

To make such estimates, we consider the demand to be comprised of two components, one related to the thermal (heating and cooling) loads, and the other related to all other (non-HVAC) demand. This approach implicitly assumes that the building system being analyzed is heated or cooled at a given time, but not both. For buildings where simultaneous heating of some zones and cooling of other zones can legitimately occur, this implies that the impact analysis must be computed at a lower level in the building hierarchy where this assumption is valid or is a more reasonable approximation.

The demand for energy is expressed as the sum of demands for cooling (Cool), heating (Heat), and other loads

$$\text{Demand}(t) = \text{Cool}(t) + \text{Heat}(t) + \text{Dist}_c(t) + \text{Lights}(t) + \text{Plugs}(t) + \text{Ext}(t) \tag{7.2.15}$$

where we explicitly account for other loads as the sum of fan and pump loads in constant volume systems (Dist_c), lights (Lights), plug loads (Plugs), and loads external to the building envelope (Ext), such as exterior lighting.

The zone heat balance or thermal load, Load(t), of a zone at any time is comprised of

- Internal heat gained from lights, Lights(t); plug loads, Plugs(t); occupants, Occ(t); and solar radiation (through glazed and opaque surfaces), Solar(t)
- Heat lost by conduction through the zone envelope to the outdoors, Cond(t)
- Heat conducted into the zone's internal thermal mass, Mass(t)
- Heat carried by the air to the outdoors by the ventilation air required for the zone's occupants, OA(t)

$$\text{Load}(t) = f_L\text{Lights}(t) + \text{Plugs}(t) + \text{Occ}(t) + \text{Solar}(t) - \text{Cond}(t) - \text{Mass}(t) - \text{OA}(t) \tag{7.2.16}$$

The fraction of the lighting energy that ends up as internal heat gain to the zone, f_L, is usually close to 100%. Heat from lights that enters the return air stream directly is included in f_L because it will return to the zone after passing through the AHU. The effect of exhausting some or all the return air with the outdoor-air/economizer system is accounted for by the OA(t) term. However, f_L will be less than 100% if some of the heat from lighting fixtures is conducted through the roof from top-floor ceiling plenums, for example.

The heating and cooling demands can be expressed as the ratio of the thermal load from the space that is seen by the HVAC system (positive for heating, negative for cooling) divided by the overall *system* energy conversion efficiency of the heating, cooling, or reheat system (COP). Because, in general, heating and cooling loads are served by systems with different thermal efficiencies or COP, the associated demands must be accounted for as separate terms. So the demand can be expressed as

$$\begin{aligned}\text{Demand}(t) = {} & \frac{\left(\text{Load}(t) - \text{Econ}(t) + f_d\text{Dist}_c(t)\right)^+}{\text{COP}_{\text{cool}}(t)} - \frac{\left(\text{Load}(t) + f_d\text{Dist}_c(t)\right)^-}{\text{COP}_{\text{heat}}(t)} \\ & + \text{Dist}_c(t) + \text{Lights}(t) + \text{Plugs}(t) + \text{Ext}(t)\end{aligned} \tag{7.2.17}$$

Econ(t) is the heat exhausted from the return air stream by an economizer introducing extra outside air beyond that required for the occupants when conditions are suitable for free cooling. $\text{Dist}_c(t)$ is the consumption of the distribution system (fans and pumps) that is relatively constant with respect to the amount of heating or cooling supplied, and f_d is the fraction of that energy entering the air and water flows as heat. (We will also include a term that is convenient for variable-volume distribution systems in the system COPs in the following discussion of specific types of faults.)

The terms enclosed in $(\ )^+$ and $(\ )^-$ in Equation 7.2.17 are the *net* cooling and heating loads seen by the HVAC system, respectively. That is, this is the amount of heating or cooling that must be delivered by the system to the space, less free cooling delivered by the economizer and heat gained from fans and pumps. By this notation, we define these terms as nonzero only when the enclosed term (the net thermal load) is positive and negative, respectively. These terms imply that normally there is no simultaneous heating and cooling for a zone (except for reheat). That is, there is a cooling demand only when the net load on the system is positive, and a heating demand only when it is negative.

The system COP includes the primary energy conversion efficiency of the heating or cooling sources at the current conditions (temperature, humidity, and part load). It also must include all duct losses, and may be defined (optionally, see later discussion) to include the energy consumption by fans and pumps for distribution, auxiliary loads, and any reheat energy required by the HVAC system for proper temperature control.

To proceed, we now make a series of assumptions and approximations. The phenomena involved in the conduction and mass terms are diverse and highly building- and even zone-specific. Without a detailed thermal simulation of the building it may be impossible to come up with good estimates of the resulting heat transfer rates at any given time. So, it is desirable to eliminate their effect from the impact estimate. It is convenient to assume that it is not necessary to estimate energy cost impacts for faults that result in appreciable changes to the zone temperature. Because this would presumably be reported by occupants or basic BAS alarms, it is not a primary target fault for FDD systems. Further, regulating it is the primary function of the control system and loss of comfort control presumably has impacts that far exceed associated energy impacts.

If the fault does not appreciably impact zone temperature, it can be assumed that the conduction and thermal mass terms are nearly the same in both the faulted and unfaulted conditions. The same assumption will be made for the plug loads and other external loads, because these are not generally the subject of either control or FDD systems.

Because we have assumed that the conduction, mass, plug loads, and occupancy terms are not appreciably affected by the fault, we can express the change in the zone thermal load as

$$\Delta\mathrm{Load}(t) = f_L \Delta\mathrm{Lights}(t) + \Delta\mathrm{Solar}(t) - \Delta\mathrm{OA}(t) \tag{7.2.18}$$

where f_L is the fraction of the lighting impact energy that is dissipated within the conditioned space. The estimated change in demand resulting from correction of a fault is

$$\begin{aligned} \cong \mathrm{Demand}(t) = &\left\{\mathrm{Cool}'(t) - \mathrm{Cool}(t)\right\} + \left\{\mathrm{Heat}'(t) - \mathrm{Heat}(t)\right\} + \left\{\mathrm{Dist}'_c(t) - \mathrm{Dist}_c(t)\right\} \\ &+ \left\{\mathrm{Lights}'(t) - \mathrm{Lights}(t)\right\} \end{aligned} \tag{7.2.19}$$

where, again, we denote condition X under normal operation as X′ when a fault exists. Equation 7.2.19 must be applied once for each fuel impacted by the fault, dropping terms for demands not served by the fuel.

Assume that the normal operating heating and cooling system COPs can be estimated or computed, and that measured heating and cooling demands are available for the system being diagnosed, (i.e., those actually occurring at time t, *including the impact of any faults*). Alternatively, normal heating and cooling demands may be known from some type of theoretical model or an empirical model of past performance.

The cooling, heating, and reheat demands that would occur if the fault was fixed are

$$\mathrm{Cool}(t) = \frac{\left(\left\{\mathrm{Load}'(t) - \Delta\mathrm{Load}(t)\right\} - \left\{\mathrm{Econ}'(t) - \Delta\mathrm{Econ}(t)\right\} + f_d\left\{\mathrm{Dist}'_c(t) - \Delta\mathrm{Dist}_c(t)\right\}\right)^+}{\mathrm{COP}_{cool}(t)} \tag{7.2.20}$$

$$\mathrm{Heat}(t) = -\frac{\left(\left\{\mathrm{Load}'(t) - \Delta\mathrm{Load}(t)\right\} + f_d\left\{\mathrm{Dist}'_c(t) - \Delta\mathrm{Dist}_c(t)\right\}\right)^-}{\mathrm{COP}_{heat}(t)} \tag{7.2.21}$$

The zone thermal load can be expressed as the difference in the net heating and cooling loads (estimated as the products of the cooling and heating COPs and demands), plus the economizer free cooling, less the heat gain from fans and pumps

$$\begin{aligned}\text{Load}'(t) &= \text{Cool}'(t)\text{COP}'_{\text{cool}}(t) - \text{Heat}'(t)\text{COP}'_{\text{heat}}(t) + \text{Econ}'(t) - f_d\text{Dist}'_c(t) \\ &= \text{Cool}'(t)\left\{\text{COP}_{\text{cool}}(t) + \Delta\text{COP}_{\text{cool}}(t)\right\} \\ &\quad -\text{Heat}'(t)\left\{\text{COP}_{\text{heat}}(t) + \Delta\text{COP}_{\text{heat}}(t)\right\} + \text{Econ}'(t) - f_d\text{Dist}'_c(t)\end{aligned} \tag{7.2.22}$$

For faults that degrade HVAC system performance, ΔCOP is normally negative. Note that Equation 7.2.22 expresses the net load in terms of both cooling and heating, and both must be included even if different fuels are used to supply them. So, Equation (7.2.22) is also valid when normal or faulted operation results in simultaneous heating and cooling.

