Sensor fault detection in building energy management systems

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Abstract. In this specific paper a methodology for detecting sensor failures in building energy management systems is presented. The fault diagnosis decision criterion is the average absolute prediction error between the actual and the predicted values of the sensor. The predicted value is calculated by a model based on normal operation data. Three experiments are presented with simulated biases in the temperature, illuminance and CO_2 sensors. Although the concept is simple, the results for fault detection are quite satisfactory.

Index Terms: Fault detection and diagnosis, sensors, building energy management systems.

I. Introduction and State of the Art

The complexity of systems deployed on modern buildings, necessitates the use of optimal control. During the last years, there is a rapid convergence of the technologies of Informatics, Microelectronics and Control Systems leading to novel approaches and solutions for energy and building automation related problems [1].
As the 'intelligent building' is passing nowadays its phase of maturity, a great number of manufacturers offer integrated solutions (i.e. the ORCA system of Delta Controls based in BACNET architecture, SIEMENS EIBUS, ABB, etc).
The fault detection and diagnosis (FDD) technology provides the capability to deal with complex problems that are related with the uninterrupted operation of various systems even even in a fault regime.
The uninterrupted system operation is based on the normal operation of each of the system parts. In building energy and indoor environment management systems these parts are: (i) sensors, (ii) actuators and (iii) interfaces and software.
A significant effort has been put in fault detection and diagnosis in sensors. The conventional method for detecting sensor failures is to check the consistency of the redundant measurements, estimate expected values from measurements, and detect, isolate, and characterize the type of anomaly in the measurement channel output.
Fault detection and diagnosis of building HVAC systems usually uses data from sensors to get information on whether the system has faults or not. A Building Energy Management System usually stores the sensors measured data and is accessible from an FDD system. The use of measured data leads to different FDD systems. These can be either knowledge- ([2], [3]) or model-based ([4] [5], [6]).
In the present paper an attempt for fault detection in building energy management system sensors algorithm is presented around the SIEMENS EIBUS architecture. The fault detection algorithm is based on specific measurements taken by a test bench especially developed for simulation of the indoor environmental parameters while using BEMS.

II. Problem Statement

The problem that we are facing is the detection of sensor failures of the control system depicted in Fig. 1. **A** and **P** on Fig. 1 denote the actuators and the plant respectively. The equations representing Fig. 1 are:

Nonlinear state equation: $x_{k+1} = f\left(x_k,\ u_k, d_k\right)$

Measurements with noise: $y_k = x_k + n_k$

Controller: $u_k = g\left(r, y_k\right)$

The state space vector is:

$$x_i = \begin{bmatrix} x_{1,i} \\ x_{2,i} \\ x_{3,i} \\ x_{4,i} \\ x_{5,i} \\ x_{6,i} \end{bmatrix} = \begin{bmatrix} T_{in} \\ T_{mr} \\ h_{in} \\ v_{in} \\ l_{in} \\ C_{in} \end{bmatrix} \qquad (1)$$

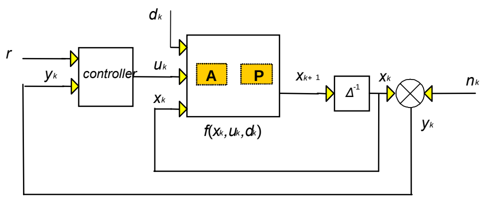

Fig. 1. The control diagram

where,
T_{in} the indoor temperature (°C)
T_{mr} the mean radiant temperature (°C), [7]
h_{in} the indoor relative humidity (%)
v_{in} the indoor wind velocity (m/s)
l_{in} the indoor illuminance levels (lux)
C_{in} the indoor CO_2 concentration (ppm)

The output vector is $y_i = x_i + n_i$ and the control vector are:

$$u_i = \begin{bmatrix} u_{1,i} \\ u_{2,i} \\ u_{3,i} \\ u_{4,i} \end{bmatrix} = \begin{bmatrix} S \\ W \\ AC \\ L \end{bmatrix} \quad (2)$$

where,
S: the shading opening ranging from 0 to 1.
W: the window opening with a 0-100% range.
AC: the air conditioning operation duration (0-100% of the sample time).
L: the lighting level (0-1).

