

APPLICATION OF MODELING AND SIMULATION IN FAULT DETECTION AND DIAGNOSIS OF HVAC SYSTEMS

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ABSTRACT

Failures can lead to a series of problems in the complex heating, ventilation and air-conditioning (HVAC) systems in buildings. Fault detection and diagnosis (FDD) is an important technology to solve these problems. Models can represent the behaviors of the HVAC systems, and FDD can be realized with models. Using the model as intermediary, a link between system simulation and FDD can be built. Simulation has provided a convenient platform of operation for FDD, the overall simulation methodology in FDD of HVAC systems is briefly introduced. Various reference models, faulty behaviors, modeling environments, and algorithms for FDD are discussed or compared. Finally, the model-based FDD schemes for HVAC systems proposed by many researchers in various ways have been reviewed.

KEYWORDS

Model; Simulation; Fault detection and diagnosis; Heating, ventilation and air-conditioning systems

INTRODUCTION

As the problems that appeared at various stages of the building life cycle, from design planning to operation, many buildings frequently fail to perform as well as expected and satisfy performance expectations envisioned at design phase (Haves 1999). The types of faults occurring in HVAC systems include process parameter changes, disturbance parameter changes, actuator problems, and sensor problems (Xu 2005). Furthermore, such failures often go unnoticed for extended periods of time. Therefore, the methodology which can apply proper operation-that can weaken or eliminate these

problems-conveniently and effectively is needed urgently. FDD technology was introduced into HVAC systems from 1970s, and the systematic research of FDD for HVAC systems began in the late of 1980's. However, the evolution was not appeared until the 1990s principally, IEA endorsed the ANNEX 25 collaborative research project on real time simulation of HVAC systems for building optimization, fault detection and diagnostics. Furthermore, the ANNEX 34 was published in 2001. Recent years, with the development of information technology and building technology, such as CAD, building energy management system (BEMS), and building automation system (BAS), the research of FDD are becoming more and more active and intensive (Bing et al. 2002). FDD is an investigation or analysis of the cause or nature of a condition, situation, or problem. There are two levels or stages: fault detection is the determination that the operation of the building is incorrect or unacceptable in some respects, and fault diagnosis is the identification or localization of the cause of faulty operation. FDD can improve indoor environment quality (IEQ), occupant comfort and health, and energy efficiency; reduce unscheduled equipment shut down time and maintenance costs; longer life cycle of equipments (Haves 1999).

FDD methods can be roughly divided into two categories as model-based and model-free. The model-based methods do employ explicit mathematical models of the target systems, while the model-free methods do not. Compared with the model-free methods, the model-based methods can hardly avoid the complexity of setting up models, but it is stronger in dealing with various faults

appeared in the large-scaled, distributed and dynamic HVAC systems, and more widely accepted in HVAC systems because of their better final solvability (Xiao 2004). Model is a mathematical description of a system, component, process, theory, or phenomenon that accounts for its known or inferred properties. The model-based FDD methods fully make use of deep level knowledge of system models, i.e. system construction, behavior and function etc., to carry out reasoning and diagnosis on system. Also, model performs as an evaluation tool for building performance diagnosis (Balqies 2000, Li 2004). The main compromise with model-based schemes is between model accuracy and configuration effort: the greater the potential accuracy of the models, the greater the effort required to configure the models for use. Simulation technology, as a kind of computer technology, is the imitation of the operation of systems or processes over time. The establishment of models is the core of system simulation (Clarke et al. 2002). The models are configured using design information and component manufacturers' data, and then fine-tuned to match the actual performance of the equipment by using data measured during functional tests of the sort using in commissioning (Xu and Haves 2002). Using the model as intermediary can build a link between system simulation and the FDD.

This article compared reference models, modeling environments and algorithms, discussed the overall simulation process for FDD and abnormal operation, and reviewed the model-based FDD schemes.

MODELING BASIC

Model-based FDD methods

The model-based methods can be divided into two groups according to how models are used, i.e. analytical redundancy (AR) and statistical process control (SPC) methods (Xiao 2004, Xu 2005).

In AR methods (Figure 1), models are acting as a reference for real processes. Residuals are used as fault indices, and are obtained by the comparing differences between process outputs and model outputs, or the comparison of two analytically

generated quantities, which are usually characteristic parameters of the concerned process. The process variables are usually divided into two groups: inputs and outputs, and the outputs variables can be predicted by the model with the inputs and parameters. The applications and performances of AR methods are limited by the difficulties in setting up accurate models, e.g. the black-box models used in AR methods demand a lot of high quality data which are often very difficult to obtain, and training black-box models is time-consuming as well.

