Bridging the Gap Between Simulation and the Real World
An Application to FDD

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ABSTRACT

Energy simulation programs are increasingly used to assess the energy performance of buildings and heating, ventilation, and air conditioning (HVAC) systems during design. Faults during operation can lead to considerable increase in energy use and associated operating costs. In 2009, 13 of the most common energy faults in U.S. commercial buildings were thought to cause wastes of over $3.3 billion per year. Fault detection and diagnosis (FDD) tools can reduce some of these energy wastes. In the buildings industry there is still a disconnect between the design phase, commissioning, and operation. This work presents a process and a tool chain for model-based real-time automated FDD. It facilitates the introduction of FDD in building applications by allowing simulation models from the design stage to be reused during operation. Our tool chain uses models that comply with the Functional Mockup Interface (FMI) standard, a standard developed by 29 partners since 2008 that is supported by more than 40 simulations tools, including Modelica simulation environments and MATLAB. Engineers that use simulation tools compliant with the FMI standard (Blochwitz, 2011) can reuse their models for creating energy-aware FDD algorithms. This work presents and explains the general software architecture and FDD algorithm, which is based on a hybrid of various existing statistical algorithms: Bayesian updating, Unscented Kalman Filtering, and back-smoothing. We also demonstrate the algorithm to analyze simultaneous faults in a chiller plant.

Introduction

In building and district energy systems, equipment often degrades or malfunctions. In many commercial heating, ventilation, and air conditioning (HVAC) systems, various types of substandard operations can occur, leading to uncomfortable occupant conditions, damage to equipment, and energy waste. Just 13 of the most common faults in U.S. commercial buildings in 2009 are thought to have caused over $3.3 billion in energy waste (Mills, 2009). A survey of over 55,000 air conditioning units (Proctor, 2009) showed that more than 90% were operating with one or several faults. Other than the typical degradation or malfunctioning, possible fault causes are manual adjustments of set points, valves, controls, and schedules for a specific event that are not returned to their normal operation. Unfortunately, a sufficient number of sensors are rarely deployed in most buildings or building systems to detect these faults in a reasonably short period of time. Fault detection and diagnostic (FDD) techniques represent a solution to the aforementioned problems.

Fault detection and diagnostics has been successfully applied in various engineering domains (e.g., automotive, aerospace, and industrial/manufacturing) for many decades, yet application in buildings is still evolving and relatively immature. While some FDD solutions have been successfully demonstrated and integrated into commercial tools, widespread adoption has been slow.

There is a considerable body of literature about FDD. Two comprehensive overviews are especially relevant in understanding the broad categories of general approaches: Venkatasubramanian (2003a,b,c) and building-specific applications Katipamula (2005a,b).

Model-based FDD approaches are attractive, as they allow the use of models from the design stage to present the expected performance during commissioning and operation. They can also be used to test different fault hypothesis and to compute the associated energy waste. There are many FDD solutions available in the literature but none of them can directly take advantage of the same models used during the design phase. This disconnection between the design phase and the operation reduces the adoption of model-based FDD techniques and increases the cost required to deploy FDD algorithms.

In this paper we describe and demonstrate an approach for model-based FDD. The presented approach and methodologies represent a step towards a whole-building energy-aware FDD that is interoperable with models created by different simulators. Simulator interoperability is realized by using the Functional Mockup Interface (FMI) standard, a standard developed for exchange of simulation models between different simulation programs.

The paper starts with an introduction to the FMI standard and explains why this technology is well suited to create an interoperable whole-building FDD approach. The next section describes how the presented tool chain couples tools used during the design phase and the FDD algorithms needed during the operation of a real building. The fourth section demonstrates how the FDD algorithm identifies single and concurrent faults in the presence of sensor noise and measurements errors in real time. The paper ends with an application of the proposed approach. The application shows how to detect simultaneous energy and hydraulic faults in a chiller.