The disturbances vector is (indicative):

$$d_i = \begin{bmatrix} d_i^m \\ d_i^u \end{bmatrix} = \begin{bmatrix} d_{1,i}^m \\ \hdashline d_{1,i}^u \\ d_{2,i}^u \\ d_{3,i}^u \\ d_{4,i}^u \\ d_{5,i}^u \\ d_{6,i}^u \\ d_{7,i}^u \\ d_{8,i}^u \end{bmatrix} = \begin{bmatrix} t_{out} \\ \hdashline s_d \\ n_p \\ v_{out} \\ d_{out} \\ o_d \\ l_{out} \\ h_{out} \\ t_{app} \end{bmatrix} \quad (3)$$

where,
t_{out}: the outdoor temperature (°)
s_d: the number of smoking people
n_p: the number of occupants
v_{out}: the outdoor wind velocity
d_{out}: the outdoor wind direction
o_d: the opening and closing of doors
l_{out}:the outdoor illuminance
h_{out}: the outdoor relative humidity
t_{app}: the thermal casual gains.

The only disturbance measured is the outdoor temperature. The outdoor wind velocity, wind direction and humidity are considered constant due to the lack of sufficient measurements. The opening and closing of doors and the number of occupants are also taken constant. The thermal casual gains are estimated by the relevant bibliography [7]. The controller that is used is a fuzzy controller developed for BEMS with inputs: The Predicted Mean Vote (PMV) for thermal comfort [7], the CO_2 for indoor air quality and the indoor illuminance for visual comfort. The reference signals of the controller are: the PMV index should be within -0.5 and 0.5, for CO_2 is 800 ppm and for indoor illuminance 500 lux [8].

The performance criteria for the fault diagnosis system are the following:

- Capability of detecting multiple faults in different sensors simultaneously.
- Detection speed.
- Number of fault alarms or non detection of existing faults.
- Size of the detecting fault.

The proposed solution is based on a function δy which represents the difference between the predicted value (y_p) and the actual value (y_m) of each measuring variable:

$$\delta y = y_p - y_m \quad (4)$$

The predicted value is calculated by a model based on normal operation data. For the specific fault detection and diagnosis system the predicted value is a linear combination of the system's variables, given by the following equation:

$$y_p(k) = y_p(k-1) + \beta_1 \cdot f_1(u(k-1), y_p(k-1), d(k-1)) + \ldots + \beta_m \cdot f_m(u(k-1), y_p(k-1), d(k-1)) \quad (5)$$

where k is the time of sampling, f a non linear function, u the actuators' values vector that influence the value of each specific sensor, y the measured values of the sensors, d the measured values of disturbances and β_i the coefficients values that are estimated using the least squares method. It should be noted that Eq. 5 is different for each sensor.
The equations used for each environmental variable are the following:

A. CO_2 concentration

The CO_2 concentration at time k is considered a function of the concentration at time k-1, the opening of windows W and the outdoor CO_2 concentration. The outdoor CO_2 concentration is considered constant. Therefore:

$$\begin{aligned} CO_2(k) &= CO_2(k-1) + \beta_1 \cdot W(k-1)\left[CO_{2,\text{out}} - CO_2(k-1)\right] = \\ &= CO_2(k-1) + \beta_1 \cdot W(k-1) + \beta_2 \cdot W(k-1) \cdot CO_2(k-1) \end{aligned} \quad (6)$$

B. Indoor illuminance

The indoor illuminance at time k is considered a function of the shading opening S, the indoor electric lighting level L, and the outdoor illuminance. The outdoor illuminance varies significantly and cannot be considered constant.

$$Ill(k) = \beta_1 \cdot S(k-1) \cdot Ill_{out} + \beta_2 \cdot L(k-1) \quad (7)$$

C. Indoor Temperature

The indoor temperature at time k is considered a function of the indoor temperature at time k-1, the window opening W and the air conditioning level AC. The window opening contributes through the temperature difference between outdoors and indoors.

