FAULT DETECTION IN INDUSTRIAL AIR - PROCESSING SENSORS CONTROLED SYSTEM

Konstantin DIMITROV
Technical University - Sofia, Bulgaria

Abstract. The paper describes the development of enhanced model-based and knowledge-based techniques, which are used for fault detection in air-processing, sensors controlled system, under real operation conditions. The developed modelling equations, knowledge based techniques and fuzzy logic decisions are applied for providing reliability enhancement and fault tolerance in industrial air-processing system, which represents an integral part of a general waste-processing system, designed for a zing galvanizing facility.

Keywords: fault detection, reliability enhancement, fault tolerance, process modelling, knowledge-based techniques, air-processing systems

1. Introduction

In general, there has always been a tendency for development of reliability requirements towards the industrial equipment, which in most cases could be described by its capabilities to provide "*safety*", "*reliability*" and "*fault tolerance*" during the operation stage(s) of the technologic system(s) [3, 4]. The need to provide such specific capabilities in the contemporary industrial equipment, have led to the development of some really sophisticated methods for its ***condition monitoring via automated diagnostic systems*** [4, 5, 8]. Some of the already developed diagnostic systems are designed to supervise mainly the life cycles of important industrial components by counting/calculating load cycles and temperature changes. Others, use sophisticated mathematical models, artificial intelligence techniques (Neural Networks, Fuzzy Logic, Expert systems, etc.) [5, 6, 8].

In general, two main methods were sufficiently developed and applied in the diagnosis algorithms and procedures, performed over the specific (i.e. the important) components of the industrial equipment.

A). *Model-based methods*, which use complicated mathematical models for detecting faults and failures in the diagnosed industrial equipment;

B). *Knowledge-based methods*, which rely on deep and/or shallow knowledge, obtained before and/or during the operation stages of the industrial equipment, to detect, evaluate and/or even to predict the faults and the failures.

Of course, in some cases (when possible), particular combinations of both these methods are developed and applied in the Fault Detection and Isolation (FDI) procedures [5].

Various kinds of steady-state models for different kinds of equipment could be built via processing the data, obtained under real operating conditions. In most cases, because of the existing measurement "noise", the developed diagnostic procedures must also include some powerful estimation techniques during the creation of the state estimation algorithms. One of the *most critical issues*, that always exist, is how to monitor the sensors controlled systems, in order to avoid the resulting systematic measurement errors, when dealing with the selected state variables. *If such issue(s) could be successfully resolved, then reliability enhancement and fault tolerance of the entire industrial system could be achieved* [5, 7].

The present paper describes the development of model-based, knowledge-based and fuzzy logic techniques, which are used for fault detection in an industrial air-processing system.

The so-developed modelling equations, knowledge based techniques and fuzzy logic decisions are applied for providing reliability enhancement (under real operation conditions), in a sensors controlled air-processing system, which represents an integral part of a general waste-processing system, designed for a zing galvanizing facility.

2. Sensors controlled system for waste air-processing – structure, operation, capabilities and application

The industrial system, designed for processing the waste air represents an essential part of technologic and logistic structures, specially developed for a Hot Dip Zinc Galvanizing Facility. The financing of this Project (including its Environmental Impact Assessment), is realized under the investment program of the US Overseas Private Investment Corporation (OPIC). The zing galvanizing facility's logistic structures, the main and the supplementary equipment, as well as all essential technologic and logistics operations are presented in details in [1] and [2].

The general waste-processing system, comprise a *waste liquids treatment equipment* and an ***air processing equipment, designated for treatment of the air emissions generated by the galvanizing furnace operation*** [2].

A particulate emission (i.e., smoke) escapes from the surface of the molten zinc as the steel work to be galvanized is dipped. This emission is caused by the volatilization of the flux and is primarily ammonium chloride, although zinc oxide is also present (please see EPA AP-40).

