A fuzzy Petri net based mode identification algorithm for fault diagnosis of complex systems

Nicholas C. Propes and George Vachtsevanos
Georgia Institute of Technology, 777 Atlantic Drive, Atlanta, GA USA 30332

ABSTRACT

Complex dynamical systems such as aircraft, manufacturing systems, chillers, motor vehicles, submarines, etc. exhibit continuous and event-driven dynamics. These systems undergo several discrete operating modes from startup to shutdown. For example, a certain shipboard system may be operating at half load or full load or may be at start-up or shutdown. Of particular interest are extreme or "shock" operating conditions, which tend to severely impact fault diagnosis or the progression of a fault leading to a failure. Fault conditions are strongly dependent on the operating mode. Therefore, it is essential that in any diagnostic/prognostic architecture, the operating mode be identified as accurately as possible so that such functions as feature extraction, diagnostics, prognostics, etc. can be correlated with the predominant operating conditions. This paper introduces a mode identification methodology that incorporates both time- and event-driven information about the process. A fuzzy Petri net is used to represent the possible successive mode transitions and to detect events from processed sensor signals signifying a mode change. The operating mode is initialized and verified by analysis of the time-driven dynamics through a fuzzy logic classifier. An evidence combiner module is used to combine the results from both the fuzzy Petri net and the fuzzy logic classifier to determine the mode. Unlike most event-driven mode identifiers, this architecture will provide automatic mode initialization through the fuzzy logic classifier and robustness through the combining of evidence of the two algorithms. The mode identification methodology is applied to an AC Plant typically found as a component of a shipboard system.

Keywords: mode identification, fuzzy Petri net, fault detection and identification

1. INTRODUCTION

Mode identification addresses the problem of determining the operating mode of a system through incoming sensor data. Modes of a system switch through the occurrence of an event. These events are triggered when controller input changes are applied to the system and/or when the state of the system moves into certain regions of the state space. For example, modes for a ship chiller system could be startup, low load, overload, full load, and shutdown modes. These modes switch by extracting features describing events from sensor signals. Figure 1 shows a mode diagram where circles are modes and arcs represent conditions that cause transitions.

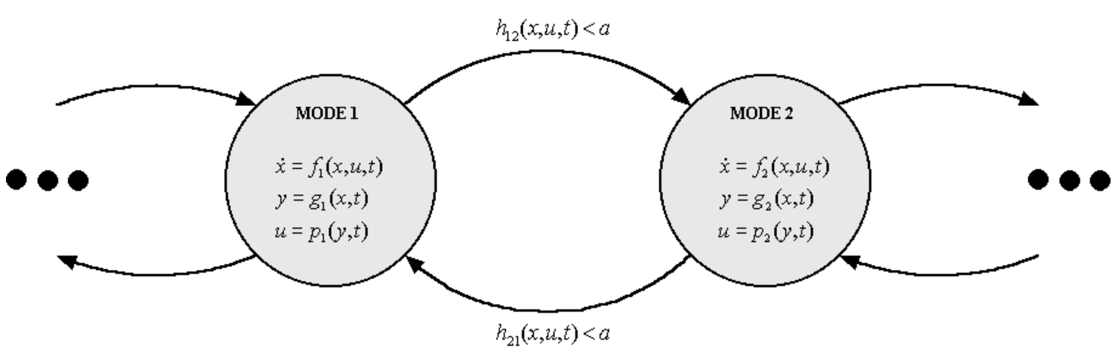

Figure 1. A mode diagram.