FMI: A Standard for Model Exchange

The FMI standard is a tool-independent standard for the exchange of models and simulation programs. The development of the FMI was initiated by Daimler within the project MODELISAR (https://itea3.org/project/modelisar.html), a research project funded by the European Union that involved 29 partners from industry, simulation tool vendors, and academia. The goal of FMI was to support the exchange of simulation models between manufacturers and suppliers in the automotive sector. Manufacturers create cars that are made of different subsystems (such as wheels, engines, and control systems) that are provided by different suppliers and then integrated into an automobile. To test the performance of the overall system, the manufacturers needed to couple various simulation models provided by the suppliers of each component. This was difficult and expensive, and it allowed limited analysis. Today more than 40 simulation programs support the FMI standard. The standard is governed by a group of companies, institutes, and universities, and is organized through the Modelica Association.

Under the umbrella of the International Energy Agency (IEA), Energy in Buildings and Communities Programme (EBC), a five-year project called *Annex 60* started in 2012. Annex 60 is an international project, led by Lawrence Berkeley National Laboratory (LBNL) and by RWTH Aachen, Germany, titled "New generation computational tools for building and community energy systems based on the Modelica and Functional Mockup Interface standards." In this project, 37 institutions from 16 countries are working together to coordinate their efforts and demonstrate that technologies based on the FMI standard and the Modelica open modeling language can be successfully applied to the design and operation of buildings and of community energy systems.

The use of the FMI standard in the context of control applications for buildings has been demonstrated by Nouidui et al., (2014). They presented how to import FMI models into the Niagara^{AX} framework®, a platform that allows integration of different building automation systems. Also, the Building Control Virtual Test Bed (Wetter, 2011) allows the import of models compliant with the FMI standard. This allows FMI models to couple with BACnet-compatible building automation systems and with web services, either as a web server or as a client.

The Model-Based FDD Workflow

This section presents the workflow for building FDD based on the FMI standard. We emphasize that the workflow uses models that were developed during design, and thereby leverages the knowledge and experiences accrued while designing the system. By reusing models from the design, users reduce the time and expertise (and therefore, costs) required to set up, develop, and deploy an online FDD system.

Figure 1 shows the workflow. During the design phase, indicated by the green box, designers use their simulation program to design the building and its HVAC systems. The simulation program provides different libraries of models that users can use to design the systems. An example could be using the Modelica Buildings Library (Wetter, 2014) within a simulation program like Dymola (Dassault Systèmes, 2013). In the workflow, this phase does not require any additional effort if simulation models are used to predict the energy performances of the building and its HVAC systems.

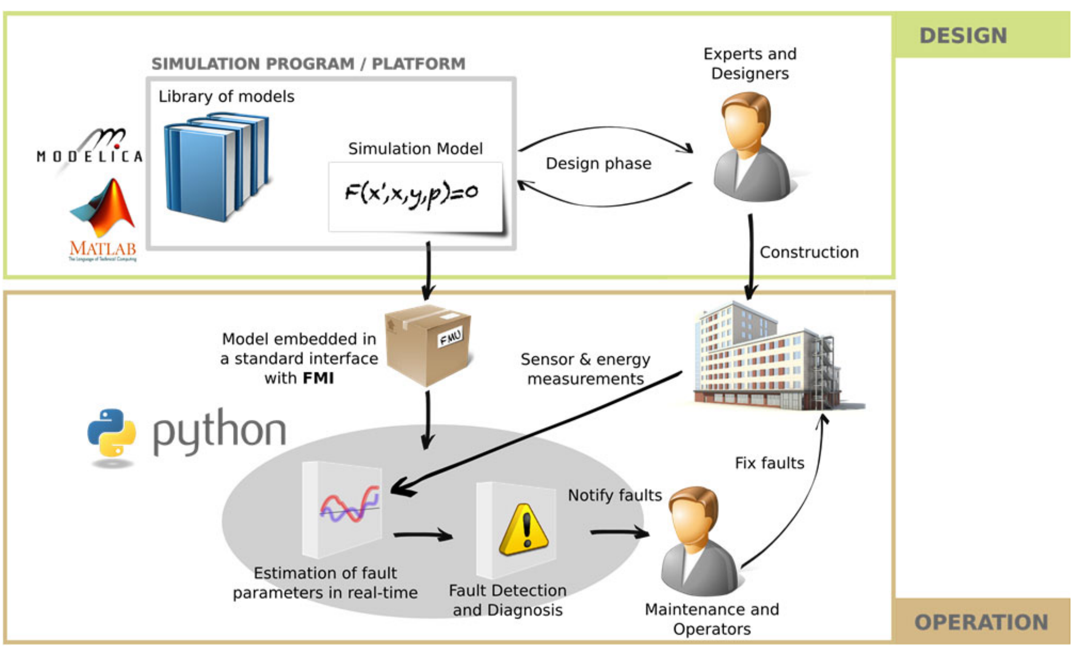

Figure 1. The model-based FDD workflow.