But in SPC methods (Figure 2), model is employed to determine the thresholds of the statistics, and to calculate the statistics of new observations. Statistics are used as fault indices, and all system variables concerned are used as the inputs of the models. SPC methods can statistically monitoring correlations among process variables using statistics, and require pre-testified statistics and fault-free training data. The statistics that widely used include mean, variance, moving average cumulative sum, HotellingT² and Q-statistic.

Types of models

According to the criterion of modeling method, three kinds of models are classified: First principle, black-box and gray models (Li 2004, Qin 2006).

First principle models (physical models or white box models), whose parameters and structures have some physical significance, are derived from fundamental physical laws. Physical models include detailed and simplified models (McIntosh and Mitchell 2000). Usually, physical models can obtain the best final results of FDD, because the parameters of a physical model are meaningful and can be used directly for diagnosis. An accurate model can not only reveal the behaviors and characteristics of the systems being modeled, but also extrapolate performance expectations well in case of limited training data. However, it is often difficult and expensive to develop and solve an accurate physical model for some complicated components or the whole system (Li 2004). Furthermore, the complex physical models may

involve large collections of nonlinear equations which are difficult to solve, and many parameters must be specified and several must be tuned in order to match specified measurements. Also, the calibration error of physical models can be large, because researchers' experiences may vary. Physical models are usually not as accurate as black-box models because of some simplifying assumptions and requirement of detailed input data and data for tuning. Physical modeling approaches are good for relatively simple components such as expansion devices that are tuned using manufacturers' performance rating data. In this case, the models can be developed inexpensively. Salsbury and Diamond (2001) develop a simplified physical model-based approach to both control and detect faults in an air handling unit (AHU). Three separate models (mixing box, heating coil, and cooling coil) act as a reference of correct operation. A field test on a single AHU demonstrated the fault detection capabilities but also highlighted some of the practical implementation difficulties including selection of model parameters, reliability of sensor signals, and difficulty in establishing a baseline of "correct" operation of the AHU.

Black-box models (empirical models or data-driven models), derived only from measurement data from the process itself, use purely empirical input/output relationships that are fit to training data, and may not have any direct physical significance. There are many black-box modeling approaches: polynomial curve fits, ANN, ARX/RARX, state space equations, PCA, regression, etc. (Rossi and Braun 1997, Sreedharan and Haves 2001). Black-box models are able to avoid the complexity of setting up physical models and have great challenge to obtain good final results, but require a lot of fault-free data with high quality and high mathematic techniques for training. When enough training data are available, black-box models are preferred for the whole system e.g. an overall system performance model, or some complicated components e.g. heat exchangers. And most sensor FDD methods used in HVAC field adopted black-box models. Rossi and

Braun (1997) presented a black-box model-based FDD method for packaged air conditioners, in which nine fundamental measurements were used to detect and diagnose five faults. A steady-state polynomial regression model was used to predict temperatures in a normally operating unit in order to generate residuals for classifier in the FDD method.

Gray models (semi-physical models), a combination of both physical and black-box models, use lumped system parameters and some semi-empirical expressions. They assume that the model structure can describe the behaviors of the concerned system and explain the system physically, and the parameters of model structure are back-out with the measured data. Parameter estimates from gray-box models tend to be more robust than those from black-box models, which can lead to better model predictions. In general, black-box models have a simple form and are, therefore, easy to use. However, the demand on model training technique is also very high, e.g. gray models do not sufficiently use the building information which may be easily obtained and may lead to too many parameters needed to be identified, or the models are not stable using measured operation data in a short period. Stylianou and Nikanpour (1996) used a model-based FDD technique for a reciprocating chiller. A gray-box model was used for fault detection. The model correlated the equipment COP with the condenser and evaporator inlet water temperatures, and this performance index is used to decide when the impact of a fault is significant enough to warrant repair. For fault diagnosis, black-box polynomial models were developed for predicting internal temperatures and pressures.