Pollution control agencies in general have ruled that, these fumes must be collected using the best available technology. This is done by using *a tightly enclosed fume hood* around the molten zinc bath (in fact, the galvanizers refer to this bath as the "kettle") and a specific type of air filter known as a *baghouse*. This filter is equipped with a powerful suction fan and cloth bags, through which the air is filtered. The fume hood also makes a significant contribution to personnel safety by containing the splatter of hot zinc that sometimes results when work is dipped.

The so-developed combination, made of a fume hood and a baghouse, will capture 99% of the particulate emission.

The floor mounted hood structure (figure 1) is designed as a truss structure, supported on columns on the working side of the kettle, which in turn supports sliding doors along the side of the kettle. The opposite side of the kettle is enclosed by a similar structure which also supports sliding doors, and the ends of the kettle are served with gate type doors which open away from the working side. The sliding doors are suspended on ball bearing rollers mounted in track, and the end doors are mounted in ball bushings for ease of operation.

A twin-module ***baghouse***, designed and built for processing of the waste air is shown on figure 2. The baghouse blowers are sized based upon 7 air changes per minute of the hood volume. (This flow rate is based on recommendations found in EPA Manual AP-40 & Industrial Ventilation published by The American Conference of Governmental Industrial Hygienists). The baghouse is sized according to the hood volume, and is made in modules with a capacity of 8,000 SCFM each. The air flow may be determined by multiplying the hood volume in cubic feet by seven. This will give the recommended number of air changes each minute.

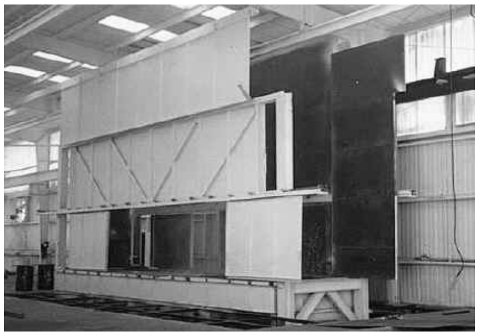

Figure 1. Floor mounted hood enclosure

Figure 2. A twin-module baghouse of the zinc galvanizing facility

The ***main structural modules*** of the air-processing equipment are:

- Baghouse - a twin module (two chamber unit);
- Bags - 156 bags in each chamber with 5" diameter by 9'2" polyester fabric approximately 2000 sq. ft. cloth area each chamber;
- Blower - 16,000 cfm - 25Hp 480/3/50 Fiberglass with weather cover and a Manometer - 0 - 8" wc;
- Electrical - motor starters, each one possessing power of 25 Hp and 1 Hp respectively, and supplied with interlock, so that both motors can not be run at the same time
- Ductwork - 18" diameter PVC ductwork is used.

The ***control*** of the entire air-processing system is effectuated by a ***sensors controlled system, composed by four sensors and micro-controller of a STM32F103 model.***

The controller uses a PWM (i.e., Pulse Weight Modulation) to control the four sensors (incremental type encoders) of a KÜBLER model.

The structure and the operation of the sensors controlled system will therefore be a subject to Fault Detection and Fault Isolation procedures (FDI procedures), developed in this paper. As result of the waste air-processing system operation, the solid waste from the baghouse remains collected in the bags (placed in the baghouse chambers) and must be disposed of.

The so-collected quantities of particulates must be disposed of as a ***solid hazardous waste***. Specific kinds of HAZMAT containers, designated for transportation & storage of solid and liquid hazardous waste are used for this purpose.

3. Modelling of the State Variables

In compliance with the developed structure of the sensors controlled air-processing system, some important *characteristics*, (referred hereto as *diagnostic parameters*), should be selected and applied during ***the condition monitoring*** of the diagnosed systems modules. However, for the modelling purposes, as well as in the sense of the terms, related to the control actions, those characteristics should be referred as ***state variables***.

