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# IFDD: Intelligent Fault Detection and Diagnosis-Application to a Cogeneration and Cooling Plant

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## ABSTRACT
Power producing plants possess a maintenance cost of about 30% of the total power generating cost. Studies also show that a cost reduction of about 30% can be achieved by shifting from preventive maintenance to condition based maintenance. This study presents an intelligent fault detection and diagnosis system designed for a cogeneration and cooling plant. Fuzzy systems are used to address multiple operating regions, nonlinear model identification and fault diagnosis. Performance of the designed system is demonstrated by conducting case studies on actual Gas Turbine Generator (GTG), Heat Recovery Steam Generator (HRSG) and steam absorption chiller. In most of the tested cases, the system was found capable of providing 95 to 100% true detection and true diagnosis, respectively. For assumed incipient faults, it was found performing better than principal component analysis or auto-associative neural networks. While having a dedicated graphical user interface, it is also designed to be applicable for steady state simulation of the GTG and HRSG, respectively.

**Key words:** Fault detection, fault diagnosis, cogeneration, fuzzy systems

## INTRODUCTION
Cogeneration and Cooling Plants (CCPs) include important elements of power generation and chilled water production systems. Their high efficiency and low greenhouse gas emission make them preferred to plants designed for separate production of power, steam and chilled water. Recent designs of CCPs are equipped with mechanisms to increase overall system efficiency while keeping $CO_2$ and $NO_x$ emission levels as low as possible. However, studies show that, CCPs exhibit high maintenance cost that could reach up to 30% of the total electricity generating cost (Graber, 2004). Since their energy throughput is high, reduced performance cannot be tolerated as it threatens economic operation of the system. Condition Based Maintenance (CBM) is known to reduce the maintenance cost significantly. One of the building blocks of CBM is decision making, which involves fault detection and diagnosis. An Intelligent Fault Detection and Diagnosis (IFDD) system, in general, has the following advantages:

- Avoids catastrophic failure
- Helps better manage maintenance resources
- Reduces greenhouse gas emissions
- Minimizes the cognitive load on maintenance operators and
- Allows better utilization of the primary energy

A fault detection and diagnosis system can be designed using either model free or model based approaches (Isermann, 2011). In model free design, methods like hardware redundancy, limit checking, spectral analysis or special sensors are applied to detect and isolate the onset of abnormal conditions. While hardware redundancy requires multiple sensors and space, spectral analysis assumes that the frequency spectrum for a fault signal is discernable, which may not be always the case. Special sensors are costly and the sensors themselves may fail. Limit checking, also overlooks the spatial and temporal correlations in the measured signals. A model based design is preferred for it is cost effective and addresses the issues related to data correlations and delays.

The model based design, in a broader sense, can be classified as qualitative model based and quantitative model based (Venkatasubramanian *et al*., 2003). The later includes analytical methods (observers, parity equations, parameter estimation and Kalman filters), multivariate statistical approaches and computational intelligence (Palade *et al*., 2006). The analytical methods are known to demand first principle models. Until 1991, most of the designs on fault detection and diagnosis were based on rule based and declarative representations (Conroy *et al*., 1989; Sztipanovits *et al*., 1990; Kumamaru *et al*., 1991; Padalkar *et al*., 1991). Starting around 1991, the use of Artificial Neural Networks (ANN) and hybrid designs became a common practice (Horiguchi *et al*., 1991; Szczepaniak, 1994; Perryman, 1995; Sreedhar *et al*., 1995; Fast and Palme, 2010). On the other hand, Lazzaretto and Toffolo (2006), used thermo-economic and exergetic approaches to detect and diagnose faults in a combined heat and power plant (CHP). This is probably the most interesting contribution from mechanical engineering point of view. From statistical process control, (Thomson *et al*., 2000) used exponentially weighted moving average to detect and diagnose faults in the heat recovery system of a combined heat and power plant. It turns out that, while the requirement in the stat-of-the-art design of IFDD systems is enormous, it is indeed difficult to meet all the needs applying only one approach. It was also observed that the effort made to deal with multiple operating regions, interconnection between subsystems and nonlinear characteristics of the plant is minimal as compared to the efforts made in areas like DC motors and pilot plants.

The objective of this study is to present the design of an intelligent fault detection and diagnosis system that can be applied in cogeneration and cooling plants. The design considers multiple operating regions, varieties of measured signals and the inter connection between subsystems. The diagnostic system is designed in such a way that the uncertainties in the diagnostic results are included.