At the end of the design phase, if the results satisfy the design intent, the building is constructed, its HVAC system is commissioned, and the building is occupied. This is indicated in the brown box in Figure 1. An energy information system (EIS) records the performance of the building, and it becomes available to building and to energy managers. The availability of an EIS or any other software that collects and provides data from the building is an essential requirement for developing any FDD system.

Some FDD systems use measurements collected by the EIS system to check whether the building and its HVAC is working as expected. The benefits are twofold: reducing the impact of the faults on the overall energy consumption of the building, and avoiding serious damage to the equipment. During operation the same models utilized in the design phase can be reused by FDD algorithm, the grey circle in Figure 1. This connection between the FDD algorithm and the simulation program is made possible by the FMI standard interface. Once the model is exported, the FDD algorithm uses it together with the data acquired by sensors and instrumentations located in the building to identify faults that increase building energy consumption.

The Model-Based FDD Tool Chain

This section describes the details and the structure of the FDD tool chain, the grey area in Figure 2.

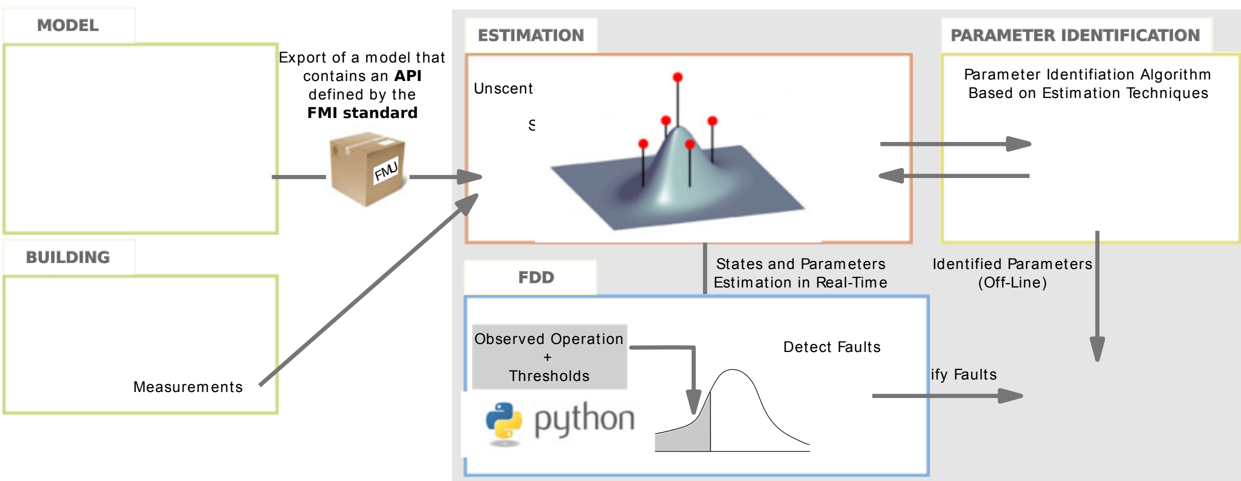

Figure 2. The model-based FDD tool chain.

The tool chain has an interface compliant with the FMI standard that allows the import of models that are exported according to the FMI standard. Such an exported model is called a *Functional Mockup Unit (FMU).* A model that has been developed in a simulation program like Dymola, OpenModelica, or MATLAB/Simulink, can be exported as an FMU and imported in the tool chain for creating the FDD. This way of exporting a simulation model allows other tools to set model parameters, inputs, and initial values for state variables; simulate the model; and retrieve its outputs. The tool chain works with models exported using the FMI standard for Model Exchange version 1.0.