Koustsoukos et al [3] describe a mode identification framework for a laser printer. They assume that the printer is running in a sensor rich environment. It contains sensors that relay discrete signals, which, in turn, trigger controls while

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audio and current sensors are used to determine the mode. Measured signals are assumed to be a linear superposition of template signals:

$$y_i(t) = \sum_{j=1}^{n} \alpha_{ij} s_j (t - \tau_{ij}), i = 1, \ldots, l \qquad (1)$$

where,

- y_i is the i^{th} measured signal
- s_j is the j^{th} template signal for mode identification
- τ_{ij} is the onset of the template, s_j, for the i^{th} measured signal
- α_{ij} the sensor gain of template, s_j, for the i^{th} measured signal

Using the coefficients α_{ij} and τ_{ij}, conditional probability distributions can be constructed to estimate the new mode based upon measured signals. This type of framework ignores the event information from the sensors that provide the discrete signals. Moreover, the continuous signals themselves are not directly associated with the dynamics of the machine (i.e. audio sensors do not measure the velocity of a drum directly). A methodology that incorporates both event information and dynamics classification would provide a more accurate determination of the operating mode.

By first identifying the operating mode of the system, fault detection and identification can reduce the number of false positive fault detections and reduce the computational burden. It is not necessary to examine all failure modes while in a particular operating mode. For example, while in shutdown operating mode, it may not be necessary to detect failure modes such as evaporator tube freezing. By reducing the failure mode search, certain features need not be extracted from sensor data and some classifiers need not be executed.

2. METHODOLOGY

The mode identification architecture is composed of three separate modules, a fuzzy logic classifier, a fuzzy Petri net, and an evidence combiner module, as shown in Figure 2. The fuzzy logic classifier is used to determine the mode by examining the features describing the dynamics of the process. The fuzzy Petri net is used to determine the mode by detecting events. The evidence combiner combines the results of the fuzzy classifier and fuzzy Petri net and then outputs the identified mode. Therefore, this mode identification scheme combines both events and dynamics information to determine the current operational mode of the system. This section describes all three of these modules in detail.

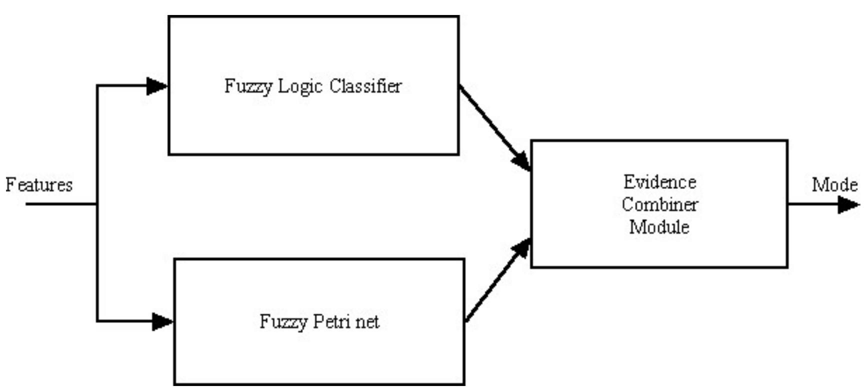

Figure 2. The mode identification architecture.

2.1 Fuzzy Petri Net as a Mode Identifier

The fuzzy Petri net has the ability to incorporate uncertainty in the detection of an event and a structure representing the relations between modes and events. Events have a degree of uncertainty associated with them and many can be expressed as if-then rules. Each mode will have a possible set of transitioning modes described by the net structure thus reducing the search space.

Events can occur from external inputs through a user, autonomously through control signals and system state variables, failures, etc. In many hybrid system frameworks, events occur when a function of the state and control variables crosses a threshold value that causes a transition from the current mode to another. Examples of event definitions are “the temperature is decreasing slowly below 80 degrees”, “the part arrived at the robot station”, “the mill has started cutting”, “the conveyor has blown a fuse”, etc.
The fuzzy Petri net is used to determine the current operating mode by detecting events signifying a switch in the operating modes. It consists of two parts, the structure of the net and the fuzzy membership function associated with each transition.

The fuzzy Petri net structure is composed of places which represent the operating mode, transitions which represent events, and arcs which describe how modes change due to events. A simple structure is shown in Figure 3.