## MATERIALS AND METHODS

The design of an IFDD system requires first principle models, data preprocessing tools, nonlinear model identification, adaptive fault detector and a diagnostics tool. In the developed design, the stated inputs are arranged in a structure as shown in Fig. 1. The whole IFDD system is characterized by three main modules: Data Preprocessing Module (DPM), Fault Detection Module (FDEM) and Fault Diagnosis Module (FDIM). Details about each module are presented as follows.

The DPM is designed to normalize the data $\mu_j \in R$ and $y_q \in R$ and remove measurement noise. While the normalization is done dividing each measured value by the corresponding alarm setting or design point data, Discrete Wavelet Transform (DWT) is assumed to reduce the effect of measurement noise and outliers.

The data from FDM is used in the FDEM, which is the module intended to perform fault detection. The FDEM is comprised of four sub-modules: FDEM-U, FDEM-Y, FDEM-S and FDEM-H that relates to the input sensors, output sensors, soft sensors and sensors with unique signal

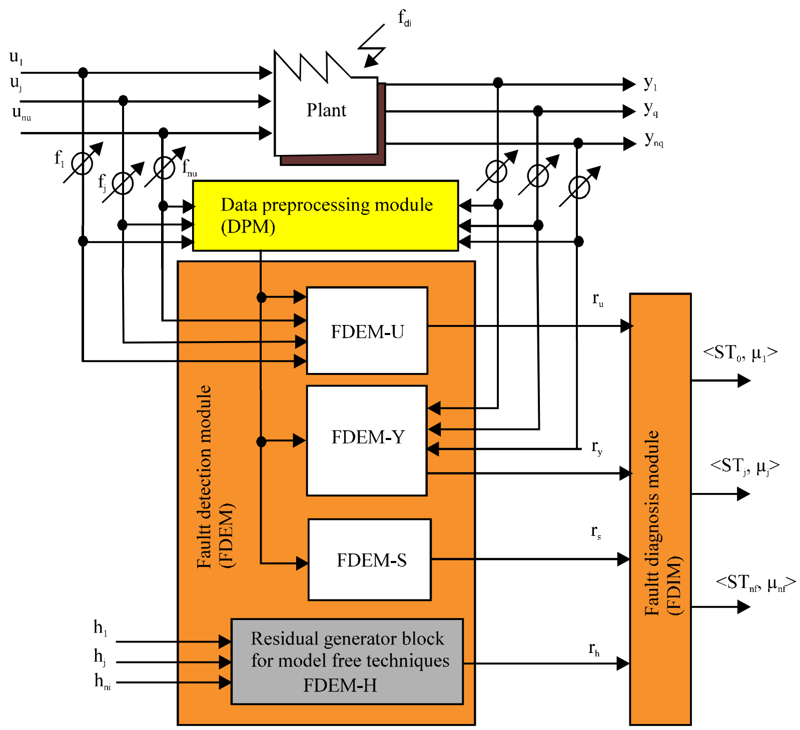


Fig. 1: Structure of the IFDD system

features, respectively. To realize the models in the first three sub modules, fuzzy systems and global optimization algorithms are considered. For FDEM-S, since it requires reliable training and validation data, which are not measurable, semi-empirical models are developed for the GTG and HRSG, respectively. In fact, the model is also applicable to generate data for an implanted fault. In case of FDEM-H, the signals (e.g., vibration signals) need more than fuzzy system. Due to this reason, no further discussion is included except stating that the develop structure is flexible enough to accommodate not only vibration signals but also qualitative data from manufacturer's catalogue and maintenance history database.

Once the residuals are calculated by the FDEM and faults are detected, the FDIM further processes the residuals to identify the highly likely cause for the abnormal condition. The diagnostics procedure works either in binary or fuzzy mode. However, since the binary approach overlooks the diagnostics uncertainty, the default setting is fuzzy approach. Construction of the FDIM is realized by developing a knowledge base through simulation of the possible fault cases. The output from the FDIM are state names $ST_j$ and fault activation level $\mu_j \in [0, 1]$. For fault free case, $ST_j$ is assigned as state name.