The center of the tool chain is the estimator, the red box in Figure 2. The estimator is an algorithm that uses an FMI model for computing in real-time estimations of state variables and parameters of the physical systems represented by the model. Examples of state variables that can be estimated are temperatures or pressures, while examples of parameters that can be estimated are thermal conductivities or heat exchange coefficients. A smoothing algorithm supports the estimator by improving the quality of the estimations when measurements are noisy.

Our implementation uses the Unscented Kalman Filter (UKF) (Julier, 1996) as state estimator and the Rauch-Tung-Striebel smoother (Sarkka, 2008) as the smoothing algorithm. State variables and parameters can be estimated simultaneously by the UKF using the implementation suggested by Van Der Merwe (2000). Further details about the implementation are described in Bonvini et al. (2014).

Once the state and parameter estimations have been computed, a fault probability needs to be computed. As shown in Figure 2, this step requires additional insights and details about the HVAC system or component that is monitored. This knowledge can be used to define thresholds that, when exceeded, indicate a fault. Once these thresholds have been defined they are used to characterize a fault region that is a subset of the parameter or variable space. Given the fault region, the algorithm computes the probability that the estimated state variables or parameters are within it. The probability is computed assuming the estimated state variables or parameters have a Gaussian probability distribution.

The FDD algorithms that results from the interaction of the components of the tool chain has the following favorable properties:

- Robustness to sensor errors and data availability due to the estimation and smoothing techniques.
- Ability to capture the dynamics of state variables since the approach is based on dynamic models.
- Multiple faults are handled because the physics-based modeling approach allows testing different simultaneous fault scenarios, thereby allowing the identification of each fault's likely cause.
- Limited computational burden.
- It deals with nonlinear models in a generalized way, without performing any linearization or differentiation.
- Standardized interface for plugging new models because it is compliant with the FMI standard. Models developed with general-purpose energy-performance simulation tools such as Dymola and MATLAB/Simulink can be plugged in directly.

Most of these properties are listed as requirements in the final publication of the IEA (International Energy Agency) Annex 34. Annex 34 was an international project focused on the use of computer-aided systems to support the use of FDD for real buildings (Dexter, 2001). If successfully applied, this approach will allow the identification of multiple simultaneous faults that are typically difficult to identify by other methods (Venkatasubramanian, 2003a,b,c) and that in average accounts for 4% to 18% of the annual energy consumption of U.S. commercial buildings (Roth, 2004).

The FDD tool chain has been implemented in Python. The use of common and easily extensible software like Python provides flexibility. The tool chain can range from embedded systems to web-based tools running on a cloud computing platform, depending on the nature and complexity of the application. The connection between the tool chain and the measurements is possible by connecting Python with one of the supported Data Base Management Systems (DBMS) while models compliant with the FMI standard can be coupled using PyFMI, a Python package for simulating models compliant with the FMI standard.

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Application: Analysis of a Chiller

The purpose of this example is to show how to detect faults in a chiller in the presence of condenser and evaporator hydraulic faults and noisy or erroneous measurements. The considered system (see Figure 3) is a subsystem of a real chiller plant for which experimental data, design data, and manufacturer data are available.

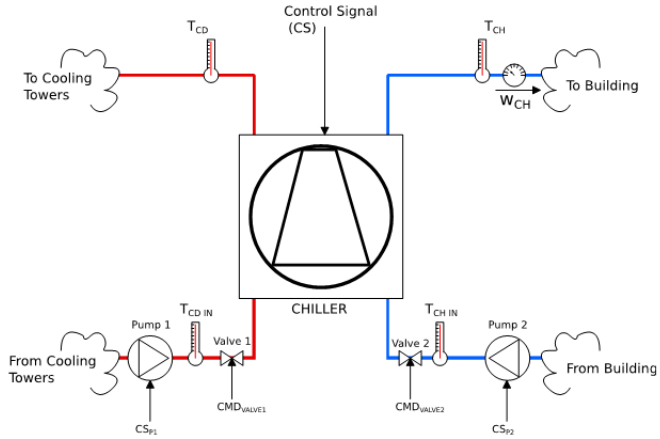

Figure 3. Chiller schematic diagram.