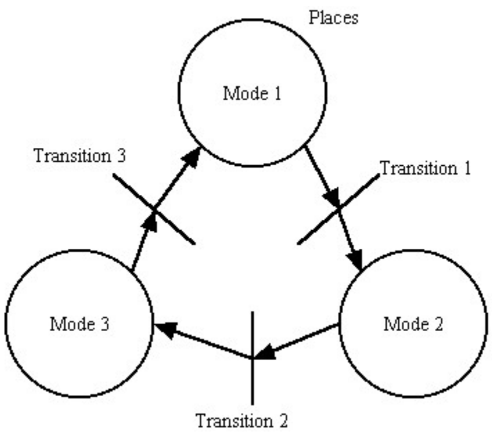

Figure 3. A Petri net structure.

The modes in the Figure 3 describe three operating modes and three transitions that determine how modes are related to each other due to events. For illustration purposes, if the past mode was Mode 1, then the only possible transition is to Mode 2 for the next mode if the event corresponding to Transition 1 fires. Two matrices are used to describe the arcs from places to transitions and arcs from transitions to places. The Input Matrix describes arcs from places to transitions and consists of the dimension, # of places by # of transitions. For the example above, this matrix would be:

$$InputMatrix = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

The Output Matrix describes arcs from transitions to places and consists of the dimension, # of place by # of transitions. For the example above, this matrix would be:

$$OutputMatrix = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{3}$$

The possible modes that can be transitioned to from an identified mode can be determined by subtracting the input matrix from the output matrix and determining which transitions can be fired.
Each transition also has at least one fuzzy membership function describing the possibility that the event has been fired due to some input features. There is also a threshold on the possibility that determines whether or not the event has

fired. If the resulting possibility is greater than or equal to the threshold, then the transition has fired. It is also important to know which side the input signal comes from towards the membership function, as shown in Figure 4.

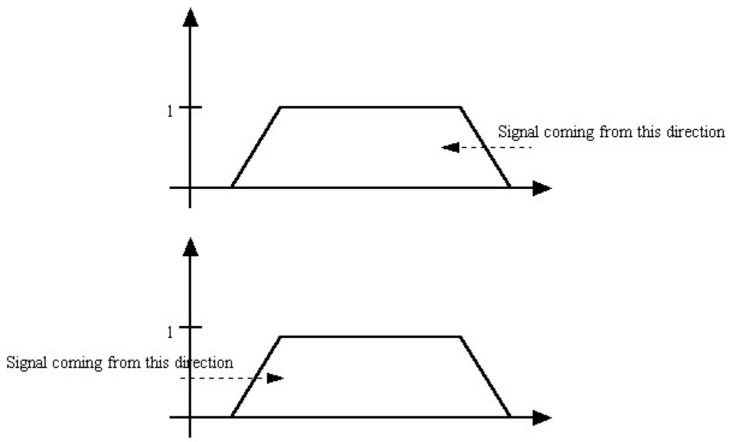

Figure 4. The direction corresponding to the membership function.

To determine the possibility that the system is in a certain mode, it is required that the possibility before and after the condition be examined. The possibility before the condition is calculated by extending the membership function to the max value in the opposite direction of the signal and then evaluating this modified membership function, as in Figure 5.

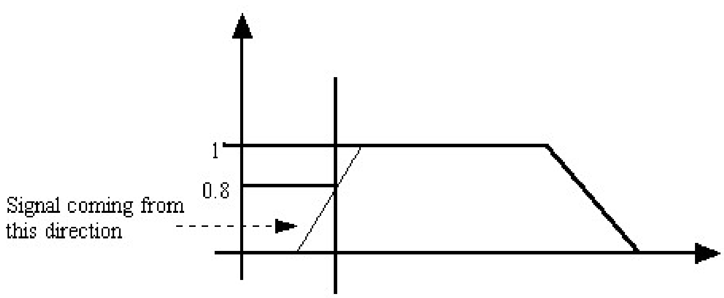

Figure 5. Possibility before the condition.

The possiblity after the condition is calculated by extending the membership function to the max value in the direction of the signal and then evaluating this modified membership function, as in Figure 6.