A specific diagnostic analysis was performed over the characteristics of main systems modules. The aim of this analysis was a determination and a selection of the necessary state variables. The analytic procedures were based on a ***genetic type of algorithm. Specific genetic operators,*** developed as ***"selection", "reproduction" and "crossing-over"*** were applied for determination of the representing sets of state variables/diagnostic parameters. The so-determined state variables can further be applied for a condition monitoring of the systems modules.

The selected state variables are included in a specific {SL} set (a list), and are defined as follows:

- mass flow rate (of the processed waste air);
- changes in the pressure in the different cross sections (mainly in the outlet zones);
- temperature changes;
- relative pressure loss;
- quality of the already processed air.

Some of these state variables can be directly measured by the sensors controlled system, others – can not be directly measured and must be calculated and/or modelled by introducing other specific sets of measurable values (for some important and typical process variables). The values, that can be ***measured*** are: *pressures and temperatures at the inlet and at the outlet of each module (subjected to FD procedures), as well as the speed of rotation for the turbo fans, and (to some point) the quantities of the particles in the filtering bags*. The correlation between the measured values and the state variables is established by reference to the specific characteristics of the diagnosed system components and the technologic/process relations. A particular methodology, based on a system similitude theory and genetic operators was developed and applied for that purpose. Some eventual deviations (of a non-linear type) in the values can be modelled thru that methodology, others – not, which means, that, the representing (i.e., the describing) modelling equations should allow changes ***only*** in the selected operation points, (referred to the nominal states).

Therefore, the modelling equations for each state variable $\boldsymbol{X_i}$ are expressed as functions of $\boldsymbol{n}$ measured values (measured by the sensors system), which compose the corresponding measurement vector $\boldsymbol{Y_j}$. The developed modelling equations are of the following type:

$$dX_i = \left[\frac{\partial X_i}{\partial Y_1}\right]_N dY_1 + \left[\frac{\partial X_i}{\partial Y_2}\right]_N dY_2 + \ldots + \left[\frac{\partial X_i}{\partial Y_n}\right]_N dY_n \qquad (1)$$

where: N represents the nominal state;
$dY_j = Y_j - Y_{jN}$, and $dX_i = X_i - X_{iN}$.

Due to reasons for generalization, the state modeling equation should be developed in a non-dimensional format, by referring the variations "Δ" only to the nominal state itself, as well as by allowing only a finite number of deviations. The equation (1) can therefore be transformed as follows:

$$\Delta X_i = \frac{Y_{1N}}{X_{iN}}\left[\frac{\partial X_i}{\partial Y_1}\right]_N \Delta Y_1 + \frac{Y_{2N}}{X_{iN}}\left[\frac{\partial X_i}{\partial Y_2}\right]_N \Delta Y_2 + \ldots + \frac{Y_{nN}}{X_{iN}}\left[\frac{\partial X_i}{\partial Y_n}\right]_N \Delta Y_n \qquad (2)$$

where: $\Delta Y_j = \frac{Y_j - Y_{jN}}{Y_{jN}}$ and $\Delta X_i = \frac{X_i - X_{iN}}{X_{iN}}$. The modeling coefficients, $K_{ij} = \frac{Y_{jN}}{X_{iN}}\left[\frac{\partial X_i}{\partial Y_j}\right]_N$, (with $i = \overline{1,k}$ and $j = \overline{1,n}$), can be determined by the specific technologic/process relations (available for each system component).

The modelling equations could therefore be expressed as a linear system of the following kind:

$$\Delta X_i = \sum_{j=1}^{n} K_{ij} \cdot \Delta Y_j \qquad (3)$$

The so-developed system *connects* the *"k" state variables of the system with the "n" (normalized) measured values.* The modelling techniques are developed via the application of an observer-based approach regarding the sensors configurations (i.e., all modules *are observable*), which means, that, the equations (2) and (3) *are solvable*. The linear system (3) can also be expressed in a vector-matrix form, of the following kind:

$$X^{(k\times1)} = [SM]^{(k\times n)} \cdot Y^{(n\times1)} \qquad (4)$$

where, the vectors $\mathbf{X}^{(k \times 1)}$ and $\mathbf{Y}^{(nx1)}$**,** correspond to the variations $\Delta\mathbf{X}$ and $\Delta\mathbf{Y}$, and the system matrix $\mathbf{[SM]}^{(kxn)}$ contains all modelling information (related to the different states), which is used for condition monitoring of the system modules.