Figure 4 (Left) shows the procedure followed to test the functionalities of the FDD algorithm, represented by the green area. For the purpose of this study, the model was calibrated against experimental data to ensure its accuracy. Rather than testing the proposed FDD tool chain using real measurements, synthetic data generated by dynamic simulation were used (Figure 5). These data were generated in order to introduce, intentionally, multiple isolated and simultaneous faults (of different magnitudes and time scales). The capabilities and robustness of the FDD algorithm have been tested for (1) various levels of noise in the sensor data (evaluating the worst case in which the data are very noisy and sometimes wrong), and (2) typical chiller plant faults. Figure 4 (Right) shows how the FDD algorithm works in a real case scenario when data coming from the plant are directly provided to the estimator.

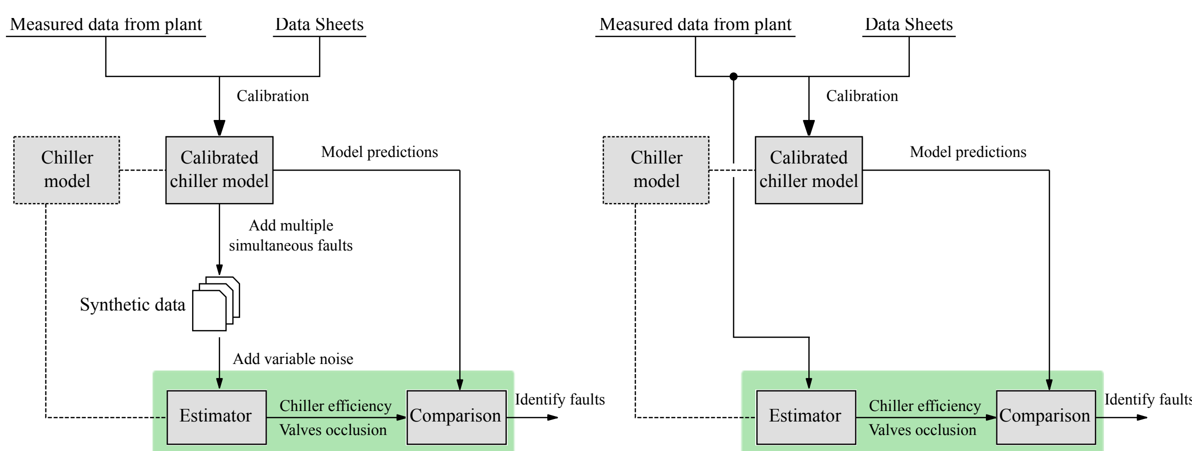

Figure 4. (Left) Procedure used to test the functionalities of the FDD algorithm represented by the green area. (Right) Real case scenario where the data measurements are directly provided to the FDD algorithm.

The following faults have been added to the data, which were then identified by the model plant faults.

- The compressor of the chiller consumed more power than the model predicted.
- The chilled water and condenser water valves are occluded. This was modeled as a modified valve flow coefficient that reduces the water flow rate).

The first step of the proposed process is to develop a continuous time dynamic model of the chiller. The models can be created using predefined models of the open source Modelica Buildings library. The model contains fault variables that have been added to represent a possible fault scenario. The added fault variables are a variable efficiency of the chiller η_{PL} and the fraction of occlusion o_1 and o_2 of the condenser and chilled water valves. The outputs of the model that correspond to the physical quantities measured in the real plant are the condenser and evaporator water temperatures leaving the chiller $T_{CD}(t)$ and $T_{CH}(t)$, and the chilled water mass flow rate w_{CH}.

Figure 5 shows the synthetic data series used to test the proposed FDD algorithm. The solid lines represent the data generated by the simulation, while the scattered points represent simulation data plus a random uniform noise. The synthetic data used in this example have greater noise than typical real data, in order to test the algorithm's robustness with respect to noisy and erroneous data.