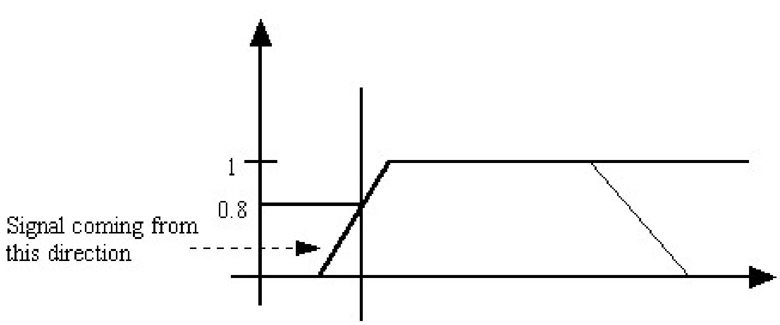

Figure 6. Possibility after the condition.

The max is taken from each set of modes from the before and after possibilities. Each possible transition from the past mode is evaluated in this manner.

2.2 Pattern Classification as a Mode Identifier

In this section, a classification technique based upon the system dynamics is presented. It is assumed here that every mode has unique features from sensor signals and set-points characterizing the dynamics. Since events are sometimes difficult to detect, this module acts as a verification to the fuzzy Petri net classifier of the previous section. Mode identification through dynamics will proceed first by extracting features from incoming sensor and control signal data. The incoming feature data is then classified through some type of pattern recognition algortihm such as a fuzzy logic rulebase or artificial neural net to determine the mode.

Features are extracted by a feature extraction module and placed into the diagnostics/prognostics database. The fuzzy logic classifer loads the required features from a database and then determines the current operating mode through a Mamdani inference engine, as shown in Figure 7.

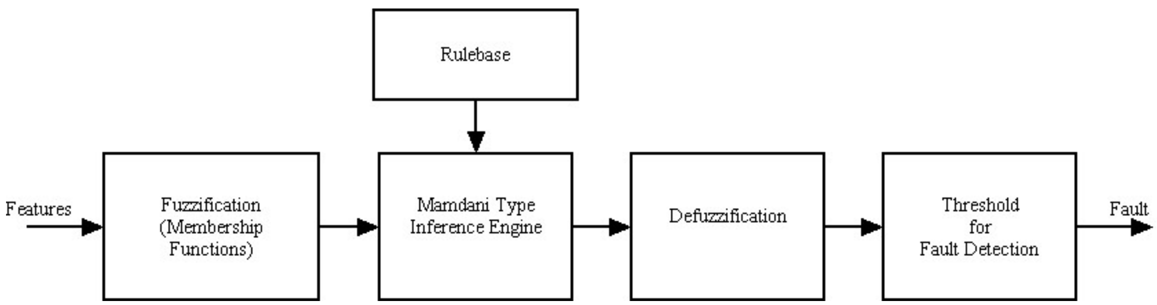

Figure 7. The Fuzzy logic classifier.

The fuzzification process fuzzifies the incoming features to values in the range of [0,1] through a membership function. This determines the degree of membership that an element belongs to a particular fuzzy set. For example, the fuzzy set "Very High" may have a membership function as shown in Figure 8.

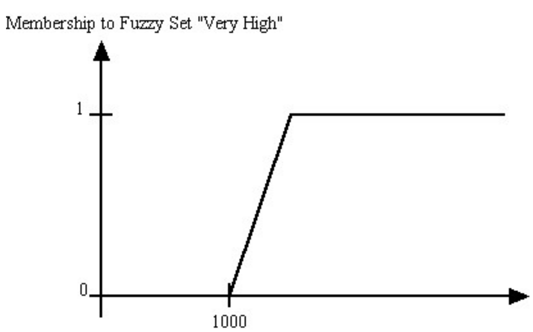

Figure 8 Membership function for fuzzy set "Very High"

In general, membership functions can come in a wide variety of shapes, however, the membership function selection has been limited to a generic set of five shapes: triangular, trapezoidal, Gaussian cure, difference of two sigmoids, and bell shaped. Parameters are provided to allow for modification of the position, width, etc. of these shapes for different fuzzy sets.