The estimated change in demand caused by a fault can be expressed as

$$\begin{aligned}\Delta\text{Demand}(t) &= \text{Cool}'(t) + \text{Heat}'(t) + \Delta\text{Lights}(t) + \Delta\text{Dist}_c(t) \\ &- \frac{\begin{pmatrix}\text{Cool}'(t)\left\{\text{COP}_{\text{cool}}(t) + \Delta\text{COP}_{\text{cool}}(t)\right\} - \text{Heat}'(t)\left\{\text{COP}_{\text{heat}}(t) + \Delta\text{COP}_{\text{heat}}(t)\right\} \\ +\Delta\text{Econ}(t) - f_d\Delta\text{Dist}_c(t) - f_L\Delta\text{Lights}(t) - \Delta\text{Solar}(t) + \Delta\text{OA}(t)\end{pmatrix}^+}{\text{COP}_{\text{cool}}(t)} \\ &+ \frac{\begin{pmatrix}\text{Cool}'(t)\left\{\text{COP}_{\text{cool}}(t) + \Delta\text{COP}_{\text{cool}}(t)\right\} - \text{Heat}'(t)\left\{\text{COP}_{\text{heat}}(t) + \Delta\text{COP}_{\text{heat}}(t)\right\} \\ +\Delta\text{Econ}'(t) - f_d\Delta\text{Dist}_c(t) - f_L\Delta\text{Lights}(t) - \Delta\text{Solar}(t) + \Delta\text{OA}(t)\end{pmatrix}^-}{\text{COP}_{\text{heat}}(t)}\end{aligned} \tag{7.2.23}$$

Note that Equation 7.2.23 must be applied separately for each fuel impacted by the fault. Entire terms for demands not served by the fuel are dropped (either both of the cooling demand terms, or both of the heating demand terms). All the subterms of the expressions for the net heating and cooling loads and the terms inside the $()^+$ and $()^-$ must be retained in their entirety to accurately characterize the net thermal load seen by the HVAC system. For example, if the impact on electrical demand is desired for a gas-heated building, the second and last terms are dropped and

$$\begin{aligned}\Delta\text{Demand}(t) &= \text{Cool}'(t) + \Delta\text{Lights}(t) + \Delta\text{Reheat1}(t) + \Delta\text{Dist}_c(t) + \Delta\text{Aux1}(t) \\ &- \frac{\begin{pmatrix}\text{Cool}'(t)\left\{\text{COP}_{\text{cool}}(t) + \Delta\text{COP}_{\text{cool}}(t)\right\} - \text{Heat}'(t)\left\{\text{COP}_{\text{heat}}(t) + \Delta\text{COP}_{\text{heat}}(t)\right\} \\ +\Delta\text{Econ}(t) - f_D\Delta\text{Dist}_c(t) - f_L\Delta\text{Lights}(t) - \Delta\text{Solar}(t) + \Delta\text{OA}(t)\end{pmatrix}^+}{\text{COP}_{\text{cool}}(t)}\end{aligned} \tag{7.2.24}$$

[electrical demand impact, nonelectric heating]

Application of First Principles Method

It is useful to consider Equation 7.2.23, which is generally applicable to multiple faults, as applied to faults associated with three specific energy using subsystems building systems: outdoor-air ventilation/economizers, lighting, and heating/cooling. These three specific applications of Equation 7.2.23 are considered in this subsection.

Ventilation Fault Impacts

Ventilation fault impacts involving outdoor-air supply generally occur at the AHU level of the building system hierarchy, and affect the net load of all the zones served by the AHU. These faults may involve supply of excess ventilation air or failure of the economizer operation to supply free cooling. In either case, we will assume that the fault manifests itself as a change in the volumetric flow rate of outside air (ΔF), and that the magnitude of this flow rate error is available from or can be estimated as a byproduct of the FDD algorithm. Further, to apply Equation 7.2.23 in its full form implies that we also know the heating and/or cooling delivered to the zones served by the AHU. This may involve metering of energy consumption in unitary packaged equipment or flow rates and enthalpies or temperatures in air handlers served by a boiler/chiller plant.

The impacts on outdoor air (OA) and economizer (Econ) are combined into a single fault. Assume (for this example) that there is no impact on the system COP, and no impact on the fan and pump consumption in constant volume systems. So, $\Delta COP(t)$ and $\Delta Dist_c(t)$ are zero. Then, the change in heat loss via the outdoor ventilation air can be expressed in terms of the air density (ρ) and the difference of the return and outdoor-air enthalpies ($h_r - h_o$) to estimate the demand impacts of ventilation system faults as

$$\begin{aligned}\Delta Demand(t) &= Cool'(t) + Heat'(t) \\ &- \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + (h_r - h_o)\Delta F(t)\right)^{+}}{COP_{cool}(t)} \\ &+ \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + Econ'(t) + (h_r - h_o)\Delta F(t)\right)^{-}}{COP_{heat}(t)}\end{aligned} \tag{7.2.25}$$

[ventilation faults with no system COP impacts]

As before, terms in Equation 7.2.25 for demands not served by a given fuel are dropped. For example, if the impact on electrical demand is desired for a nonelectrically heated building, one would not include the second and last terms.

It may not be possible to measure or estimate the heating and cooling demands at the air handler level, and the assumption must be made that the mode of the air handler (heating or cooling) would be unchanged if the fault was corrected. Then, Equation 7.2.25 reduces to

$$\Delta Demand(t) = \frac{\tilde{n}(h_o - h_r)\Delta F(t)}{COP_{cool}(t)} \tag{7.2.26}$$

[cooling impact, no change in cooling mode caused by fault]

for impacts when cooling and

$$\Delta Demand(t) = \frac{\tilde{n}(h_r - h_o)\Delta F(t)}{COP_{heat}(t)} \tag{7.2.27}$$

[heating impact, no change in heating mode caused by fault]

for heating, because $Econ'(t)$ in a heating mode is zero if the entire fault is included in ΔF. The OAE diagnostician used Equation 7.2.26 and Equation 7.2.27 to estimate the energy impacts from improper operation of the outdoor-air controls or economizer.

Note that the impact of faults in ventilation systems can increase or decrease the demand for cooling, depending upon the difference in the indoor and outdoor temperatures and humidities, and whether the fault results in too much or too little flow at any given time. For example, cooling loads are increased by excess flow when it is hotter or more humid outside than inside. They decrease when either the relative indoor and outdoor conditions or the sign of the flow rate error are reversed, but not both.

When the system is in the heating mode, the outdoor-air temperature is almost always less than the indoor-air temperature, otherwise heating would not be required. One notable, but rare exception to this generalization is during warmups on relative mild mornings. Therefore, the outdoor-air enthalpy is almost always less than the indoor-air enthalpy, and excess outdoor ventilation air flow will not result in a change in mode from heating to cooling, and Equation 7.2.27 usually applies for faults involving excess ventilation air. Note that negative flow rate errors during heating modes suggest that the outdoor-air volumes are less than needed for the occupants, with consequent negative effects on indoor air quality.

Whether during heating or cooling, faults that reduce ventilation air flow to levels below those required by the occupancy have negative air-quality impacts that should be considered far more valuable than the positive energy benefit. This suggests that positive cost benefits for such faults probably should not be displayed to users.