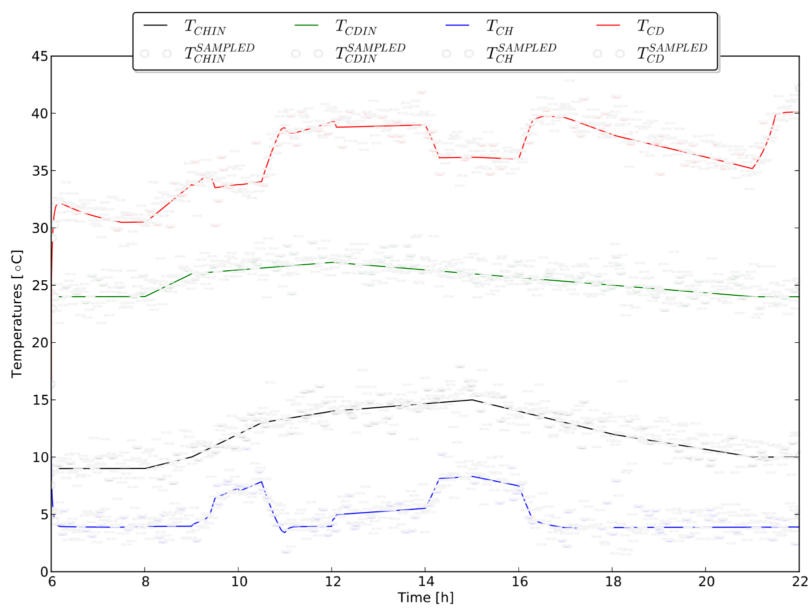

Figure 5. Temperatures of the condenser and chilled water leaving and entering the chiller. The solid lines are simulated data, while the scattered points are noisy data used to test the algorithm.

The chiller has two faults, the first between 9:00 am and 11:00 am and the second between 2:00 pm and 4:00 pm. The chilled water valve has a fault between 10:00 am and 12:00 pm, the condenser water valve starts faulting at 12:00 pm, and the temperature and flow sensors also have faults, between 6:00 pm and 6:20 pm.

Figures 5 and 6 show the results provided by the FDD tool chain. Figure 5 shows the estimation of the fault variables computed by the UKF and the smoother; the blue line represents the ideal efficiency of the chiller that varies depending its working condition. The dotted blue line represents the reduced efficiency that has been affected by the faults. The red and green lines represent the estimation of the chiller efficiency computed by the UKF and the smoother. The red- and green-colored areas around the estimations represent the confidence interval. The estimations are able to detect the reduction in chiller efficiency when the faults are present. Figure 7 shows the fault probabilities and the faults identified using the estimations shown in Figure 6. The red line shows the results based on the estimation of the UKF, while the black line is based on the results provided by the smoother. The results provided by the smoother identify more precisely the presence of the fault.

During the operation of the chiller, other faults occur. For example between 10:00 am and 12:00 am the chilled valve is occluded, while between 06:00 pm and 06:20 pm the sensors provide wrong measurements due to a noise level higher than usual (see Figure 4). All these faults have a limited impact on the ability of the FDD algorithm to correctly identify when the chiller is faulting. The red lines in Figure 7 are slightly affected by those external faults; however, the results computed by the smoother are not affected by these events. Even if there is no measurement of the condenser water mass flow rate, the results show that the FDD algorithm is able to identify faults in the condenser water loop (i.e., identified as the fraction of valve that is occluded).

This application shows how the tool chain for model-based FDD can be used to detect multiple and simultaneous faults in presence of noisy and erroneous measurements.