As explained above, these three types of models have their own merits, and in some cases, it would be possible to combine them into one practical method. In this way, employing hybrid models can effectively use the building information which can be obtained easily, and assume a physical structure to handle the building information which may not be obtained easily or even impossible to obtain, and obtain good results. For example, Li (2004)

developed a decoupling-based FDD technique that handled multiple-simultaneous faults and had low implementation costs. Instead of system-specific overall system models, various component models and virtual sensors were used to generate decoupled features: Physical models for expansion devices, a gray-box model for compressor, and a polynomial plus general regression neural network black-box model for the overall system. These models were low-cost in that they exploited manufacturers' performance rating data and only required limited and readily available data for training.

Abnormal Operation

The fault-free data were used to train the models for normal operation and determine statistical thresholds for fault detection, while models of faulty components or processes may either be used on-line as part of an FDD system or may be used in simulations to train or test FDD procedures. Some faults may be modeled by choosing suitable values of the parameters of fault-free models (e.g. coil fouling may be treated in a simple coil model by reducing the UA value), whereas other faults require specific extensions to fault-free models (e.g. fouling may be defined by a parameter that specifies the thermal resistance of the deposits in a detailed coil model) (Haves 1997). Simulated faults are useful in situations where it is physically impossible or too expensive or too dangerous to introduce the actual faults. Therefore, whether there is a need to model faulty behaviors is depended on the system under study and the specific FDD approach which we employ. For example, Dexter and Ngo (2001) proposed a multi-step fuzzy model-based approach to improve their earlier diagnosis results for AHUs. This approach was based on two kinds of models, a fault-free model and models describing faulty behavior, to perform multiple-diagnosis.

Modeling environments

A handful of software tools have been developed to provide modeling environments for FDD, which making the modeling for FDD of HVAC systems more convenient and efficient. These tools include

component-based simulators such as TRNSYS or HVACSIM+, equation-based tools like SPARK or IDA (Sowella and Haves 2001), numerical basic tools such as MATLAB or EES, and so on.

TRNSYS and HVACSIM+ are both based on subroutines containing algorithmic models of the underlying physics for the represented building system component. TRNSYS, a transient system simulation program with a modular structure, is used to simulate the energy and control characteristics of HVAC systems. It allows performing detailed simulations of multizone buildings and their equipments, as well as thermal systems in general. And it facilitates the addition to the program of mathematical models not included in the standard TRNSYS library. HVACSIM+ assembles a vector of the interface variables throughout the model and employs a Newton-like solution strategy. Although the advantages of HVACSIM+ are robustness and efficiency, it is often less efficient than TRNSYS in practice for the need to calculate Jacobian and solve linear equation set that it represents at each iteration.

SPARK and IDA represent a new departure in that they formulate the model and its solution, in terms of equations rather than the algorithmic subroutines employed in TRNSYS and HVACSIM+. SPARK establishes object oriented modeling and graph theoretic solution techniques for building simulation. The distinctive attributes of SPARK are that: The graph, rather than the matrix, is the primary data structure for storing the problem structure and data, and graph algorithms are employed to determine a solution sequence that operates directly on the nonlinear equations; The model equations are stored individually, rather than packaged into modules, and are treated as equations rather than as formulae with assignment. Differently, the equations are formed as residual formulas In IDA. IDA can solve non-linear algebraic problems without requiring initial guesses from the user. The advantage of IDA is that Modeling is input/output free, i.e. the same component model can be used for a variety of different input and output designations.

MATLAB provides ready access to many mathematical models. The most important feature of MATLAB is easy to expand, which allows users to set up their own designated function of M documents. The system simulations in HVAC systems mainly use the Simulink Module. EES, the solution of a set of algebraic equations, can efficiently solve hundreds of coupled non-linear algebraic equations and initial value differential equations. A major difference between EES and existing equation solving programs is the many built-in mathematical and thermophysical property functions, which are helpful in solving problems in thermodynamics, fluid mechanics, and heat transfer for HVAC systems.

Reference algorithms

Nowadays, some more powerful algorithms have been introduced to solve simulation models and obtain the solution values, such as principal component analysis (PCA) method, genetic algorithm (GA), and artificial neural networks (ANN). They're stronger in dealing with problems than traditional methods and have their special merits: PCA method produces a lower dimensional representation in a way that preserves the correlation structure between the process variables, and uses pure mathematic models (Xiao 2004). GA can find a sufficiently good solution quickly without initialization while other methods have to start from initial guesses of parameter, and GA estimator is developed for model parameter optimization. ANN can provide solutions for problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found, and they allow going directly from factual data to the models without any human subjective interference (Niculescu 2003).

