Robust Model Selection Decision-making using a Fuzzy Supervisory Approach

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Abstract—Industrial machinery/assets are usually operated under different operating conditions or modes. Local empirical models can be built within specified operating condition boundaries to represent system dynamics more accurately than a global model, which is generally applicable over the entire operating regime. However, when the change of system operating regime occurs, none of local models can capture the characteristics of the system outside of the operating condition boundaries they were built upon. This paper presents a novel approach to model selection decision-making based on a fuzzy supervisory approach. The supervisory method selects local models and fuses these models to represent system dynamics as system transits from one operating regime to another. Through this fuzzy supervisory approach, the modeling errors caused by an operating regime switch can be significantly reduced. We present experimental results from the application of this approach to high bypass commercial aircraft engine.

I. INTRODUCTION

CONDITION based maintenance (CBM) has recently been the growth driver to remote monitoring service business in both commercial and military platforms to assure asset readiness and minimize total ownership cost while increasing operation safety margin. One of key enabling technologies of CBM is anomaly detection (AD), which typically triggers follow-on diagnosis process if anomaly is found. It involves monitoring change to system state to detect "anomalous" behavior. Timely and reliable detection of anomaly that indicates faulty conditions can help in early fault diagnostics. This will allow for timely maintenance actions to be taken before the fault progresses and before it causes secondary damage to the system leading to system downtime.

Among many ways to detect anomalies in complex industrial system with multiple sensor feeds, one effective approach is to build a system model to capture the dynamics of system, which can provide the estimation of the sensor values under normal operations. Further analysis, such as statistical tests and machine learning techniques can then be performed on residuals between raw sensor measurements and sensor estimations by the system model. Depending on aggregated measure on residuals and predefined threshold, alert may be generated to inform occurrence of "anomalous" behavior of system. As for the system model, it can be physics-based, which is usually defined by a set of governing physical laws with a set of controlling factors as independent variables, or so-called model parameters. To build physics-based model (PBM) requires thorough domain knowledge of system. This is sometimes difficult to acquire. Legacy critical assets/systems are more likely to have PBM available. For systems without PBM, it is necessary to derive an empirical (data-driven) system model from historic data. There are a variety of computational intelligence (CI) techniques in the literature, including neural networks, fuzzy logic, support vector machine and etc. to build models that capture system dynamics empirically. Empirical approaches are applicable generally across platforms, and the focus of anomaly detection in CBM, and consequently of this paper.

As industrial assets are usually operated under different operating regimes or modes, under which systems may behave quite differently, it is necessary to build local models within specified operating regimes. Typically, these local system models together can represent system dynamics more accurately than a global model, which is built on the entire operating regime. However, when the operating regime of the system transits, especially at the boundary or in-between of local regimes, none of these local models can represent characteristics of system sufficiently and it is when the residuals will most likely exceed predefined alerting thresholds and cause false alarms. One way to mitigate the false alarm problem is to identify the changes of operating regimes and to ignore all the alarms generated during the transition phase. But this will cause interruption of condition monitoring process and might neglect the true alarms that indicate faults.

It is clear that, beside true system anomalies, there are other causes that could trigger similar anomalous behaviors. Sudden operational transients, faulty sensors, and inadequate AD models could all produce changes that could be similarly misinterpreted as system anomalies. Operational transients can be tracked and explained away by monitoring state trajectories and comparing them with typical steady state regimes (e.g., clusters in the state space). Faulty sensors usually produce signatures/residuals that profoundly affect the variable being measured by the sensor, when compared with the other variables. This situation can be disambiguated by using specialized modeling techniques, such as the Auto-associative neural networks (AANN), which we will

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describe in Section II B. These techniques provide virtual sensor outputs that, when compared with actual sensor readings, help us in the identification of sensor faults. Therefore, we are now left with the third cause of spurious anomaly signatures: inadequate AD models. The best way to prevent this situation is to resort to a model design that is complete (for coverage), high-fidelity (for accuracy), and transparent (for maintainability).

This paper focuses on the tradeoff designs for such model. We want to guarantee coverage throughout the state space by developing many local AD models, each of which has been trained on overlapping regions of the state space. We develop each model with techniques that minimize its variance within its region of competence. Finally, we capture the criteria for model applicability by using a fuzzy supervisory model approach that leverages linguistic fuzzy rules to integrate local models to better represent system dynamics as system transits from one operating regime to another. Through this fuzzy supervisory approach, the magnitude of residuals caused by the operating regime transition can be significantly reduced so that false alarms can be avoided.