**Semi-empirical models for the GTG and HRSG:** Development of the semi-empirical model starts with the preparation of database for the working fluids. Since the CCP uses air, combustion gas and steam/water at different stages of the whole process, the property database includes the three fluids. For air and combustion products, empirical equations are adopted from (Walsh and Fletcher, 2004). For steam, all the data are taken from (Irvine and Liley, 1984). In the modeling of the GTG, duct pressure loss, combustion efficiency, generator efficiency, gearbox efficiency and turbine blade cooling are all included. For the HRSG, the effect of blow-down heat exchanger is accounted by including mass and energy conservation equations in the overall model. The models for the two systems are for design point and off-design point calculation, respectively. Unique to the present work is the model for the axial compressor in the GTG. Instead of developing a performance map applying scaling method, non-dimension correlation constructed from actual data itself are employed to characterize the compressor over the whole operating region.

**Nonlinear model identification:** The equations that govern characteristics of the GTG and HRSG at any operating point are in the form of ordinary or partial differential equations. It may involve also empirical models. In general, the models happen to be nonlinear due to the complex interaction between the rotating parts and the working fluid. GTG and HRSG are highly specialized machines. Details about geometric information are hardly available for proprietary reasons. Instead, what is available are measured input and output data. In the present work, the models needed to fill the FDEM and FDIM knowledge bases are constructed using either measured or simulated data. Accordingly, the state space model for a discrete system is considered. Assuming multi-agent design, the general equation describing ith Multiple Input and Single Output (MISO) dynamic system is given by:

$$\begin{cases} x^{(i)}(k+1) = \Phi x^{(i)}(k) + \Gamma u^{(i)(k)} \\ y^{(i)}(k) = \Psi(x^{(i)}(k)) + \varepsilon(k) \end{cases} \tag{1}$$

where, $y^{(i)}$ (k) $\in$ R is the output; $\mu^{(i)}$ (k) $\in$ R is the input; $x^{(i)}$ (k) is the state vector; $\varepsilon$ (k) is the modeling and measurement error. The symbols $\Phi$ and $\Gamma$ refer to the matrices formed from the input vector. Implementation of Eq. 1 is realized applying fuzzy Takagi-Sugeno-Kang (TSK) model (Nelles, 2001). The choice on TSK model is due to transparent characteristics of the fuzzy systems. Block diagram representation of the overall model that works for either GTG or HRSG is shown in Fig. 2. The model training is performed applying Local Linear Model Tree Algorithm (LOLIMOT) (Nelles, 2001) followed by Particle Swarm Optimization (PSO).

**Adaptive fault detector and fault diagnosis:** In fault detection and diagnosis, the uncertainty equation or confidence limit $CI^{(i)}$ (k) together with residual models are used. The general steps in fault detection are as follows:

**Step 1:** Calculate the residual $r^{(i)}$ (k) for the ith model and compare it with the corresponding confidence limit $CI^{(i)}$ (k) that decides the region for normal operation

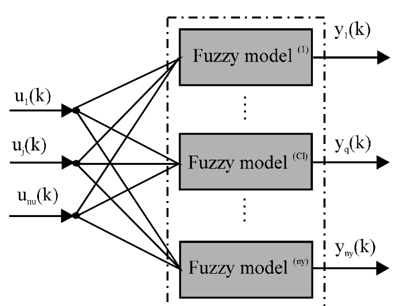


Fig. 2: Fuzzy based multiple-model structure

**Step 2:** If the condition $r^{(i)}(k) > CI^{(i)}(k)$ is satisfied, then it is concluded that a fault is detected

**Step 3:** Once a fault is detected, the residuals are evaluated according to Eq. 2 to construct the fault signatures

**Step 4:** Use the fault signatures from step-3 in a pre-designed Binary Diagnostic Matrix (BDM) that is system specific. This step leads to isolation of the cause behind the abnormal condition

The binary diagnostic signal $s^{(i)}(k)$ is obtained from:

$$s^{(i)}(k) = \begin{cases} 1, \text{if } r^{(i)}(k) > CI^{(i)(k)} \\ 0, \text{if } r^{(i)}(k) > CI^{(i)(k)} \end{cases} \tag{2}$$

