MODELING AND SIMULATION FAULT DETECTION AND DIAGNOSTICS OF HVAC SYSTEMS

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Abstract

Systems health management includes fault detection, fault diagnostics (or fault isolation), and fault prognostics. Failures can lead to a series of problems in the complex heating, ventilation and air-conditioning (HVAC) systems. Fault detection and diagnostics (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.

Key words : fault detection and diagnostics, heating, ventilation and air-conditioning systems

INTRODUCTION

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 system is incorrect or unacceptable in some respects, and fault diagnostics is the identification or localization of the cause of faulty operation. FDD can improve indoor environment quality (IEQ), energy efficiency, reduce unscheduled equipment shut down time and maintenance costs, longer life cycle of equipments. 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. The model-based FDD methods fully make use of deep level knowledge of system models to carry out reasoning and diagnostics on system. Simulation technology is the imitation of the operation of systems or processes over time. The establishment of models is the core of system simulation. Using the model as intermediary can build a link between system simulation and the FDD.

The model-based methods can be divided into two groups according to how models are used, analytical redundancy (AR) and statistical process control (SPC) methods. In AR methods (Fig. 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.

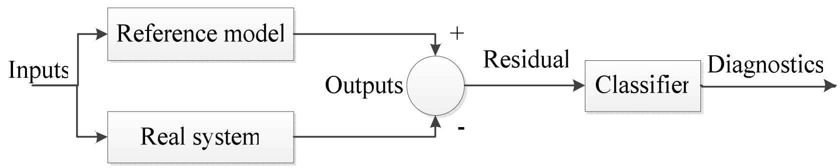

Fig. 1. Schematic of model-based FDD methods (AR)

But in SPC methods (Fig. 2), model is employed to determine the thresholds of the statistics, and to calculate the statistics of new bservations. 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.

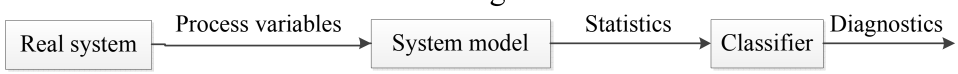

Fig. 2. Variation of operating parameters of the diffusion tower

According to the criterion of modeling method, three kinds of models are classified: first principle, black-box and gray models. First principle models (physical models or white box models), whose parameters and structures have some physical significance, are derived from fundamental physical laws. 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 diagnostics. 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. 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. Gray models are a combination of both physical and black-box models. They assume that the model structure can describe the behaviors of the concerned system and explain the system physically. Parameter estimates from gray-box models tend to be more robust than those from black-box models, which can lead to better model predictions.

MATERIAL AND METHODS

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, whereas other faults require specific extensions to fault-free models. Simulated faults are useful in situations where it is physically impossible or too expensive or too dangerous to introduce the actual faults.

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, 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. 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.

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. 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.

RESULTS AND DISCUSSION

Simulation has provided a convenient platform of operation for FDD of HVAC systems and offers the following benefits: 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. It strengthens the research and the analysis of process characteristics, with dynamic analysis method substituting tradition static state analysis method. The computer-aid FDD environment substitutes tradition experimental technique and 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.

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 (Fig. 3) consists of the following four major steps :

- 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.

- 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.

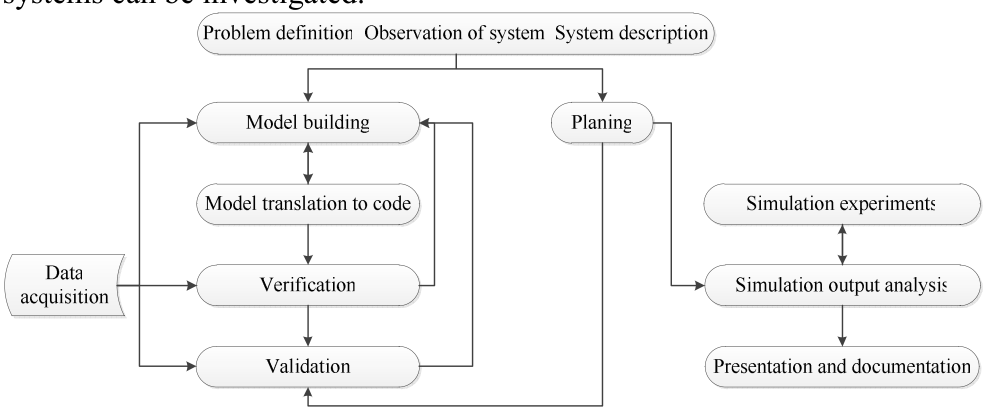

Fig. 3. Overall simulation methodology

CONCLUSIONS

Model-based FDD are useful for the operator of HVAC system to recognize the faults and disturbances. The use of software support is of great practical interest in order to make the modeling for FDD more convenient and efficient. 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 multivarious FDD algorithms and methods which should gain more effective results.

REFERENCES

1. Donca G., I. Mihăilă, M. Ganea, D. Hirțe, M. Nica, 2007, *Maintenance role in life cycle management*, in Analele Universității din Oradea, Fascicola Management şi Inginerie Tehnologică, volumul XVI, Editura Universității din Oradea, pp. 2158-2163
2. Donca G., I. M. Mihăilă, 2009, *Aspects of maintenance strategy selection process*, in Analele Universității din Oradea, Fascicola Management şi Inginerie Tehnologică, volumul XVIII, Editura Universității din Oradea, pp. 1654-1659
3. Donca G., Mihăilă I. M., 2010, *Health diagnostic for complex acting mechanism*, in Analele Universității din Oradea, Fascicola Management şi Inginerie Tehnologică, volumul IX, Editura Universității din Oradea
4. Donca G., Mihăilă I. M., 2010, *Aspects regarding data mining applied to fault detection*, in Analele Universității din Oradea, Fascicola Management şi Inginerie Tehnologică, volumul IX, Editura Universității din Oradea
5. Laxman S., P. S. Sastry, and K. P. Unnikrishnan, 2007, *Discovering frequent generalized episodes when events persist for different durations,* IEEE Transactions on Knowledge and Data Engineering, vol. 19
6. Lan L. and Chen Y., 2007, *Application of modeling and simulation in fault detection and diagnosis of hvac systems*, Building Simulation Conference and Exhibition, September 3 - 6, 2007, Beijing, China
7. Laxman S., Basel Shadid, P. S. Sastry and K. P. Unnikrishnan, 2009, *Temporal data mining for root-cause analysis of machine faults in automotive assembly lines*, arXiv, USA
8. Moerchen F., 2007, *Unsupervised pattern mining from symbolic temporal data*, ACM SIGKDD Explorations, vol. 9, pp. 41-55
9. Niculescu S. P., 2003, *Artificial neural networks and genetic algorithms in QSAR*, Journal of Molecular Structure (Theochem), pp. 71-83
10. Qin J. Y., 2006, *A fault detection and diagnosis strategy for VAV air distribution system*, Ph.D. Thesis, The Hong Kong Polytechnic University, 234 pages
11. Weidl G., Madsen, A.L., Israelsson S.. 2005, *Object-Oriented Bayesian Networks for Condition Monitoring, Root Cause Analysis and Decision Support on Operation of Complex Continuous Processes*, Technical Report 2005-1, IST - University of Stuttgart.