SIMULATION PLATFORM

Benefits of simulation platform

Simulation has provided a convenient platform of operation for FDD of HVAC systems, which improves the reliability of FDD, and offers the following benefits (Juricic et al. 1996, Balqies 2000,

Bing et al. 2002): It can simulate organizational and environmental changes and obtain the effect of these changes on the model's behavior, and no need to disturb the real system. The internal interactions of the complex HVAC systems and subsystems are able to be studied. It strengthens the research and the analysis of process characteristics, with dynamic analysis method substituting tradition static state analysis method. And it provides the analyst with a tool to conduct some FDD experiments that doing them could be expensive. These experiments often require some expensive measurements, such as enough sensors installed at the building system level or component level of the HVAC terminals to provide enough information. As a good testing tool, it gains a computer-aid FDD environment substitutes tradition experimental technique, researchers are able to test a variety of FDD methods in a simulation environment, find possible shortcomings and obtain new ideas for further development, which saves the massive manpower, contributes to lowering the cost of FDD, and finally enhances the FDD development efficiency.

Simulation process

Generally, the three main factors that constitute system simulation are: system, model, and computer. The FDD process is simulated with computer through the life cycle helping the designer in problem solution, and the simulation environment has the ability to allow for experiments on the model and highlight the relevant aspects of the problem. The overall simulation methodology (as shown in Figure 3) consists of the following four major steps (Balqies 2000):

- Pre-modeling or planning step: Define the purpose of FDD system, and use system analysis, including physical construction of the object, preliminary requirements of the FDD system, potential fault sources etc., to describe and extract the relevant causal relationships in the FDD system under study.
- Modeling step: Models are the main components of simulation programs, and the behavior of HVAC systems as it evolves with time can be studied with

models. Such models take the form of a set of assumptions about the system under study. The assumptions are represented by mathematical, logical or symbolic relationships. Fault symptoms are voluntarily generated via changes in model parameters or expert system for the purpose of FDD. Once the symptoms have been defined, the decision making in terms of fault detection follows instantly, and then the solution of problems can be obtained.

- **Verification and validation step:** In this stage, whether the modeling satisfies the requirement is determined. Verification is the process of determining that the simulation model accurately represents the developer's conceptual description of the system. Validation is the process of determining whether the model is an accurate representation of the real-world from the intended use of the model. The model validation for FDD of HVAC systems may carry out under different weather conditions using either laboratory or field data.

- **Experimentation and application step:** The solution is tested and evaluated by performing various simulation experiments in this last stage. Simulation runs are made under different conditions and inferences are drawn about the relationship between the controllable variables and measured performance matrixes. It is important to conduct experiments because they reveal many of the characteristics of the system being modeled, and a wide variety of questions and behaviors for FDD of HVAC systems can be investigated.

APPLICATION SURVEY

The model-based FDD schemes have been proposed with a variety of models by many researchers in different respects.

Methods comparison

Sreedharan and Haves (2001) evaluated three different modeling approaches for their applicability to model-based FDD of vapor compression chillers. The models included: the Gordon and Ng Universal Chiller model and a modified version of the ASHRAE Primary Toolkit model, which are both based on first principles, and the DOE-2 chiller

model, which is empirical. Shaw et al. (2002) compared results of two techniques for using electrical power data for FDD in AHUs. One technique relies on gray-box correlations of electrical power with such exogenous variables as airflow or motor speed. The second technique relies on physical models of the electromechanical dynamics that occur immediately after a motor is turned on. Norford et al. (2002) compared results of two methods for FDD in HVAC equipment from controlled field tests. One method used first-principles-based models of system components; the second method was based on semi-empirical correlations of sub-metered electrical power with flow rates or process control signals.

For different HVAC systems or components

Benouarets et al. (1994) presented two model-based schemes and examined their ability to detect water-side fouling and valve leakage in the cooling coil subsystem of an AHU. Haves et al. (1996) employed first principles models to diagnose faults appeared in cooling coils. Ahn et al. (2001) used a model-based method for FDD in the cooling tower circuit of a central chilled water facility employing a simple model for the cooling tower. Wray and Matson (2003) used a hybrid DOE-2/TRNSYS sequential simulation approach to model the energy use of a low-pressure terminal-reheat VAV system with six duct leakage configurations in nine prototypical large office buildings. Wang and Qin (2005) have built and employed a PCA based sensor FDD strategy. PCA models at both system and terminal levels were constructed.