In the case of fuzzy evaluation of the residual signals, the membership functions are defined in terms of the adaptive model confidence interval $CI^{(i)}(k)$:

$$\mu_{i,1}\left(\hat{r}^{(i)}(k)\right) = \begin{cases} 1, \hat{r}^{(i)}(k) > R_{min} \\ \dfrac{\hat{r}^{(i)}(k) - R_{max}}{R_{max} - R_{min}}, R_{min} \le \hat{r}^{(i)}(k) \le R_{max} \\ 0, \hat{r}^{(i)}(k) > R_{max} \end{cases} \tag{3}$$

$$\mu_{i,2}\left(\hat{r}^{(i)}(k)\right) = \begin{cases} 0, \hat{r}^{(i)}(k) < R_{min} \\ \dfrac{\hat{r}^{(i)}(k) - R_{min}}{R_{max} - R_{min}}, R_{min} \le \hat{r}^{(i)}(k) \le R_{max} \\ 1, \hat{r}^{(i)}(k) > R_{max} \end{cases} \tag{4}$$

where, $\hat{r}^{(i)}(k) = \|r^{(i)}(k)\|$; $R_{min} = b \times CI^{(i)}(k)$; $R_{max} = \alpha \times CI^{(i)}(k)$; $\alpha$ and b are constants. The proposed IFDD system uses 1.0 and 0.5 as the value of $\alpha$ and b, respectively.

## RESULTS AND DISCUSSION

A CCP from Universiti Technologi PETRONAS, Malaysia, is chosen as a case to demonstrate application of the developed IFDD system. The whole setup has two gas turbines working in either droop mode or isochronous mode and each working in harmony with separate HRSGs. The steam from the two HRSGs is collected in the steam header and SACs are run by the steam from the steam header. Nominal capacity of one gas turbine is about 5.2 MW. When the gas turbines are set as droop mode and isochronous mode, the one with the droop setting is allowed to work in small variation in shaft speed (usually 3% change from nominal) while the shaft speed of the isochronous turbine remains constant. With this combination of control setting, the droop turbine delivers the base load while the isochronous turbine is dedicated to take the extra load. Because more load variations are experienced by the isochronous turbine, the data from this turbine is considered for testing the IFDD system. Design specifications of the HRSG and SAC are as given in Table 1.

**Validation of semi-empirical models:** The validation graphs for the GTG are illustrated in Fig. 3. All the graphs are plotted in normalized form. For loads lower that 50% of rated capacity, the parameters gradually increase with the load. Since the VIGV position is at fully open position,

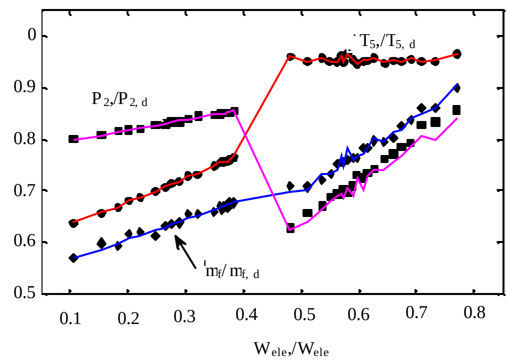


Fig. 3: Graphs for the GTG, Line: Real data, Marks: Model

Table 1: Design point data for the HRSG and SAC in the cogeneration and cooling plant

| System | Capacity |
|---|---|
| HRSG | 12 ton $h^{-1}$, Saturated Steam at 0.85 MPa |
| HRSG-pump | 15.5 $m^3$ $h^{-1}$ (Liquid Temp. less 100°C) and 11 kW |
| SAC | 1250 RT, 5500 kg $h^{-1}$ steam consumption |
| SAC-pump | 920 $m^3$ $h^{-1}$ (Liquid Temp. less 100°C) and 7.5 kW |

Table 2: Models performance for traiuing and test data: GTG high load operating region

| | | Training data | | | Test data | | |
|---|---|---|---|---|---|---|---|
| Parameter | $n_k$ | RMSE | AIC | VAF | RMSE | AIC | VAF |
| $P_2$ | 5 | 0.0077 | -8.93 | 98.2 | 0.0084 | -8.5 | 98 |
| $W_{ele}$ | 4 | 0.0092 | -8.35 | 98.3 | 0.0093 | -8.3 | 98 |

AIC: Akaike's information criterion, VAF: Variance accounted for

the trend is reasonable. For higher load, the GTG is in temperature and load control. As such, both the VIGV position and fuel flow rate are manipulated to keep the temperature constant and cover the load. Again, the increasing trends are what were anticipated.