Expert information about the symptoms of failures is used to create both the membership functions and the rules to detect failures. Examples of such rules are:

If the *Tank Level Noise Level is High* and the *Tank Level Slope is Large Negative*
then the *Current Operating Mode is Mixer-and-Pump On*
If the *Tank Level Slope is Large Negative*
then the *Current Operating Mode is Pump On*

For each rule, Mamdani type implication is performed which takes the form of equation 4 for the generic rule, If *A* then *B*.

$$\mu_R(x,y) = \max\{\min[\mu_A(x), \mu_B(x)], 1-\mu_A(x)\} \tag{4}$$

where, $\mu_R(x,y)$ is the result of the implication, $\mu_A(x)$ is the input membership function for fuzzy set, *A*, and $\mu_B(x)$ is the output membership function for fuzzy set, *B*.

Output membership functions such as (*Current Operating Mode is Mixer-and-Pump On*) and (*Current Operating Mode is Pump On*) are defined on the universe of discourse within the range [0,100]. This is to convey the belief that a rule will correctly determine the operating mode.

After the Mamdani implication has been performed for each of the rules for a particular failure, a union (Maximum type, OR) operation is performed upon all the resulting membership functions. This results in a single fuzzy set, $\mu_C(z)$. Following these operations, a centroid type defuzzification is performed upon the resulting membership functions as in equation 5.

$$Z = \frac{\int \mu_C(z) z dz}{\int \mu_C(z) dz} \tag{5}$$

2.3 Evidence Combiner

The evidence combiner module combines the possibilities of both the fuzzy classifier and fuzzy Petri net to determine the mode. The combination involves the multiplication of the possibilities of each mode from the separate modules. This is also known as an AND operation, as in a fuzzy logic rule. The mode corresponding to the maximum value from this result then is chosen to determine the mode.

2.4 The Mode Identification Software Architecture

The mode identification software architecture is shown in Figure 9. The past operating mode is read in from a stored location to initialize the mode of the system. The fuzzy classifier module is then run to determine the new operating mode. If this is the first run of the mode identification module then, only the fuzzy classifier is run to determine the mode, else the fuzzy Petri net proceeds to identify the mode based on events. Next, the evidence is combined from both the fuzzy classifier and fuzzy Petri net.