Lighting Fault Impacts

Impacts of faults resulting in excess gains from solar radiation, such as errors in day lighting sensors controlling active shading devices, are entirely analogous to the impacts of lighting faults. So, the discussion and the equations developed here can be used to estimate impacts for them by simply substituting the relevant load terms for the lighting terms.

Assume, for this example, there is no impact of the lighting fault on the system COP or the fan and pump consumption in constant volume systems. So, $\Delta COP(t)$ and $\Delta Dist_c(t)$ are equal to zero. If the lighting fault affects only one zone served by a constant-volume multizone AHU and if that zone is reheating, the change in lighting demand will simply be offset by an equivalent change in the need for reheat and the following analysis will not apply. In the case of electric resistance heating (COP = 1.0) and if f_L is 1.0, then net impact on the total demand will be zero. However, generally, lighting faults are likely to impact all zones served by an AHU. In such cases, the effect of changed reheat requirements is minimal and will be neglected as a second order effect. There is only a similar effect on reheat for variable air-volume systems for zones where air flow is at minimum, so this will also be neglected here.

From Equation 7.2.23, the estimated reduction in demand that would result from correcting a fault with lighting control causing excess consumption ΔLights, but not affecting the system COPs or the fan/pump power in constant volume system, is

$$\begin{aligned}\Delta Demand(t) &= Cool'(t) + Heat'(t) + \Delta Lights(t) \\ &- \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + \Delta Econ(t) - f_L \Delta Lights(t)\right)^{+}}{COP_{cool}(t)} \\ &+ \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + Econ'(t) - f_L \Delta Lights(t)\right)^{-}}{COP_{heat}(t)}\end{aligned} \tag{7.2.28}$$

But, any change in lighting load may simply be absorbed by a corresponding change in the economizer operation, if it is not already operating at full flow. Because there is no fault in the economizer operation in this example, this implies that outdoor conditions are suitable for free cooling and there is no cooling demand, i.e., $Cool'(t)$ is zero. Therefore, the contribution of a normally operating economizer toward meeting the cooling loads in faulted and unfaulted conditions must be estimated.

Let the volumetric flow rate required for the occupants at any time (of day and week) be $F_{req}(t)$. If the flow rate under faulted conditions, $F'(t)$, is known or can be estimated, then

$$Econ'(t) = \tilde{n}\left\{F'(t) - F_{req}(t)\right\}\left(h_r - h_o\right) \tag{7.2.29}$$

Let the maximum achievable flow rate be F_{max} when the economizer should fully open the outside-air dampers. An economizer normally operates to minimize cooling whenever possible. The maximum cooling load displaced by the economizer ($Econ'_{max}$) is the product of the air density, the volumetric flow rate, the return- and outdoor-air enthalpy difference, and two control functions

$$Econ'_{max}(t) = \left\{F_{max} - F_{req}(t)\right\}(h_r - h_o)\overbrace{\frac{(y_c - y_o)^+}{y_c - y_o}}^{1^{st}\ \text{function}}\overbrace{\frac{T_r - \max[T_o, T_{min}]}{T_r - T_o}}^{2^{nd}\ \text{function}} \qquad (7.2.30)$$

where the first control function defines whether the economizer is operating or not (values of zero or one), and the second control function defines the fraction of full flow at which it operates (values between zero and one). The variable y in the first control function is either temperature or enthalpy corresponding to the basis for the economizer control. The subscript c indicates the controlling variable, either return air for differential control or a high limit (usually temperature) for high-limit control.

Then, the maximum *increase* in the heat exhausted by the economizer, $\Delta Econ_{max}(t)$, is

$$\Delta Econ_{max}(t) = Econ_{max}(t) - Econ'(t) \qquad (7.2.31)$$

and the maximum *decrease* in the heat exhausted by the economizer is equal to $Econ'(t)$.

For faults that *increase* the lighting load, i.e., $\Delta Lights(t)$ greater than zero, increased flow in the economizer will absorb the increased cooling load resulting from the higher lighting level until the economizer reaches maximum flow. Thus

$$\begin{aligned}\Delta Demand(t) &= Cool'(t) + Heat'(t) + \Delta Lights(t) \\ &- \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + \left(\Delta Econ_{max}(t) - f_L \Delta Lights(t)\right)^-\right)^+}{COP_{cool}(t)} \\ &+ \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + Econ'(t) - f_L \Delta Lights(t)\right)^-}{COP_{heat}(t)}\end{aligned}$$

(7.2.32) [fault which increases lighting demand]

For faults that *decrease* the lighting load, i.e., $\Delta Lights(t)$ less than zero, the lower cooling load resulting from decreased lighting is offset by decreased flow in the economizer until it reaches the minimum required flow. Thus $\Delta Econ(t)$ is equal to $-Econ_{max}(t)$ and

$$\begin{aligned}\Delta Demand(t) &= Cool'(t) + Heat'(t) + \Delta Lights(t) \\ &- \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + \left(-Econ_{max}(t) - f_L \Delta Lights(t)\right)^+\right)^+}{COP_{cool}(t)} \\ &+ \frac{\left(Cool'(t)COP_{cool}(t) - Heat'(t)COP_{heat}(t) + Econ'(t) - f_L \Delta Lights(t)\right)^-}{COP_{heat}(t)}\end{aligned}$$

(7.2.33) [fault which decreases lighting demand]

When the system is cooling in the faulted condition and correcting the lighting fault would not result in a change in mode from cooling to heating, then the economizer is already at maximum flow during free cooling conditions and Equation 7.2.32 and Equation 7.2.33 reduce to

$$\Delta Demand(t) = \Delta Lights(t) + \frac{f_L \Delta Lights(t)}{COP_{cool}(t)}$$

(7.2.34) [cooling mode in faulted and unfaulted conditions]

where the lighting fault increases the impact of the fault.

For the simple case where the system is heating in the faulted condition and correcting the lighting fault would not result in a change in mode from heating to cooling, then Econ′(t) is zero and both Equation 7.2.32 and Equation 7.2.33 reduce to

$$\Delta \text{Demand}(t) = \Delta \text{Lights}(t) - \frac{f_L \Delta \text{Lights}(t)}{\text{COP}_{heat}(t)} \tag{7.2.35}$$

[electric heat, heating mode in faulted and unfaulted conditions]

where the change in the lights is partially offset by the increased requirement for heat, as expected. For nonelectric heating, Equation 7.2.35 must be applied twice, once for the heating fuel impact with the lighting term, ΔLights(t), equal to zero, and once for the electricity impact when the second term is dropped.

HVAC Equipment Fault Impacts

For a fault whose impact is confined to the system COPs, the impact on the total demand is (from Equation 7.2.23)

$$\begin{aligned}\Delta \text{Demand}(t) &= \text{Cool}'(t) + \text{Heat}'(t) \\ &- \frac{\left(\text{Cool}'(t)\left\{\text{COP}_{cool}(t) - \Delta\text{COP}_{cool}(t)\right\} + \text{Heat}'(t)\left\{\text{COP}_{heat}(t) + \Delta\text{COP}_{heat}(t)\right\} + \Delta\text{Econ}(t)\right)^{+}}{\text{COP}_{cool}(t)} \\ &+ \frac{\left(\text{Cool}'(t)\left\{\text{COP}_{cool}(t) - \Delta\text{COP}_{cool}(t)\right\} + \text{Heat}'(t)\left\{\text{COP}_{heat}(t) + \Delta\text{COP}_{heat}(t)\right\} + \text{Econ}'(t)\right)^{-}}{\text{COP}_{heat}(t)}\end{aligned} \tag{7.2.36}$$

The system COPs must be estimated over the range of operating conditions, under both normal and faulted operations. For systems without preheat or dehumidification loads, the heating and cooling delivered by the system (exclusive of the economizer and constant distribution loads to be consistent with Equation 7.2.23 is

$$\text{Delivered}(t) = \text{Cool}(t)\text{COP}_{cp}(t) - \text{Heat}(t)\text{COP}_{hp} - \text{Reheat}(t)\text{COP}_{rh}(t) - f_d \text{Dist}_v(t) + f_D \text{Loss}(t) \tag{7.2.37}$$

where Reheat(t) is the heat demand required for proper temperature control in multizone systems; $\text{Dist}_v(t)$ is the fan and pump energy that varies with the load; Loss(t) is heat loss from the ducts and pipes caused by conduction and air leakage; f_D is the fraction of the duct loss that is retained in the conditioned space; and $\text{COP}_{cp}(t)$, $\text{COP}_{hp}(t)$, and $\text{COP}_{rh}(t)$ are the COPs of the primary cooling, heating, and reheating energy conversion equipment at the current load and temperature conditions.