**Validation of fuzzy models:** For the gas turbine generator, fuel flow rate $m_f$ and Variable Inlet Guide Vane (VIGV) position are manipulated to meet the total electric load demand and the high temperature exhaust gas needed to run the HRSG. Simultaneous control of the two inputs is especially true in the high load region. Even though models are developed for all the measurable parameters in the CCP (gas path, lubrication system, generator coils, HRSG and SAC), the models demonstrated hereunder are limited to the compressor discharge pressure $P_2$ and electric power output at the generator terminal $W_{ele}$. This was done so for space limitation reasons. The data needed for model training and validation are collected every 10 sec. About 1200 data points are used for model training while an equivalent number is considered for model testing or validation. The fuzzy models required to construct the IFDD knowledge base are trained by a Local Linear Model Tree (LOLIMOT) algorithm (Nelles 2001) followed by Particle Swarm Optimization (PSO). The number of fuzzy rules $n_k$ and performance parameters for the developed models are given in Table 2. Fig. 4 and 5 show the validation graphs for compressor discharge pressure $P_2$ and electric power output at the generator terminal $W_{ele}$. Performances of the models are given in terms of Root Mean Square Error (RMSE), Akaike's Information Criterion (AIC) and Variance Accounted For

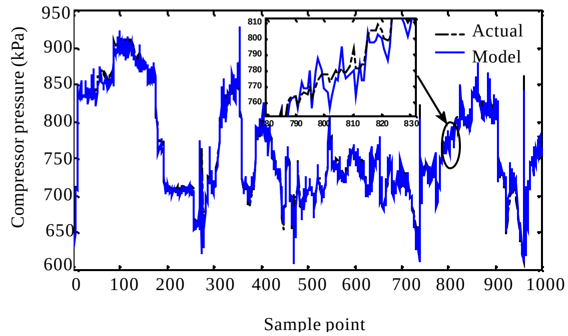


Fig. 4: Validation graph for $P_2$

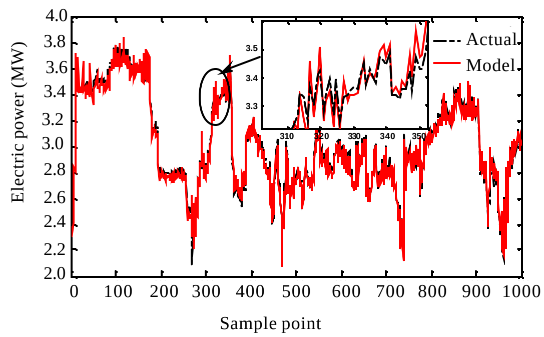


Fig. 5: Validation Graph for $W_{ele}$

(VAF). As can be seen from Table 2, Fig. 4 and 5, the actual data and the predictions compare well. The number of rules in the fuzzy models are also relatively low indicating the power of LOLIMOT algorithm in optimizing the model structure.

**Performance of the IFDD system:** In this section, application of the IFDD system is demonstrated by considering abrupt and incipient sensor faults, respectively. Variations of the implanted faults for a given sensor are governed by Eq. 5 and 6. For abrupt fault, the added bias is:

$$\Delta x(k) = \begin{cases} 0, \text{for } k < 300 \\ \Delta x_{max}, \text{for } k > 300 \end{cases} \tag{5}$$

In case of incipient fault:

$$\Delta x(k) = \begin{cases} \frac{\Delta x_{max}}{200}(k-200), \text{for } 200 \le k \le 400 \\ \Delta x_{max}, \text{for } k > 400 \end{cases} \tag{6}$$

where, k is the data point; $\Delta x_{max}$ is the maximum change assumed with respect to the alarm setting or design point data. The two models are common in testing a fault detection and diagnosis system for different magnitudes of fault. In order to quantify the performance of the IFDD system for each test, the following parameters are additionally considered:

Table 3: Principal component analysis (PCA) models for the GTG

| Model | No. of variables | No. of PCs | Cum $var_j$ (%) |
|---|---|---|---|
| Gas path | 13 | 5 | 98.85 |
| Lube system | 6 | 2 | 99.70 |
| Generator coils | 3 | 1 | 99.44 |
| $T_5$ sensors and $P_{SD}$ | 7 | 2 | 99.77 |

Table 4: Structure of the autoassociative neural network (AANN) models for the GTG

| | AANN structure | | | | | |
|---|---|---|---|---|---|---|
| Model | nx | nl | nc | nm | ny | Learning algorithm |
| Gas path | 13 | 8 | 2 | 8 | 13 | LM |
| Lube system | 6 | 8 | 2 | 8 | 6 | LM |
| Generator coils | 3 | 8 | 2 | 8 | 3 | LM |
| $T_5$'s and $P_{SD}$ | 7 | 8 | 2 | 8 | 7 | LM |