The remainder of the paper is organized as follows. Section II introduces some backgrounds that suffice the fuzzy supervisory model approach, including the physics-based model that simulate aircraft engine, auto-associative neural network (AANN) that models the system in local regimes and the basics of fuzzy logic. Section III presents the fuzzy supervisory model approach and the experimental results on data from aircraft engine model. We then discuss the constraints and potential improvement of the technique in Section IV. Section V concludes the paper at the end.

II. BACKGROUND

A. Physics-Based Model

To demonstrate the feasibility of the proposed fuzzy supervisory approach and more conveniently control the transition of operational regimes, we leveraged a Component Level Model (CLM). It is a physics-based thermodynamic model that has been widely used to simulate the performance of a commercial aircraft engine. Flight conditions, such as altitude, Mach number, ambient temperature, and engine fan speed, and a large variety of model parameters, such as module efficiency and flow capacity are inputs to the CLM (see Fig. 1). The outputs of the CLM are the values for pressures, core speed and temperatures at various locations of engine, which simulate sensor measurements. Realistic values of sensor noise can be added after the CLM calculation. In this study, a steady state CLM model for a commercial, high-bypass, twin-spool, turbofan engine is used. We can manipulate flight conditions to simulate different operation regimes (i.e. flight envelopes of aircraft) and generate data corresponding to them.
to develop a compact representation of the input data, and two additional hidden layers.

Because of its auto-association property, AANN can be used to infer nominal sensor values from raw measurements when information in the measurements is analytically redundant in the sense that if one measurement is missing, it can be replaced with an estimate from the remaining valid sensors [2]. In [3], we used AANN to estimate sensor measurement under normal conditions and then the residual between raw measurement and normal measurement can be used to infer conditions of the component/system.

C. Fuzzy Logic

There are a number of references devoted to fuzzy logic and its use in rule-based approximate reasoning [4]. Fuzzy logic (FL) gives us a language, with syntax and local semantics by which we can translate qualitative knowledge about the problem to be solved. In particular, FL allows us to use linguistic variables to model dynamic systems. These variables take fuzzy values that are characterized by a label (a sentence generated from the syntax) and a meaning (a membership function determined by a local semantic procedure). The meaning of a linguistic variable may be interpreted as an elastic constraint on its value. These constraints are propagated by fuzzy inference operations, based on the generalized modus-ponens. This reasoning mechanism, with its interpolation properties, gives FL a robustness with respect to variations in the system's parameters, disturbances, etc., which is one of FL's main characteristics.

The most common definition of a fuzzy rule base R is the disjunctive interpretation initially proposed by Mamdani [5] and found in most Fuzzy Controller applications

\[
R = \bigcup_{i=1}^{m} r_i = \bigcup_{i=1}^{m} (\bar{X}_i \rightarrow Y_i) \tag{1}
\]

R is composed of a disjunction of m rules. Each rule defines a mapping between a fuzzy state vector and a corresponding fuzzy action. The Cartesian product operator represents each rule.

The inference engine of a FC can be defined as a parallel forward-chainer operating on fuzzy production rules. An input vector \( \bar{I} \) is matched with each n-dimensional state vector \( \bar{X}_i \), i.e., the Left Hand Side (LHS) of rule \( (\bar{X}_i \rightarrow Y_i) \).

The degree of matching \( \lambda_i \) indicates the degree to which the rule output can be applied to the overall FC output. The main inference issues for the FC are: the definition of the fuzzy predicate evaluation, which is usually a possibility measure [6]; the LHS evaluation, which is typically a triangular norm [7]-[9]; the conclusion detachment, which is normally a triangular norm or a material implication operator; and the rule output aggregation, which is usually a triangular conorm for the disjunctive interpretation of the rule base, or a triangular norm for the conjunctive case. Under commonly used assumptions we can describe the output of the Fuzzy System as

\[
\mu_{r_i}(y) = \max_{j=1}^{n} \{ \min(\lambda_j, \mu_{Y_j}(y)) \} \tag{2}
\]

where \( \lambda_i \) is the degree of applicability of rule \( r_i \)

\[
\lambda_i = \min_{j=1}^{n} \Pi(X_{i,j}, I_j) \tag{3}
\]

and \( \Pi(X_{i,j}, I_j) \) is the possibility measure representing the matching between the reference state variable. These three equations describe the generalized modus-ponens [10], which is the basis for interpreting a fuzzy-rule set.