Some new approaches

Bechtler et al. (2001) described a new approach to modeling dynamic processes of vapour compression liquid refrigeration systems using a dynamic neural network model for the performance prediction. Henry et al. (2002) proposed a new approach to the problem of on-line model-based FDD for multivariable uncertain systems. The method was based on frequency-domain model invalidation tools.

CONCLUSION AND IMPLICATIONS

Model-based FDD are useful for the operator of building HVAC system to recognize the faults and disturbances. Reference models can be categorized into three types: First principle, black-box and gray models. The use of software support is of great practical interest in order to make the modeling for FDD more convenient and efficient. Simulation technology is the imitation of the operation of HVAC systems and the establishment of model is its core. In order to carry out FDD in HVAC systems through simulation, it is needed to observe the operation of the system, formulate assumptions that account for its behavior, predict the prospective behavior of the system based on assumptions and compare predicted behavior with real behavior. Simulation together with modeling provides a convenient platform of

operation for FDD of HVAC systems.

Due to the complexity of the real HVAC systems, appearance of multiple failures simultaneously and the limitation of every kinds of FDD methods, it is impossible to solve practical problems only utilizing one method. The more attractive employ is integrating multifarious FDD algorithms and methods, e.g. expert system, fuzzy mathematics and ANN, which should gain more effective results. Such as, introduce simulation technology into failure diagnostic expert system to form a new fault diagnosis knowledge acquisition mode, or bring simulation into failure analysis to come up with flexible residual generation algorithms which use simulation system as baseline. And much further work is waited for us to investigate and research.

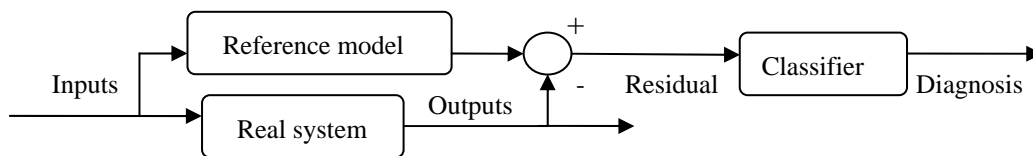


Figure 1 Schematic of model-based FDD methods (AR)

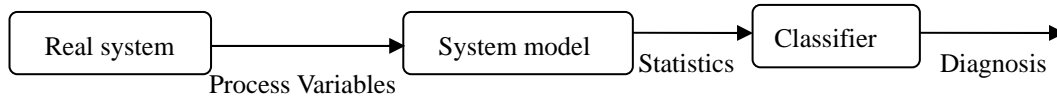


Figure 2 Schematic of model-based FDD methods (SPC)

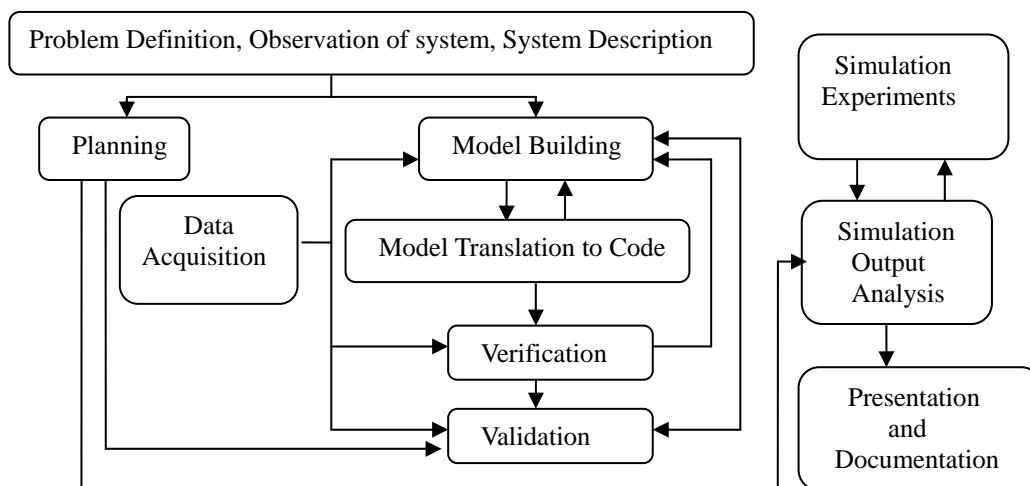


Figure 3 Overall simulation methodology

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