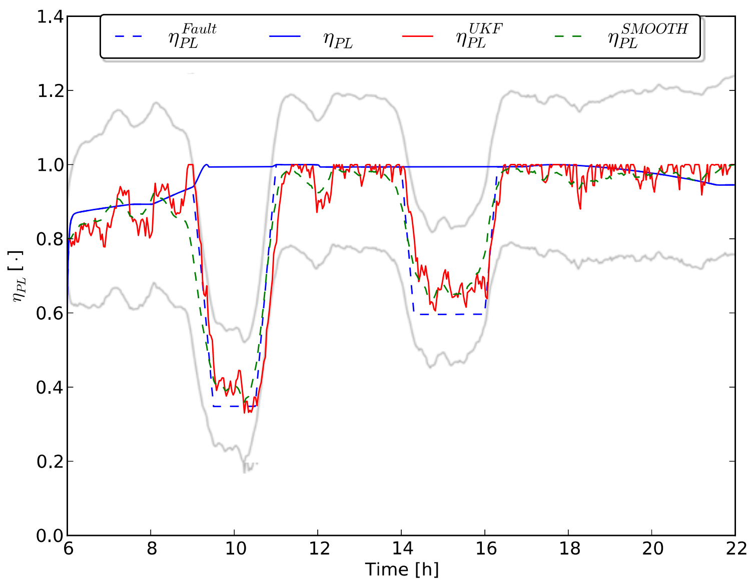

Figure 6. Estimation of the chiller efficiency. The blue line represents the ideal chiller efficiency; the dotted blue line represents the modified chiller efficiency representing a fault. The red and the green lines represent the estimation of the efficiency using the UKF and the smoother. The red- and green-colored areas are the confidence intervals of the estimations.

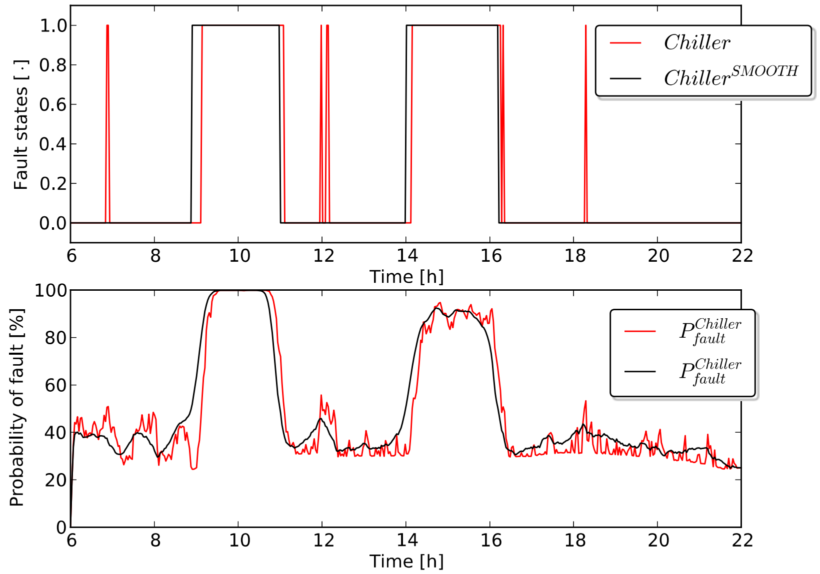

Figure 7. The plot on the top shows the presence of a fault in the chiller, while the plot on the bottom shows the probability that the chiller is faulting. Red lines are obtained using the results provided by UKF, while black lines are obtained using the results computed by the smoother.

Conclusions

Fault detection and diagnostics techniques could reduce the energy consumption of commercial and residential buildings, but the implementation of these techniques is not yet standard practice in the buildings industry. Most FDD techniques that are used in buildings are rules-based methods derived from experience. Fault detection and diagnostics techniques based on models can improve the robustness with respect to measurements errors, transient operations and multiple simultaneous faults.

This work presented a tool chain for model-based FDD. It uses in the FDD algorithm models that may have been used during the design. This contributes to bridging the gap between models used during the design phase and the operational phase.

The authors are developing the tool-chain for model-based FDD within a project in collaboration with the U.S. Department of Defense. The project focuses on district cooling plants where multiple chillers and components like pumps, valves, and controls are working together. This work leverages the Modelica Buildings library, an open-source library developed by LBNL that contains more than one hundred models for building energy and control systems. This project focused on chillers but it could be extended to almost any system for which models are available. If a model is not available, it could be created ad hoc with a limited effort—an advantage not available for similar energy simulation programs (e.g., EnergyPlus, DOE-2). The authors are coupling the model-based FDD tool chain with an EIS. Once the tool chain is fully developed, it is expected to be easy to reuse it in other contexts because the overall architecture uses an abstract representation of physical systems.

The authors believe that this tool chain will reduce the effort required to create model-based FDD approaches for buildings and HVAC components, easing its adoption in the engineer community.

Acknowledgments

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