For systems without preheat or dehumidification loads, the demand of the system (exclusive of the constant distribution loads to be consistent with Equation 7.2.23 is

$$\text{Demand}(t) = \text{Cool}(t) - \text{Heat}(t) - \text{Reheat}(t)\text{COP}_{rh}(t) - \text{Dist}_v(t) + \text{Aux}(t) \tag{7.2.38}$$

where Aux(t) is the energy consumption of auxiliary HVAC equipment such as condenser and cooling towers fans.

The system COPs are defined as the ratio of the delivered energy to the demand. The cooling system COP is

$$\text{COP}_{cool}(t) = \frac{\text{COP}_{cp} + \text{COP}_{rh}\dfrac{\text{Reheat}(t)}{\text{Cool}(t)} + f_d\dfrac{\text{Distrib}(t)}{\text{Cool}(t)} + f_D\dfrac{\text{Loss}(t)}{\text{Cool}(t)}}{1 + \dfrac{\text{Reheat}(t)}{\text{Cool}(t)} + \dfrac{\text{Distrib}(t)}{\text{Cool}(t)} + \dfrac{\text{Aux}(t)}{\text{Cool}(t)}} \tag{7.2.39}$$

and the heating system COP is

$$\mathrm{COP}_{heat}(t) = \frac{\mathrm{COP}_{hp} + f_d \dfrac{\mathrm{Distrib}(t)}{\mathrm{Cool}(t)} - f_D \dfrac{\mathrm{Loss}(t)}{\mathrm{Cool}(t)}}{1 + \dfrac{\mathrm{Distrib}(t)}{\mathrm{Cool}(t)} + \dfrac{\mathrm{Aux}(t)}{\mathrm{Cool}(t)}} \tag{7.2.40}$$

Under unfaulted operation, the primary COPs can be estimated from manufacturer's data. These formulations of the system COPs are convenient because they express the effect of reheat, distribution, auxiliary consumption, and duct losses as ratios that tend to remain somewhat constant in many situations and that can be readily approximated for many systems. Alternatively, they can be estimated based on design calculations. Estimation of the system COPs under faulted conditions typically requires an estimate of the impact of the fault on only one of the terms.

In general (for an air conditioner, for example) the primary COP is a function of the latent cooling fraction, the supply and outdoor temperatures, and the part load ratio. These can be estimated from the manufacturer's data for various conditions under normal operation. The effect of the faults must then be estimated also. The primary COP is often discontinuous, such as for staged cooling devices. At rated conditions, the primary COP for combustion equipment is often between 0.8 to 0.95, for absorption cooling equipment between 0.45 to 0.7, for cooling equipment between 3 to 5, for electric heat pumps between 3 to 4, and for electric resistance heating equipment it is 1.0.

At full load conditions, fan power for air distribution systems is typically in the range of 5 to 10% of the delivered energy. For water distribution systems, this is typically in the range of 2 to 5%. These fractions are building and system specific, and are primarily dependent on flow rates, supply temperatures, and pipe and duct sizes and lengths. In constant volume systems, the distribution power is essentially constant, whereas in variable volume systems it varies approximately with the square of the flow rate (and may have a lower limit corresponding to a minimum flow rate).

The distribution power also generally results in heat being added to the flow. This displaces some need for thermal energy from the primary heating source and adds to that from the primary cooling source. Because of friction in the fan and duct or pump and pipe, virtually all the mechanical power input into the fan or pump is converted to heat. The total (thermal and fluidic) power input is the product of the volumetric flow rate (F) and total pressure increase across the fan or pump (Δp), with proper unit conversion factor (k)

$$\mathrm{Distrib}(t) = \frac{F\Delta pk}{\eta} \tag{7.2.41}$$

where (η) is the efficiency of a fan motor outside an air stream whose waste heat is not added to the flow; otherwise η is 1.0.

Reheat occurs in single-duct multizone HVAC systems in the cooling mode whenever air volumes are constant. Even in variable-air volume systems designed to reduce the need for reheat, once air volumes are reduced to a minimum (determined by the need for outdoor air), some reheat is necessary.

Reheat is necessary because each zone has its flow rate set based on design conditions. Differences in balance temperatures (defined below) among zones served by a single AHU will cause their cooling loads to drop at different rates as the outdoor temperature drops below design conditions. Their cooling loads do not decrease in proportion to their design flow rates, so some zones will receive more cooling than they require to satisfy the zone with the highest relative cooling load.

A simple analysis can be developed that expresses the reheat required as a ratio to the zone's cooling load as follows:

$$\frac{\text{Reheat}(t)}{\text{Load}(t)} = \left(\frac{T_o^* - T_b}{T_o - T_b}\right)\left(\frac{T_o - T_b''}{T_o^* - T_b''}\right) - 1 \tag{7.2.42}$$

where the balance temperature for the zone, T_b, is expressed as a function of the zone temperature (T_z), the internal heat gains to the zone, and the heat loss coefficient (UA).

$$T_b = T_z - \frac{f_L \text{Lights}(t) + \text{Plugs}(t) + \text{Occ}(t) + \text{Solar}(t) + f_D \text{Dist}(t)}{\text{UA}} \tag{7.2.43}$$

So, if the balance temperatures for the zones served by an AHU are known or estimated, the ratio of their reheat to their load can be estimated from Equation 7.2.42.

Integrating of Impacts Over Time

The primary purpose of providing energy impact information to users of FDD systems is to give a sense of scale for problems detected so that operators can prioritize corrective actions among their other work duties. Problems with small impacts can be ignored or fixing them can be put off, while problems with large impacts may justify immediate action. Clearly, FDD systems will not have any beneficial effect on building operation if significant problems are not corrected. Users and potential users of FDD systems have consistently placed high value on such feedback.

The time scale over which a problem's impact is presented fundamentally determines its value. It also seems likely that users will compare this value or cost to fix a problem, perhaps an hourly labor rate or the cost of a service call. With 168 hours in a week, presenting the impact in terms of a weekly cost impact magnifies the user's *perception* of the value of fixing the problem by two orders of magnitude compared to presenting an hourly impact. Small problems can result in large cost impacts if they affect every hour of every day. Since most problems targeted by FDD systems go undetected for months, if not years, presenting impact estimates over even longer intervals is probably desirable.

However, this raises a set of issues about how to construct such estimates. First, the impact of problems is not steady, either from hour-to-hour within a day, from one day to another, or from one season to another. An economizer that fails to operate when it should provides a simple illustration of this. At night or on weekends, the impact may be zero if the cooling system is shut off. The impact may also be zero in the winter and the summer when the economizer cannot operate anyway. Providing an annual estimate of the impact may be the fairest way to present FDD impacts, but is not useful in setting immediate priorities for action. In this example, fixing the economizer in the winter is not an *immediate* priority, while getting it fixed by spring is. The value of the corrective action and the benefit of the FDD system are best represented by the annual number.