III. FUZZY SUPERVISORY MODEL

In general, when a system is operated under different operating regimes, multiple local system models built within individual operating regimes can represent system dynamics more accurately than a global model, which is built to be generally applicable over the entire operating regime. AANN can be one realization of empirical local models because of its autoassociation property. It embeds system dynamics through training into network weights matrix. If the system operates normally in the regime, where the AANN model was built upon, the sensor estimations from AANN output should approximately be the same as raw sensor measurements, resulting in very small residuals. Conversely, if the system operated outside of its defined operating regime, large residuals are usually generated indicating "anomalous" behavior and triggering alerts. Multiple AANNs can be customized and trained individually to model system within multiple operating regimes of system, respectively. However, none of these local models can accurately capture system dynamics as system transits from one operating regime to another. In this case, residuals generated during the transition phase will most likely exceed the prespecified alarming threshold and cause false alarms. One common solution deployed to this problem is to ignore the alarms if it is known that the system is undergoing operating regime transition phase. One disadvantage of this approach is it causes the interruption of system monitoring using local models and having the risk of missing true fault alarms generated during the transition phase. In this section, we describe the use of fuzzy logic to write rules for a supervisory model to control the transition of local models when operating regime changes. Then we demonstrate the proposed approach using data generated from a cycledeck model of aircraft engine.
Figure 3. The illustration of system operating regime transition – across 3 flight envelops (FE).

Leveraging cycledeck model, within the normal flight regimes, we specified three flight envelops (FE) within the typical cruise flight regime, defined by altitude (ALT), ambient temperature (T1A) and mach number (XM) to represent three local operating regimes. Three AANNs with same structure as 9-5-3-5-9 can be built to model local dynamics within individual operating regimes. By configuring the cycledeck model parameters, which includes ALT, T1A, XM, model efficiency and flow, simulated sensor measurement data (9 sensor variables are selected in this study) can be acquired. The training of AANN has two phases. Phase one trains the network using normal data. Phase two involves the modification of training set to include false data in the sense of faulty measurement. After the local AANN models are properly trained, a new set of data were generated to simulate the transition of operating regimes along the trajectory depicted in Fig. 3(b). Fig. 3(a) shows the values of flight envelope variables through the transition phase. The scales of all the plots are intentionally left out to protect proprietary information.

Fig. 4 defines the fuzzy membership functions for "Low", "Medium" and "High" of flight envelope variables. Then we can specify a set of fuzzy rules, such as the ones described in the table in Fig. 5, which describe the applicability of local models under different operating regimes defined in fuzzy terms. Fig. 5 depicts the scheme of using a fuzzy supervisory approach to control the fusion of local models and assure the smoothness of residuals by interpolation as operating regime transits. Raw sensor measurements are presented to three local AANN models to generate the residuals, respectively. The three variables (T1A, ALT and XM) that define operating regimes are fed through the fuzzy rule set to determine the applicability of each local AANN model. The normalized applicability of each model is then used to perform a weighted average of the residuals from each individual local model to generate an integrated residual. Alerts should be issued only if the integrate residual exceeds predefined thresholds regardless of the behavior of residuals from individual local models.

In Fig. 6 (a) – (c) we show examples of residuals between actual sensor measurements and estimations from local model AANN-1, AANN-2 and AANN-3, respectively as the flight regime transits along the trajectory defined in Fig. 3. Note that each variable has the same range in y-axis of each subplot. Clearly, a local model can only minimize the residuals within the flight regime, which it was trained for. However, the fuzzy supervisory model can leverage the superiority of individual local models in the flight regimes, which they were built upon and blend the output of local models to ensure the smoothness of residuals during operating regime transition phase.