Table 5: Fanlt detection and diagnosis system performance: Gas path sensors

| | PCA | | | | AANN | | | | IFDD | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sensors | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ |
| $T_1$ | 6.50 | 98.33 | - | 44 | 19.5 | 4 | - | 244 | 9.2.0 | 61.7 | 100.0 | 131 |
| $P_2$ | 4.10 | 100.0 | 100 | 42 | 13.5 | 10 | 100 | 135 | 3.1.0 | 100.0 | 99.5 | 57 |
| $P_{vc}$ | 0.29 | 100.0 | 100 | 6 | 1.1 | 100 | 100 | 26 | 0.89 | 100.0 | 100.0 | 20 |
| $T_{enc}$ | 3.80 | 100.0 | 100 | 44 | 12.5 | 12 | - | 244 | 11.00 | 34.5 | - | 131 |

PCA: Principal component analysis, AANN: Autoassociative neural network, IFDD: Intelligent fault detection and diagnosis

Table 6: Fanlt detection and diagnosis system performance: GTG lubrication system

| | PCA | | | | AANN | | | | IFDD | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sensors | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ | $\tau_{md}$ | $\tau_{tdp}$ | $\tau_{tip}$ | $\tau_{dd}$ |
| $T_{lb1}$ | 2.6 | 100 | 100 | 27 | 2.60 | 100 | - | 95 | 1.7 | 100 | 100 | 51 |
| $T_{lb2}$ | 3.0 | 100 | 100 | 18 | 2.80 | 100 | - | 108 | 1.5 | 100 | 100 | 40 |
| $T_{lb3}$ | 2.4 | 100 | 100 | 24 | 2.10 | 100 | - | 139 | 2.8 | 100 | - | 35 |
| $T_{lb4}$ | 1.0 | 100 | 100 | 24 | 0.85 | 100 | - | 95 | 0.52 | 100 | 100 | 26 |
| $T_{lb5}$ | 1.0 | 100 | 100 | 18 | 1.05 | 100 | - | 109 | 0.51 | 100 | 100 | 40 |
| $P_{lb1}$ | 4.5 | 100 | 0 | 24 | 4.50 | 100 | - | 95 | 6.6 | 100 | - | 64 |

PCA: Principal component analysis, AANN: Autoassociative neural network, IFDD: Intelligent fault detection and diagnosis

- Minimum percentage bias that can be detected ($\tau_{md}$)
- True detection percentage ($\tau_{tdp}$)
- True diagnosis percentage ($\tau_{tip}$) and
- Detection delay ($\tau_{dd}$)

The presentation compares the IFDD designed applying fuzzy systems against FDD systems constructed on the bases of Principal Component Analysis (PCA) and Autoassociative Neural Network (AANN), respectively. Structures of the reference models in the later two approaches are outlined in Table 3 and 4. The AANN models are trained by Levenberg-Marquardt algorithm, which is a derivative based optimization algorithm.

The test results associated with sensors in the gas path and lubrication systems of the GTG are shown in Table 5 and 6. For the gas path sensors ($T_1$, $P_2$, $P_{vc}$, $T_{enc}$), the IFDD performed as good as PCA and better than AANN. The low accuracies in $T_1$ and $T_{enc}$ sensors are attributed to the weak correlations with the rest of the signals and the effect of measurement noise. For the lubrication system, five temperature and one pressure signals are included. The lubrication system is one of the auxiliary systems vital for safe running of the GTG. Apart from lube oil monitoring for wear rate prediction, temperatures and pressure data at different locations are monitored to ensure that the system is safe to run. High lube oil temperature indicates excessive vibration and even oil leak. A drop in pressure also signals oil leak. Lube oil valve, pressure controller or actuator malfunctions are often detected by the change in the temperature and pressure trends. While a fault in a gas path sensor outside the control loop is somehow less destructive and tolerable, the consequence due to a missed fault in the lube system is quite destructive. As can be seen from Table 6, IFDD demonstrated a performance in the range of 95 to 100%, which is attractive enough for practical use.

## CONCLUSION

In purpose of this study is to present an IFDD system designed for a cogeneration plant. The design is equipped with nonlinear models, adaptive fault detector and a fuzzy based diagnostic method. The case study showed that, the steady state model for the GTG is accurate for inlet temperatures in the range of 24 to 34 °C. In the fault detection and diagnosis test, the IFDD system demonstrated a true detection percentage higher than 95% and true diagnosis percentage higher than 93%. The numbers are attractive enough for practical application. Future work will focus on arranging the IFDD system in a standalone decision support system.

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