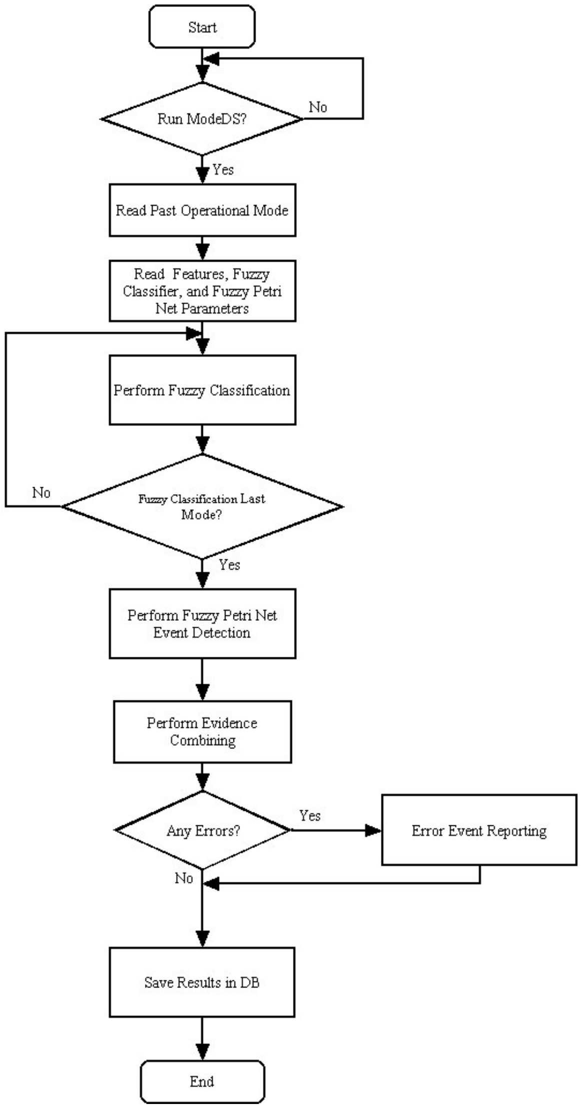

Figure 9. The mode identification software operational chart.

3. RESULTS

Mode identification was performed on simulated data for a ship chiller system. The discrete chiller operating modes and their relations are shown in the mode diagram (Fig. 10) and were derived from a FMECA study. Failures to be detected and identified are associated with each mode. Each mode also has information describing the sensor conditions while in each mode.

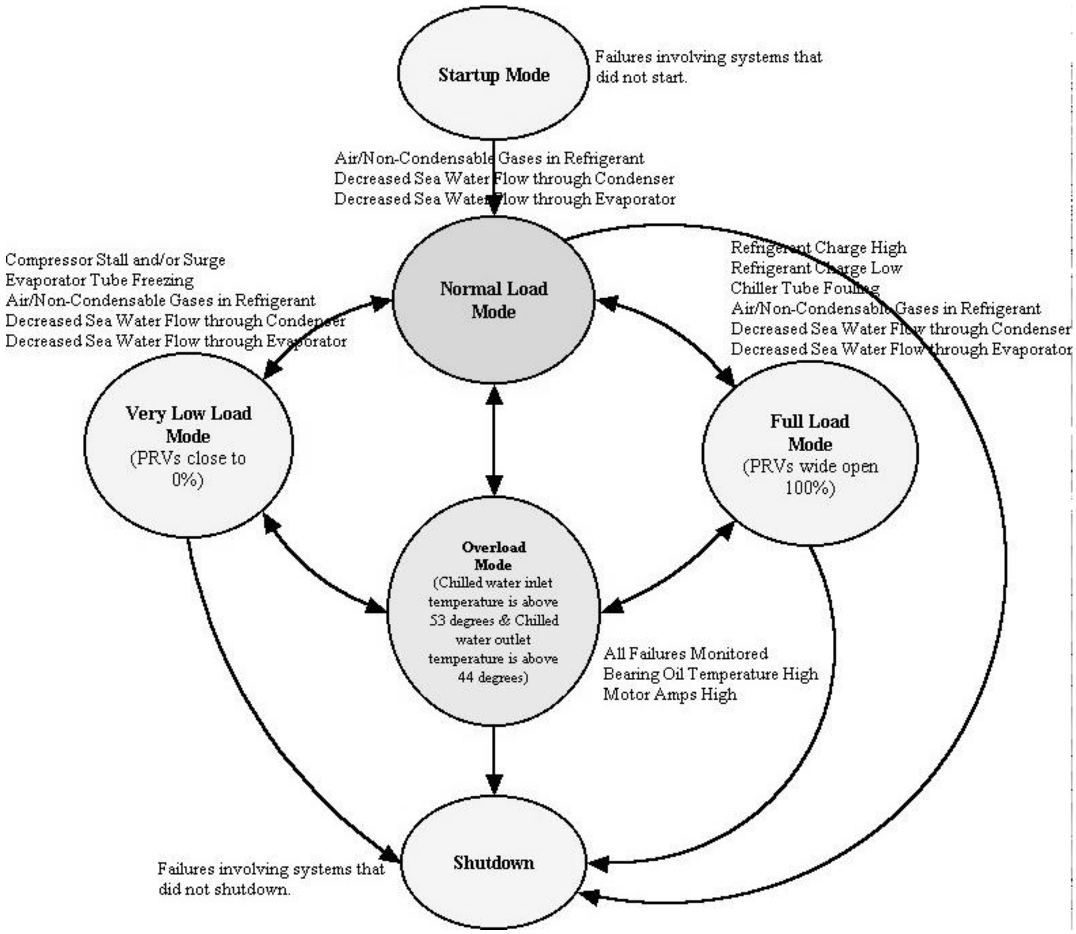

Figure 10. A ship chiller mode diagram.