Figure 4. Fuzzy membership function for variables defining flight operating regimes.
Figure 5. The scheme of model selection/fusion by fuzzy supervisory model.

\[
w_j = \prod_{k=1}^{3} v_{j,k}(\text{Input}_k)
\]

Operating regimes

Raw Sensor Measurement \( X \)

Local Models

\( Y(AANN_1) \)

Residuals Generation

\( R_i(AANN_1) = X_i - Y_i(AANN_1) \)

\( Y(AANN_2) \)

Residuals Generation

\( R_i(AANN_2) = X_i - Y_i(AANN_2) \)

\( Y(AANN_3) \)

Residuals Generation

\( R_i(AANN_3) = X_i - Y_i(AANN_3) \)

Aggregated Residuals of multiple local models

\[
\hat{R} = \sum_{j=1}^{3} w_j \times R_i(AANN_j)
\]

\[
= \frac{1}{\sum_{j=1}^{3} w_j} \sum_{j=1}^{3} w_j \times R_i(AANN_j)
\]
To automate the detection process, we suggest normalizing the residuals of variable $i$ at data point $j$: $R_{ij}$ using the average of the raw data measurements, i.e.: $E_{ij} = R_{ij} / \overline{X}_i$, where $\overline{X}_i$ is the average of variable $i$. Then we can use a figure of merit (FOM) such as

$$FOM = \sqrt{\frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (R_{ij} / \overline{X}_i)^2}$$

where $n$ is the number of variables and $m$ is the number of data points, to evaluate the overall magnitude of the residuals. If $FOM$ is smaller than a prespecified threshold, we can declare that no anomalies are present. Otherwise, the anomaly is detected. When there is a large (in percentage) residual only from one particular variable, we identify the anomaly as a sensor fault. When residuals from all the variables are larger than the baseline but are roughly equally contributing to the $FOM$, then there are two possibilities:

1. It is a system fault; or
2. The set of local models are not sufficient to capture the system dynamics (i.e., the current local models were trained in different regions of operating regimes from the one where the test data have been extracted.)

When it is the second case, additional local operating regimes might need to be identified and additional local models will need to be built to better capture local characteristics of system.

IV. DISCUSSIONS AND FUTURE WORK

A. Prerequisite of Deployment of AANN

AANN model leverages covariance information to reconstruct the network input. For it to work properly, there has to be dependencies (correlations or interactions) among the variables being monitored. This prerequisite is generally met for most of complex industrial systems we are interested, such as sensor data collected from turbine, aircraft engine and etc. However it is worthwhile to confirm the correlation of system-associated variable before applying AANN.

B. Improvement of Fuzzy Supervisory Model

There are two main factors affecting the performance of the fuzzy supervisory model. One of them is related to local operating regimes and local models built on them, how local operating regimes are defined, i.e. how well local empirical models perform with individual operating regime boundaries. The other is closely dependant to fuzzy rules, i.e. how to define the applicability of local models as operating regime changes. To that end, fuzzy membership functions that interpret crisp parametric values into fuzzy terms play a critical role. Fuzzy membership function defines the fuzzy space and then determines the degree of matching to each rule. In the experiments, we have done some heuristic tuning of fuzzy membership functions in Fig. 4 and were able to improve the overall performance of the supervisory model. In order to optimize the performance, we need to introduce membership function that is parameterizable. One of forms is a generalized bell function [11]:

![Figure 6](image-url)
where \( \{a_i,b_i,c_i\} \) is the parameter set. As the values of these parameters change, the bell-shaped function varied accordingly, thus exhibiting various forms of membership functions for a fuzzy set \( A \). Fig. (7) illustrate examples of bell-shaped membership function and traditional trapezoidal membership function. Now having the differentiable membership function, learning algorithms like backpropagation can be applied to tune the parameters in bell function to achieve optimal performance of overall supervisory model.

![Bell-shaped and trapezoidal membership functions.](image)

V. CONCLUSIONS

When operating regime/model of industrial system changes, the characteristics of system also tend to vary. This will cause invalidity of the local empirical models, leading to inaccurate system state estimation, as system operates outside of operating regime boundaries, which the local models were trained upon. A fuzzy supervisory model selection decision-making approach is introduced to offer a potential solution to this problem by supervising the fusion/selection of local models to assure the smoothness in operating regime transition and then provide continuous condition monitoring to the system. Experiments on simulated data from a high bypass, turbofan aircraft engine model demonstrated promising results.

REFERENCES