There are also procedural difficulties in computing impacts over time. When hourly (for example) time-series impacts are computed by the FDD algorithm, it may be quite simple and useful to display the sum of the hourly impacts for the last week or month. The issue here is that a new problem may have a large impact, but this will not be apparent if these impacts are just starting to accumulate. This suggests that either the onset of the problem is taken into account, adding another layer of complexity to the FDD system, or future impacts are forecast based on the nature of the problem. The latter requires some type of model to project impacts. This model could be theoretical, based on assumptions about loads as a function of weather and a typical weather year, for example. On the other hand, the model could be empirical, based on the conditions seen over the last year, if such data has been stored by the FDD system. In either case, the effect of the problem must be superimposed on the model. Examples of how this can be done were presented in the previous section, but making such estimates reasonably accurate over widely varying conditions is complex.

In summary, it is important to keep in mind the purpose for the impact estimates. For the reasons cited above, it may be appropriate to provide impact estimates over more than one time interval, and perhaps targeted at various uses and users. For this to be effective, multiple impact results must be presented by the FDD system to clearly distinguish their basis and their use or target audience. It is also important to keep in mind that making some kind of impact estimate, even one with significant uncertainty, is probably always better than providing none at all.

Since increased energy costs are not the only impact of many problems in buildings, it is very important to place energy cost impacts in their proper context. For example, faults that cause inadequate outdoor air to be supplied to building spaces (i.e., below the amount specified by code) actually *save* energy and lower costs substantially in most conditions. Nevertheless, they have adverse impacts on occupant health and productivity that overshadow their energy cost benefits and open up the owner/operator to potential liability. Similarly, faults in a chiller may result in a lack of capacity that limits consumption, but any associated energy savings are likely to be overshadowed by the failure to provide comfort conditions and potential damage to the chiller that may result from continued operation.

Therefore, FDD systems should be careful about displaying energy cost *benefits* from faults (perhaps avoiding doing so altogether) that may distract the user from the real issues involved. Even if nonenergy impacts of faults are not quantified by an FDD tool, they should be presented to the user in qualitative fashion to prompt their consideration as the operators decide on a response to a detected fault.

7.2.13 The Future of Diagnostics in Buildings

In the 1990s, there was significant growth in the development of fault detection and diagnostic methods and methodologies for building systems. However, very few commercial products exist today, and the ones that exist are very specialized or not fully automated. There are several reasons for lack of widespread availability and deployment of FDD systems: lack of sensors on building systems, unavailability of low cost reliable sensors, high cost-to-benefit ratio of deploying FDD systems with current sensor technologies, lack of acceptable benchmarks to quantify the potential benefits from deploying FDD systems, lack of easy access to real-time data, and lack of infrastructure to gather data from existing BASs.

The functionality/benefits and costs of a fully automated FDD system differ significantly from those of a service tool. With the development of low-cost reliable sensor technology, FDD systems would soon be integrated into individual equipment controllers and would provide continuous monitoring, fault detection and diagnostic outputs, and recommendations for when service should be performed. Ultimately, as networking infrastructure matures, the use of automated FDD systems could allow a small support staff to operate, monitor, and maintain a large number of different systems from a remote, centralized location. Local FDD systems would communicate across a network to provide a status report on the "health" of the equipment that they monitor. Failures that lead to loss of comfort could be identified quickly before there is a significant impact on comfort. In many cases, degradation faults could be identified well before they lead to loss of comfort or uneconomical operation, allowing more efficient scheduling (lower cost) of service.

As the cost of sensors and control hardware continues to drop, chillers will probably be the first application of automated FDD within the HVAC&R industry because of a low cost-to-benefit ratio. Once fully developed, the technology could be integrated into all controllers associated with vapor compression cooling equipment. When fully mature, the costs associated with implementing the technology should be primarily the result of the addition of low-cost temperature sensors. These costs should be a relatively small fraction of the controller costs. The same technology would also be applicable to refrigeration and residential space cooling. Furthermore, the technology could be implemented in add-on systems to existing cooling equipment, which would increase the rate of market penetration.

Open communication standards for building automation systems are catching on as well, and use of Internet and Intranet technologies is pervasive. These developments enable FDD systems to be deployed more readily. In addition, the structure of the industry that provides services for the operations and maintenance of buildings is changing; companies are consolidating and offering whole-building operations and maintenance packages. Furthermore, as utilities are deregulated they will begin to offer new services, including complete facility management. With complete and distributed facility management, the cost-to-benefit of deploying FDD systems will improve because the cost can be spread over a large number of buildings (Katipamula et al., 1999). To benefit from these changes, facility managers, owners, operators, and energy service providers are challenged to acquire or develop new capabilities and resources to better manage this information and, in the end, their buildings and facilities.

Although the technology and incentives for application of FDD systems for vapor compression cooling equipment have never been greater, there still are several obstacles to their development and deployment. First, there is a need to quantify the potential benefits to establish benchmarks for acceptable costs and to provide marketing information. Specific research issues related to FDD methods include development of methods for detection and diagnosis of sensor faults and multiple simultaneous faults, identification of appropriate models and training approaches, and evaluation of the tradeoffs between sensors (type and quality) and FDD performance. The testing of FDD methods should be performed first in the laboratory and then in the field.

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References

Agrusa, R. and Singers, R.R. 1999. Control Your World in a Glance. *Building Systems Innovation, Heating, Piping and Air-Conditioning Supplement to the January Issue of HPAC Engineering*, pp. 21–32, Penton Media, Cleveland, Ohio.

Anderson, D., Graves, L., Reinert, W., and Kreider, J.F. 1989. A Quasi-Real-Time Expert System for Commercial Building HVAC Diagnostics. *ASHRAE Transactions*, Vol. 95, Part 2, pp. 954–960.

Bailey, M.B., Kreider, J.F., and Curtiss, P.S. 2000. Results of a Probabilistic Fault Detection and Diagnosis Method for Vapor Compression Cycle Equipment. *Proceedings of the International Conference of Chartered Institution of Building Services Engineers and ASHRAE*, College of Surgeons, Dublin, Ireland. September 21–23, 2000; see also by the first author, *The Design and Viability of a Probabilistic Fault Detection and Diagnosis Method for Vapor Compression Cycle Equipment*. Ph.D. Thesis, JCEM, College of Engineering, University of Colorado, Boulder, Colorado, 1998.

Bayne, J.S. 1999. Unleashing the Power of Networks. *Supplement to the January Issue of HPAC Engineering*, Penton Media, Cleveland, Ohio.

Brambley, M.R., Pratt, R.G., and Katipamula, S. 1999. Use of Automated Tools for Building Commissioning. Presented at the 7th National Conference on Building Commissioning, May 1999.

Brambley, M.R., Pratt, R.G., Chassin, D.P., and Katipamula, S. 1998. Automated Diagnostics for Outdoor Air Ventilation and Economizers. *ASHRAE Journal*, Vol. 40, No. 10, pp. 49–55.

Braun, J.E. 1999. Automated Fault Detection and Diagnostics for the HVAC&R Industry. *HVAC&R Research*, Vol. 5, No. 2, pp. 85–86.

Breuker, M.S. 1997. *Evaluation of a Statistical, Rule-Based Fault Detection and Diagnostics Method for Vapor Compression Air Conditioners*. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Breuker, M.S. and Braun, J.E. 1998a. Common Faults and Their Impacts for Rooftop Air Conditioners. *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 4, No. 2, pp. 303–318.

Breuker, M.S. and Braun, J.E. 1998b. Evaluating the Performance of a Fault Detection and Diagnostic System for Vapor Compression Equipment. *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 4, No. 4, pp. 401–425.

Cikanek, H.A. 1986. Space Shuttle Main Engine Failure Detection. *IEEE Transactions on Automatic Control*, Vol. 6, pp. 13–18.

Clark, D.R. 1985. *HVACSIM+ Program Reference Manual.* NBSIR 84-2996, National Institute of Standards and Testing, Gaithersburg, Maryland.

Chen, J. and Patton, R.J. 1999. *Robust Model-Based Fault-Diagnosis for Dynamic Systems.* Kluwer Academic Publishers, Norwell, Massachusetts.

Daisey, J.M. and Angell, W.J. 1998. *A Survey and Critical Review of the Literature on Indoor Air Quality, Ventilation and Health Symptoms in Schools.* Report No. LBNL-41517, Lawrence Berkeley National Laboratory, Berkeley, California.