The relation (4) can also be developed as a measuring-based equation:

$$Y[M] = [MM]^{(n\times k)} \cdot X[M] \qquad (5)$$

where, Y[M] is the measurement vector, $[MM]^{(nxk)}$ is an (n x k) dimensional measurement matrix, which result from the system matrix $[SM]^{(kxn)}$. A relatively simple kind of algorithm was developed and applied for explicit calculation of [MM] matrix, once the [SM] is built.

4. Knowledge-based methods for sensors fault detection

The components of the measurement vector Y_j, represent in fact the measured quantities, which express the states of the diagnosed system modules. The selected state variables are chosen from the {SL} set.

A specific algorithmic criteria, related to the states variables values was developed and applied for systems condition monitoring. The created algorithms are created on the principle, that, all states ***are normalized***, which means, that ***for all "fault/failure – free" cases they must be equal to zero, and respectively - an eventual positive values indicate the existence of one or more sensors faults.*** *The physical sense of this algorithm can therefore be applied as* ***sets of specific rules,*** *which respectively can be developed into two main categories*:

- Category 1: "Sensor-Based Rules - SENBAR"
- Category 2: "State-based rules -STATBAR".

The rules can thus provide ***indications*** for an ***already generated*** sensors fault/failure, or can ***exclude the existence*** of fault(s) in a particular (or in all) sensor(s). The "STATBAR" algorithms are trained to search for possible consequences in some specific state $\mathbf{S_i}$, generated by the performances of all sensors [$\mathbf{Y_i}$], which are linked with the state $\mathbf{S_i}$ via relation (4). The "SENBAR" algorithms work in the opposite way, i.e., they are trained to search for consequences in all groups of states [$\mathbf{S_j}$], if there is a fault occurrence in some specific sensor $\mathbf{Y_i}$**.**

In fact, during the processing of both algorithms two particular types of sets, containing the faulty sensors can be defined:

- $\mathbf{[FS]^{ST}}$ – set of faulty sensors, defined by STATBAR algorithm;
- $\mathbf{[FS]^{SE}}$ **–** set of faulty sensors, defined by SENBAR algorithm.

The union of both these particular sets, defines a new (global) set $\mathbf{[FS]^{G}}$ **,** which contains all faulty sensors, existing ***simultaneously*** in $\mathbf{[FS]^{ST}}$ and $\mathbf{[FS]^{SE}}$**, and** at the same time i***nfluencing*** the states, in case, there is a ***fault occurrence(s) in the sensors measuring system***. The global set is determined as follows:

$$[FS]^G = \left\{[FS]^{ST} \cap [FS]^{SE}\right\} \cup \left\{\left|Y^{[FS]ST}\right|_j / f_c\right\} > \delta \quad (6)$$

where δ is the limited value for application of the sensors sets (i.e., the restricted number of sensors involved);

f_c is the certitude factor for existence of faulty sensors in the STATBAR. The values of f_c are selected by experimentally and in this case are determined to be between 0.7 and 0.8. Thus, in the worst case scenario, the number of possible faulty sensors could be reduced to 70% (of the total number of sensors). The remaining (selected) sensors, are analyzed by the model-based techniques, which can provide quantitative results.