Simulated sensor signals for PRV rotation (starting at 50), chilled water inlet temperature (starting at 30), and chilled water outlet temperature (starting at 25) are shown in Figure 11.

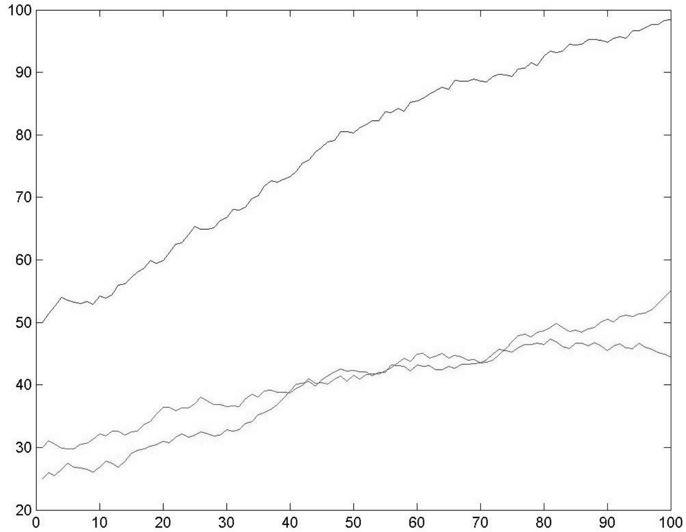

Figure 11. PRV rotation, chilled water inlet temperature, and chilled water outlet temperature.

The possibilites of different modes (signals between 0 and 1) and the identified mode (integers 1,2,3,4,5, and 6) extracted from the mode identifier are shown in Figure 12.

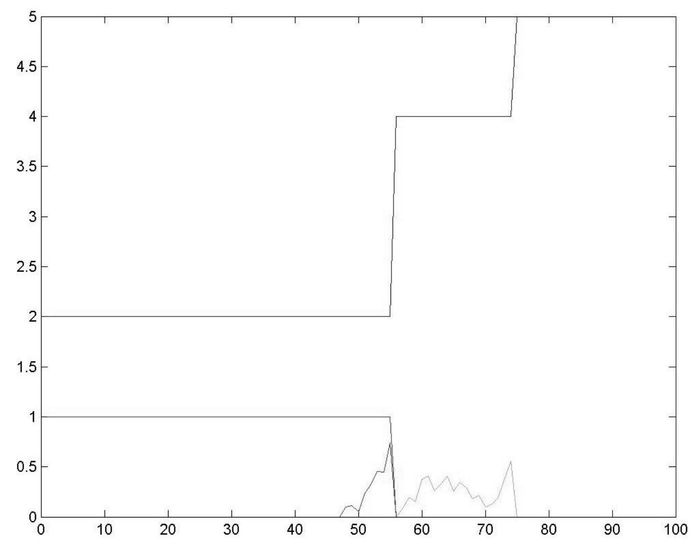

Figure 12. Possibilities of different modes and identified modes.

The modes are correctly identified from the data provided. The mode switches from normal mode (2) to full load mode (4), and from full load mode (4) to overload mode (5). The normal mode switches to full load mode because the PRV rotation grows past 75 %. The transition from full load to overload mode is due to the inlet and outlet water temperatures increasing past 53 and 44 degrees F, respectively.

4. CONCLUSIONS

The mode identification methodology provides a robust way of identifying the current operating modes for a wide variety of systems by combining both event and dynamics information. The fuzzy logic classifier identifies the mode by examining features describing the dynamics of the system and can also be used to initialize the mode upon start up of the mode identification module. The computational burden can be reduced for fault detection and identification modules by detecting the operating mode by associating failure modes with operating modes.

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