Dalton T., Patton, R.J., and Miller, P.J.H. 1995. Methods of Fault Detection for a Centrifugal Pump System. *On-Line Fault Detection and Supervision in the Chemical Process Industries, IFAC Workshop*, Newcastle Upon Tyne, U.K., Pergamon Press, New York.

Dexter, A.L. and Benouarets, M. 1996. Generic Approach to Identifying Faults in HVAC Plants. *ASHRAE Transactions*, Vol. 102, No. 1, pp. 550–556.

Dodier, R.H. and Kreider, J.F. 1999. Detecting Whole Building Energy Problems. *ASHRAE Transactions*, Vol. 105, No. 1.

EUN, *Energy User News*, Vol. 24, No. 3, pp. 43–48, March 1999.

Fasolo, P.S. and Seborg, D.E. 1995. Monitoring and Fault Detection for an HVAC Control System. *International Journal of Heating, Ventilation, and Air-Conditioning and Refrigeration Research,* Vol. 99, Part 1, pp. 3–13.

Frank, P.M. 1987. Fault Diagnosis in Dynamic Systems via State Estimation: A Survey. *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches*, Vol. 1, pp. 35–98, D. Reidel Publishing Company, Dordrecht, Holland.

Frank, P.M. 1990. Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge-Based Redundancy — A Survey and Some New Results. *Automatica*, Vol. 26, pp. 459–474.

Frank, P.M. 1997. New Developments Using AI in Fault Diagnosis. *Engng. Applic. Artif. Intell.* Vol. 10, No. 1, pp. 3–14.

Fukunaga, K. 1990. *Introduction to Statistical Pattern Recognition*. Academic Press, Purdue University, W. Lafayette, Indiana.

Georgescu, C., Afshari, A., and Bornard, G. 1993. A Model-Based Adaptive Predictor Fault Detection Method Applied to Building Heating, Ventilating, and Air-Conditioning Process. *TOOLDIAG '93*, Organized by Département d'Études et de Recherches en Automatique, Toulouse, Cedex, France.

Gertler, J. 1988. Survey of Model-Based Failure Detection and Isolation in Complex Plants. *IEEE Control Systems Magazine*, Vol. 8, No. 6, pp. 3–11.

Gertler, J. 1998. *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker, New York.

Glass, A.S., Gruber, P., Roos, M., and Todtli, J. 1995. Qualitative Model-Based Fault Detection in Air-Handling Units. *IEEE Control Systems Magazine*, Vol. 15, No. 4, pp. 11–22.

Gordon, J.M. and Ng, K.C. 1995. Predictive and Diagnostic Aspects of a Universal Thermodynamic Model for Chillers. *International Journal of Heat and Mass Transfer*, Vol. 38, No. 5, pp. 807–818.

Gordon, J.M. and Ng, K.C. 2000. *Cool Thermodynamics*, Cambridge International Scientific Publishers, Cambridge, U.K.

Gregerson, J. 1997. *Commissioning Existing Buildings, E-Source Tech Update*. TU–97–3, E-Source Inc., Boulder, Colorado.

Grimmelius, H.T., Woud, J.K., and Been, G. 1995. On-line Failure Diagnosis for Compression Refrigerant Plants. *International Journal of Refrigeration,* Vol. 18, No. 1, pp. 31–41.

Han, C.Y., Xiao, Y., and Ruther, C.J. 1999. Fault Detection and Diagnosis of HVAC Systems. *ASHRAE Transactions*, Vol. 105, Part 1.

Haves, P., Salsbury, T., and Wright, J.A. 1996. Condition Monitoring in HVAC Subsystems Using First Principles. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 519–527.

Himmelblau, D.M. 1978. *Fault Detection and Diagnosis in Chemical and Petrochemical Processes*. Elsevier Scientific Publishing Company, New York.

House, J.M., Lee, W.Y., and Shin, D.R. 1999. Classification Techniques for Fault Detection and Diagnosis of an Air-Handling Unit. *ASHRAE Transactions*, Vol. 105, Part 1.

Hyvärinen, J. and Kärki, S., Eds. 1996. *International Energy Agency Building Optimisation and Fault Diagnosis Source Book*. Published by Technical Research Centre of Finland, Laboratory of Heating and Ventilation, Espoo, Finland.

Inatsu, H., Matsuo, H., Fujiwara, K., Yamada, K., and Nishizawa, K. 1992. Development of Refrigerant Monitoring Systems for Automotive Air-Conditioning Systems. *Society of Automotive Engineers*, SAE Paper No. 920212.

Issermann, R. 1984. Process Fault Detection Based on Modeling and Estimation Methods — A Survey. *Automatica*, Vol. 20, No. 4, pp. 387–404.

Issermann, R. and Nold, S. 1988. Model Based Fault Detection for Centrifugal Pumps and AC Drives. In *11th IMEKO World Congress*. Houston, Texas, U.S.A., pp. 16–21.

Issermann, R. and Ballé, P. 1997. Trends in the Application of Model-Based Fault Detection and Diagnosis of Technical Process. *Control Engineering Practice*, Vol. 5. No. 5, pp. 709–719.

Jarrell, D.B. and Meador, R.J. 1997. *Twenty-nine Palms Final Report*, Volume I, *PNNL-11582*, Pacific Northwest National Laboratory, Richland, Washington.

Jiang, Y., Li, J., and Yang, X. 1995. Fault Direction Space Method for On-Line Fault Detection. *ASHRAE Transactions*, Vol. 101, Part 2, pp. 219–228.

Katipamula, S.T., Reddy, A., and Claridge, D.E., Effect of time resolution on Statistical modeling of cooling energy use in large commericial buildings, A*SHRAE Transactions*, Vol. 101, Part 2, pp. 172–185, 1995.

Katipamula, S., Pratt, R.G., Chassin, D.P., Taylor, Z.T., Gowri, K., and Brambley, M.R. 1999. Automated Fault Detection and Diagnostics for Outdoor-Air Ventilation Systems and Economizers: Methodology and Results from Field Testing. *ASHRAE Transactions*, Vol. 105, Part 1.

Kumamaru, T., Utsunomiya, T., Iwasaki, Y., Shoda, I., and Obayashi, M. 1991. A Fault Diagnosis Systems for District Heating and Cooling Facilities. *Proceedings of the International Conference on Industrial Electronics, Control, and Instrumentation*, Kobe, Japan (IECON 91), pp. 131–136.

Lee, W.Y., Park, C., and Kelly, G.E. 1996a. Fault Detection of an Air-Handling Unit Using Residual and Recursive Parameter Identification Methods. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 528–539.

Lee, W.Y., House, J.M., Park, C., and Kelly, G.E. 1996b. Fault Diagnosis of an Air-Handling Unit Using Artificial Neural Networks. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 540–549.

Lee, W.Y., House, J.M., and Shin, D.R. 1997. Fault Detection of an Air-Handling Unit Using Residual and Recursive Parameter Identification Methods. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 528–539.

Li, X., Hossein, V., and Visier, J. 1996. Development of a Fault Diagnosis Method for Heating Systems Using Neural Networks. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 607–614.

Li, X., Visier, J., and Vaezi-Nejad, H. 1997. A Neural Network Prototype for Fault Detection and Diagnosis of Heating Systems. *ASHRAE Transactions*, Vol. 103, Part 1, pp. 634–644.

Mangoubi, R.S. 1998. *Robust Estimation and Failure Detection*. Springer-Verlag, New York.

McKellar, M. G. 1987. *Failure Diagnosis for a Household Refrigerator*. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Mylaraswamy, D. and Venkatsubramanian, V. 1997. A Hybrid Framework for Large Scale Process Fault Diagnosis. *Computers Chem. Engng*. Vol. 21, pp. S935–S940.

Ngo, D. and Dexter, A.L. 1999. A Robust Model-Based Approach to Diagnosing Faults in Air-Handling Units. *ASHRAE Transactions*, Vol. 105, Part 1.