An enhancement of the knowledge-based techniques can be achieved thru correlation methods, i.e., via creating combinations between vector-matrix relation (4) and measuring based relation (5). The resulting expression is:

$$Y^{[FS]ST} = [MM] \cdot [SM] \cdot Y^{(IN)} \qquad (7)$$

where $\mathbf{Y^{(IN)}}$ is the ***simulated*** input vector**,** which is determined by the expression.

$$Y^{(IN)} = [0 \quad \dots \quad -0.04 \quad \dots \quad 0]^T \qquad (8)$$

The so-defined input vector provides options for fault simulation (with a value of – 4%), in a particular sensor "J" (with $0 < J \leq n$). Such techniques can be developed for all "n" sensors, and the respective patterns of the kind ($\mathbf{Y}^{[FS]ST]})_J$ are stored in the knowledge bases of the SENBAR and STATBAR algorithms. If the sensors faults in the real measurement vector $\mathbf{Y_J}$, ***exist simultaneously also in at least one*** of the already stored patterns ($\mathbf{Y}^{[FS]ST]})_J$ - ***then*** the sensors faults are generated in the same sensor. All similar sensors can be determined by the global set $\mathbf{[FS]^G}$ - (eq. 6). The so-defined sensors are compared with those in the real measurement vector $\mathbf{Y_J}$, by using equation (7) and a particular criteria for resemblance, expressed by a specific ***coefficient of resemblance*** R_C^J, of the following kind:

$$R_C^J = \frac{1}{n}\sum_{i=1}^{n} e^{-K\left|(Y_{FSST})_{J,I} - (Y_{FSST})_I\right|} \qquad (9)$$

where K represents an empirical constant, which for the actual analysis is chosen to be equal to 8. The current values of R_C^J belong to the interval [0, 1]. The maximal value of $R_C^J = \left(R_C^J\right)_{\max}$, determines the correct location of the fault, generated in the "J-sensor". If there are more than one sensor fault – then, the principle of the superposition could be applied for their determination.

The results, obtained during an experiment, performed over the diagnosed systems modules are presented on figure 1, and in Table.1. Three sensors faults were simulated during the experiments, which were carried out over the real measurement data (obtained under real operating conditions). The sensors faults were set as follows:

- For sensor N^o 2 (rotational speed of the blowers shaft): average value of the fault is -2.5 %;
- For sensor N^o 5 (temperature in the outlet zone): average value of the sensors fault is -3.5 %;
- For sensor N^o 7 (dynamic pressure in the outlet ductwork): average value of the fault is -1.5 %;

The sensors combinations are calculated in eq. (6). The obtained global sets are analyzed thru eq. (9) and submitted to a following model-based procedure. Some samples of obtained results for eight combinations of sensors faults, (including the calculated values for R_C^J), are shown on figure 3. Extracts of the numerical results, obtained during the performed experimental analysis and the numeric calculations are placed in Table 1.

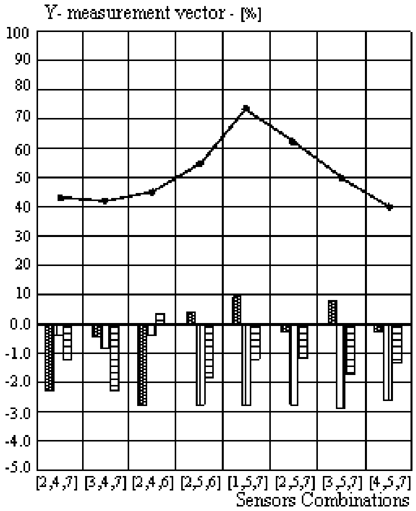

Figure 3. Experimental results for a sensors fault detection

Table 1. Extracts of numerical values, calculated from some combinations of sensors faults and the resemblance coefficients

Sensors Combinations	Sensors faults			R_C^J
[2,4,7]	-2.234	-0.347	-1.258	0.422
[3,4,7]	-0.544	-0.899	-2.188	0.419
[2,4,6]	-2.897	-0.344	+0.249	0.448
[2,5,6]	+0.438	-2.883	-1.911	0.547
[1,5,7]	+0.998	-2.882	-1.221	0.735
[2,5,7]	-0.343	-2.883	-1.222	0.617
[3,5,7]	+0.866	-2.939	-1.821	0.501
[4,5,7]	-0.357	-2.799	-1.355	0.411

The calculated resemblance coefficients R_C^J reflect the different sensors combination without the existence of ambiguity, since the values of the sensors faults are confined to the accuracy of the developed models. The values of the sensors faults belong to their corresponding sensors configuration (presented on the left column of Table 1).

5. Development and application of Fuzzy Logic (FL) modules for interpretation of the diagnostic data-bases

Almost every sensors system generates some disturbances (i.e., measurement faults) during the done measurement procedures. In general, the nature of these measurement faults is influenced by the applied methods and equipment, but mostly – by the process development, (the non-predictable and stochastic changes in the process behaviour have strong effect on these faults). The so-generated measurements are transferred in the system states and inevitably provoke some uncertainties in the diagnostic data bases. Another important aspect of the generated measurement faults is their disturbance effect on the system matrix **[SM],** resulting in eventual defects in the developed modelling techniques.

These considerations are in the core of the reason for development and application of ***Fuzzy Logic (GL) modules*** for interpretation of the relations between the state variables and the measured quantities of the process variables. The MATLAB toolbox Fuzzy Logic was applied for the purpose.

The system state $\mathbf{X_i}$ ($i = \overline{1, n}$) is a function of the measured quantities (i.e., the components of the measurement vector) – $\mathbf{Y_j}$ ($j = \overline{1, m}$). In the aspect of FL the following relation could therefore be developed:

$$X_i = F\left[M_{Y1}(X_i),\ M_{Y2}(X_i), \ldots, M_{Ym}(X_i),\ \right] \quad (10)$$

where $\mathbf{M_{YJ}(X_i)}$ are the membership functions, which express the degree of uncertainty of the relation $\mathbf{X_i(Y_J)}$**.** The example, provided on figure 4, shows, that for a system state $\mathbf{X_4}$ (of the diagnosed component), the influence function is selected as a triangular function, where the shape of the lines are determined by the elements of the system matrix **[SM]**.

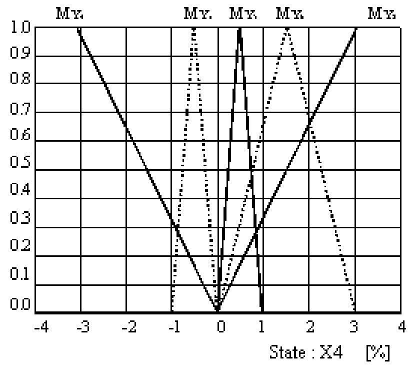

Figure 4. Fuzzy Logic functions, applied for interpretation of particular system state X_4

The analysis, performed over the obtained function shapes show, that, large values of the elements of [**SM**]**,** ***have strong effect*** over the relation $\mathbf{X_i(Y_J)}$**,** while small values of the elements of **[SM],** ***have only a little influence*** over the relation $\mathbf{X_i(Y_J)}$**, (**expressed by a very narrow strip on the axe $\mathbf{X_4}$ (figure 2). For this particular example the measurement quantities Y_1, Y_2, Y_4, Y_5 and Y_6, influence the system state $\mathbf{X_4}$**, -** please see again relation (10). Similar sets and relations can be composed for all considered system states. Since, the diagnosis procedures generate fault-free system states, a measurement values with faults will have very high influence effect over the composed sets. Such a particularity can be used for a criteria to separate (i.e. to isolate) such values from the others (i.e. from the "healthy" ones) ***providing options for high fault tolerance of the sensors measurement system***.

6. Conclusions

6.1. The structure and the operation procedures for a sensors controlled system, designed for waste air-processing was developed.

6.2. Techniques for modelling of the State Variables, were developed and applied in FD procedures.

6.3. Knowledge-based methods for sensors fault detection were also developed and applied in combination with FL techniques for FD of the diagnosed modules.

6.4. The developed modeling and knowledge based techniques were applied in an industrial waste air-processing system, under real operation conditions, thus providing fault tolerance and reliability enhancement of the entire technologic system.

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