Norford, L.K. and Little, R.D. 1993. Fault Detection and Monitoring in Ventilation Systems. *ASHRAE Transactions*, Vol. 99, Part 1, pp. 590–602.

Noura, H., Aubrun, C., Sauter, D., and Robert, M. 1993. A Fault Diagnosis and Reconfiguration Method Applied to Thermal Plant. *TOOLDIAG '93*, Organized by Département d'Études et de Recherches en Automatique, Toulouse, Cedex, France.

Pape, F.L.F., Mitchell, J.W., and Beckman, W.A. 1990. Optimal Control and Fault Detection in Heating, Ventilating, and Air-Conditioning Systems. *ASHRAE Transactions*, Vol. 97, Part 1, pp. 729–736.

Patel, S.A. and Kamrani, A.K. 1996. Intelligent Decision Support System for Diagnosis and Maintenance of Automated Systems. *Computers and Industrial Engineering*, Vol. 30, No. 2, pp. 297–319.

Patton, R., Frank, P., and Clark, R. 1989. *Fault Diagnosis in Dynamic Systems: Theory and Application*. Prentice Hall, Englewood Cliffs, NJ.

Pau, L.F. 1981. *Failure Diagnosis and Performance Monitoring*, Marcel Dekker, New York.

Peitsman, H.C. and Bakker, V. 1996. Application of Black-Box Models to HVAC Systems for Fault Detection. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 628–640.

Peitsman, H.C and Soethout, L.L. 1997. ARX Models and Real-Time Model-Based Diagnosis. *ASHRAE Transactions*, Vol. 103, Part 1, pp. 657–671.

Pearl, J. 1988. *Probabilistic Reasoning in Intelligent Systems*. Morgan Kaufmann, San Mateo, California.

Portland Energy Conservation Inc. (PECI). 1997. *Commissioning for Better Buildings in Oregon*, Oregon Office of Energy, Salem, Oregon.

Rossi, T.M. 1995. *Detection, Diagnosis, and Evaluation of Faults in Vapor Compression Cycle Equipment*. Ph.D. thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Rossi, T.M. and Braun, J.E. 1996. Minimizing Operating Costs of Vapor Compression Equipment With Optimal Service Scheduling. *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 2, No. 1, pp. 3–26.

Rossi, T.M. and Braun, J.E. 1997. A Statistical, Rule-Based Fault Detection and Diagnostic Method for Vapor Compression Air Conditioners. *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 3, No. 1 pp. 19–37.

Seem, J., House, J.M., and Monroe, R.H. 1999. On-Line Monitoring and Fault Detection, *ASHRAE Journal*, Vol. 41, No. 7, pp. 21–26.

Stallard, L.A. 1989. *Model Based Expert System for Failure Detection and Identification of Household Refrigerators*. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Stylianou, M. and Nikanpour, D. 1996. Performance Monitoring, Fault Detection, and Diagnosis of Reciprocating Chillers. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 615–627.

Stylianou, M. 1997. Classification Functions to Chiller Fault Detection and Diagnosis. *ASHRAE Transactions.* Vol. 103, Part 1, pp. 645–648.

Tutsui, H. and Kamimura, K. 1996. Chiller Condition Monitoring Using Topological Case-Based Modeling. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 641–648.

U.S. DOE/PECI. 1998. *Model Commissioning Plan and Guide Commissioning Specifications, Version 2.05*, PECI, Portland, OR, February.

Wagner, J. and Shoureshi, R. 1992. Failure Detection Diagnostics for Thermofluid Systems. *Journal of Dynamic Systems, Measurement, and Control*, Vol. 114, No. 4, pp. 699–706.

Willsky, A.S. 1976. A Survey of Design Methods for Failure Detection in Dynamic Systems. *Automatica*, Vol. 29, pp. 601–611.

Yoshida, H., Iwami, T., Yuzawa, H., and Suzuki, M. 1996. Typical Faults of Air-Conditioning Systems, and Fault Detection by ARX Model and Extended Kalman Filter. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 557–564.

Yoshida, H. and Kumar, S. 1999. ARX and AFMM Model-Based On-Line Real-Time Data Base Diagnosis of Sudden Fault in AHU of VAV System. *Energy Conversion and Management*, Vol. 40, pp. 1191–1206.

Yoshimura, M. and Ito, N. 1989. Effective Diagnosis Methods for Air-Conditioning Equipment in Telecommunications Buildings. *INTELEC 89: The Eleventh International Telecommunications Energy Conference*, October 15–18, Centro dei, Firenze, Vol. 21, pp. 1–7.

Bibliography

Bagby, D.G. and Cormier, R.A. 1989. A Heat Exchanger Expert System. *ASHRAE Transactions*, Vol. 95, No. 2, pp. 927–933.

Chassin, D. P. 1999. Computer Software Architecture to Support Automated Diagnostics, In *Proceedings of CIB W78 Workshop on Information Technologies in Construction*, Vancouver B.C., Canada, June.

Clark, D.R. and May, W.B. 1985. *HVACSIM+ Users' Guide*. NBSIR 85-3243, National Institute of Standards and Testing, Gaithersburg, Maryland.

Clark D.R., Hurley, C.W., and Hill, C.R. 1985. Dynamic Models for HVAC System Components. *ASHRAE Transactions*, Vol. 91, No. 1B, pp. 737–751.

Culp, C.H. 1989. Expert Systems in Preventive Maintenance and Diagnosis. *ASHRAE Journal*, Vol. 31, No. 8, pp. 13–18.

Culp, C.H., Haberl, J.S., Norford, L., Brothers, P., and Hall, J.D. 1990. The Impact of AI Technology Within the HVAC Industry. *ASHRAE Journal*, Vol. 31. No. 12, pp. 12–22.

De Kleer, J. and Williams, B. 1987. Diagnosing Multiple Faults. *Artificial Intelligence*, Vol. 32, No. 1, pp. 97–130.

Dexter, A.L. 1993. Fault Detection in Air-Conditioning Systems Using Fuzzy Models. *IEEE Colloquium 'Two Decades of Fuzzy Control—Part 2'.* Digest No. 1993/118.

Dexter, A.L., Fargus, R.S., and Haves, P. 1994. Fault Detection in Air-Conditioning Systems Using A.I. Techniques. In *Proceedings of the Second BEPAC Conference BEP 94,* York, U.K.

Dexter, A.L. and Hepworth, S.J. 1993. *A Comparison of Fuzzy and Neural Methods of Detecting Faults in an Air-Handling Unit.* University of Oxford, Dept. of Eng. Science, Report No. OUEL 1981/93, Oxford University, Oxford, England.

Dexter, A.L. and Mok, B.K.K. 1993. *Fault Detection in HVAC Systems Using Fuzzy Models.* University of Oxford, Dept. of Eng. Science, Report No. OUEL 1977/93, Oxford University, Oxford, England.

Dexter, A.L. and Benouarets, M. 1996. A Generic Approach to Modeling of HVAC Plants for Fault Diagnosis, *Proceeding of 4th IBPSA International Conference:* Building Simulation 95, Madison, Wisconsin, pp. 339–345.

Dexter, A.L. and Ngo, D. 1997. Fault Diagnosis in Large-Scale Air-Conditioning Systems. *Proceeding of IFAC Symposium SAFEPROCESS 97,* Vol. 2, pp. 737–741.

Dialynas, E.N., Machias, A.V., and Souflis, J.L. 1987. Reliability and Fault Diagnosis Methods of Power System Components. *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches*, Vol. 1, pp. 327–341, D. Reidel Publishing Company, Dordrecht, Holland.

Dodier, R.H., Curtiss, P.S., and Kreider, J.F. 1997. *Small Scale, On-Line Diagnostics for an HVAC System*. RP-883, JCEM Technical Report TR/96/30, University of Colorado, Colorado.

Dodier, R.H., Curtiss, P.S., and Kreider, J.F. 1998. Small-Scale On-Line Diagnostics for an HVAC System. *ASHRAE Transactions*, Vol. 104, No. 1, pp. 530–539.

Duyar, A. and Merill, W. 1992. Fault Diagnosis for the Space Shuttle Main Engine. *AIAA, Journal of Guidance, Control, and Dynamics*, Vol. 15, No. 2, pp. 384–389.

Fasolo, P.S. 1993. *On-Line Statistical Methods for Fault Detection in an HVAC Process*. Master's thesis, University of California, Santa Barbara, California.

Fasolo, P.S. and Seborg, D.E. 1994. An SQC Approach to Monitoring and Fault Detection in HVAC Control Systems. In *Proceedings of the 1994 American Control Conference,* pp. 3055–3059, IEEE, New York.

Formera, L., Glass, A.S., Gruber, P., and Todtli, J. 1994. Qualitative Fault Detection based on Logical Programming Applied to a VAV Air Handling Unit. *Second IFAC Workshop on Computer Software Structures Integrating AI/KBS Systems in Process Control*, Lund, August 10–12.

Grimmelius, H.T., Woud, J.K., and Been, G. 1995. On-line Failure Diagnosis for Compression Refrigeration Plants. *International Journal of Refrigeration*, Vol. 18, No. 1, pp. 31–41.

Haberl, J.S. and Claridge, D.E. 1987. An Expert System for Building Energy Consumption Analysis. *ASHRAE Transactions*, Vol. 93, No. 1, pp. 979–998.

Haberl, J.S., Norford, L.K., and Spadaro, J.S. 1989. Expert Systems for Diagnosing Operation Problems in HVAC Systems. *ASHRAE Journal,* Vol. 31, No. 6.

Haves, P., Salsbury, T.I., and Wright, J.A. 1996. Condition Monitoring in HVAC Subsystems Using First Principles Models. *ASHRAE Transactions*, Vol. 102, Part 1, pp. 519–527.

Haves, P., Norford, L.K., DeSimone, M.A. 1998. Standard Simulation Test Bed for the Evaluation of Control Algorithms and Strategies. *ASHRAE Transactions*, Vol. 104, Part 1A, pp. 460–473.

Himmelblau, D.M. 1992. Fault Detection in Heat Exchangers. In *Proceedings of the 1992 American Control Conference,* pp. 2369–2372. IEEE, New York.

Hiroshi, I.H., Matsuo, K., Fujiwara, Yamada, K., and Nishizawa, K. 1992. Development of Refrigerant Monitoring Systems for Automotive Air-Conditioning Systems. *Society of Automotive Engineers*, SAE Paper No. 920212.

Hyvarinen, J. and Kohonen, R., Eds. 1993. *Building Optimisation and Fault Diagnosis System Concept.* Tech. Research Centre of Finland (VTT), Laboratory of Heating and Ventilation. (ISBN 952-9601-16-6). VTT, Espoo, Finland.

Jardine, A.K.S. 1973. *Maintenance, Replacement, and Reliability.* Halsted Press, John Wiley & Sons Inc., New York.

Jones, A.H. and Burge, S.E. 1987. An Expert System Design Using Cause-Effect Representations and Simulation for Fault Detection. *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches*, Vol. 2, pp. 71–80, D. Reidel Publishing Company, Dordrecht, Holland.

Johnson, D.M. 1996. A Review of Fault Management Techniques Used in Safety-Critical Avionic Systems. *Prog. Aerospace Sci.* Vol. 32, pp. 415–431.

Kaler, G.M. 1988. Expert System Predicts Service. *Heating, Piping, and Air Conditioning*, Vol. 11, pp. 99–101.

Kaler, G.M. 1990. Embedded Expert System Development for Monitoring Packaged HVAC Equipment. *ASHRAE Transactions*, Vol. 96, Part 2., p. 733.

Kitamura, M. 1980. Detection of Sensor Failures in Nuclear Plant Using Analytic Redundancy. *Transactions of the American Nuclear Society*, Vol. 34, pp. 581–583.

Koscielny, J.M. 1995. Fault Isolation in Industrial Process by the Dynamic Table of States Method. *Automatica*, Vol. 31, No. 5, pp. 747–753.

Liu, S.T and Kelly, G.E. 1988. Knowledge-based front-end input generating program for building system simulation. *ASHRAE Transactions*, Vol. 94, Part 1, pp. 1074–1084.

Liu, S.T. and Kelly, G.E. 1989. Rule-Based Diagnostic Method for HVAC Fault Detection. In *Proceedings of IBPSA Building Simulation 93*, pp. 319–324, Vancouver, Canada.

Loparo, K.A., Buchner, M.R., and Vasudeva, K.S. 1991. Leak Detection in an Experimental Heat Exchanger Process: A Multiple Model Approach. *IEEE Trans. Auto. Control*, Vol. 36, Part 2, pp. 167–177.

Ngo, D. and Dexter, A.L. 1998. Fault Diagnosis in Air-Conditioning Systems Using Generic Models of HVAC Plants. *Proceedings of the International Conference on System Simulation in Buildings*, SSB 98, Liege, Belgium.

Park, C., Clark, D.R., and Kelly, G.E. 1986. *HVACSIM+ Building Loads Calculation*. NBSIR 86-3331, National Institutes of Standards, Gaithersburg, Maryland.

Park, C. and Bushby, S.T. 1989. Simulation of a Large Office Building System Using the HVACSIM+ program. *ASHRAE Transactions*, Vol. 95, Part 1, pp. 642–651.

Rossi, T. and Braun, J. 1995. Thermodynamic Impact of Detecting Refrigerant Leaks in Vapor Compression Equipment. *1995 American Control Conference*, IEEE Control Systems Society, Seattle, Washington.

Salsbury, T.I., Haves, P., and Wright, J.A. 1995. A Fault Detection and Diagnosis Method Based on First Principles Models and Expert Rules. *Proceedings of HVAC 95 2nd International Symposium on Heating Ventilating and Air Conditioning*, Beijing, China.

Sami, S.M., Zhou, Y., and Tulej, P.J. 1992. Development of a Diagnostic Expert System for Heat Pumps. *Proceedings of the 2nd Annual Conference on Heat Pumps in Cold Climates*, Moncton, New Brunswick, August 16–17, pp. 475–489.

Tzafestas, S.G. 1987. A Look at the Knowledge-Based Approach to System Fault Diagnosis and Supervisory Control. *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches*, Vol. 2 pp. 3–15, D. Reidel Publishing Company, Dordrecht, Holland.

Usoro, P.B. and Schick, I.C. 1985. A Hierarchical Approach to HVAC System Fault Detection and Identification. In *Proceedings of Dynamic Systems: Modeling and Control, Winter Annual Meeting of ASME*, pp. 285–291, Miami, Florida.

Usoro, P.B., Schick, I.C., and Negahdaripour. 1985. An Innovation-Based Methodology for HVAC System Fault Detection, *ASME Journal of Dynamic Systems, Measurements, and Control*, Vol. 107, pp. 284–289.

Visier, J.C., Vaezi-Nejad, H., and Corrales, P. 1999. A Fault Detection Tool for School Buildings. *ASHRAE Transactions*, Vol. 105, Part 1.

Watanabe, K., Hirota, S., Hou, L., and Himmelblau, D.M. 1994. Diagnosis of Multiple Simultaneous Faults via Hierarchical Artificial Neural Networks. *AIChE Journal*, Vol. 40, No. 5, pp. 839–848.

Xiao, Y. and Han, C.Y. 1998. An OOM-KRES Approach for Fault Detection and Diagnosis. *Springer Verlag Lecture Notes on AI,* Vol. 1415, pp. 831–839.

Yang, C.H.Y. and Jiang, Y. 1995. Sensor Fault Detection of HVAC System — System Constraint and Voting. *Proceedings of Pan Pacific Symposium on Building and Urban Environmental Conditioning in Asia*, Nagoya, Japan.

Yu, C.C. and Lee, C. 1991. Fault Diagnosis Based on Qualitative/Quantitative Process Knowledge, *AIChE Journal,* Vol. 4., p. 617.