$$T_{in}(k)=T_{in}(k-1)+\beta_1\cdot W(k-1)\cdot\left[T_{out}(k-1)-T_{in}(k-1)\right]+$$
$$+\beta_2\cdot AC(k-1) \tag{8}$$

D. Relative Humidity

The relative humidity at time k is considered a function of the relative humidity at time k-1, the window opening W, the air conditioning level AC and the outdoor relative humidity.

$$Hum(k)=Hum(k-1)+\beta_1\cdot W(k-1)\cdot\left[Hum_{out}(k-1)-Hum_{in}(k-1)\right]+$$
$$+\beta_2\cdot AC(k-1) \tag{9}$$

III. Decision function

The decision function is the average absolute prediction error (MAE) defined in the following equation:

$$\varepsilon(k)=\left|\, y_p(k)\text{-}y_m(k)\,\right| \tag{10}$$

The MAE is compared to an upper value which is calculated by the sample data under normal operation with the use of the following equation:

$$\hat{\varepsilon}=\frac{1}{N}\sum_{i=1}^{N}\left|y_p(i)-y_m(i)\right| \tag{11}$$

where N is the sample size. The methodology followed to decide whether there is a fault in the sensors or not is the following:

- At time k the function $\varepsilon_{nw}(k)$ is calculated based on the equation:

  $$\varepsilon_{n_w}(k)=\frac{1}{n_w}\sum_{k-n_w+1}^{k}\left|y_p(n_w-i)-y_m(n_w-i)\right|$$

  where n_w is the window length used to robustify the procedure.
- If $\varepsilon_{n_w}(k)>c\cdot\hat{\varepsilon}$ then there is a fault in the specific sensor, otherwise not. If the error condition remains for a significant number of samples then the fault certainty increases.

The parameters n_w and c are estimated using trial and error in order for the overall procedure to satisfy the performance criteria. In the specific study n_w=100 and c=2.

IV. Diagnostic Results

Three experiments are performed using the data collected by a test bench especially developed for testing control algorithms in BEMS. The test bench is depicted in Fig. 2 and is equipped with the following sensors: (i) temperature, (ii) relative humidity, (iii) CO_2 concentration, (iv) indoor illuminance, (v) mean radiant temperature and (vi) indoor wind velocity. Since the test bench has limited space comparing to a room, the sensors are positioned in the centre of the bench. The test bench is connected with MATLAB and it controls automatically its heating and cooling requirements, its indoor lighting levels by movable shading devices and its indoor air quality by movable windows.

In each experiment a simulated bias of -40% in the corresponding sensor was effected at time k=20. For each sensor three graphs are produced(Fig. 3-Fig. 13:

1. The evolution of the decision criterion, i.e. the windowed average absolute mean error (MAE) (blue line in upper graph) together with its upper level for each sensor (red line in upper graph). This graph shows that a malfunction of a sensor is not detected as a malfunction of another sensor or is mistakenly detected.
2. The evolution of the predicted (red line in middle graph) and actual values (green line in middle graph).
3. The evolution of the actuators value in order to have an indication of bad performance for the diagnosis (lower graph).

The simulation time step is 120 sec. The disturbances are measured or taken by the bibliography for simplification of the procedure. The variations of the measured parameters are not significant in a room or a building zone. The window shading and ventilation operates with motors.

A. Malfunction of indoor temperature sensor

The problem in the operation of the temperature sensor is detected only for the specific sensor as it is shown in Fig. 5 (MAE for Tin is higher than its upper level). No fault is detected for all the other sensors (Fig. 3, 4 and 6) apart from relative humidity. The reason for the detection of error in relative humidity sensor is that the relative humidity model is estimated with W equal to 20% and the model does not recognize the 40% of window opening that occurs at time $k\approx$180. This can be overcome if the learning data are improved.

B. Malfunction of indoor illuminance sensor

The malfunction of the indoor illuminannce sensor does not cause fault alarms for any of the other sensors as depicted inFig. 7, Fig. 9 and Fig. 10. In Fig. 8 the MAE for illuminance is higher than its upper level indicating the fault of the specific sensor.

C. Malfunction of CO_2 sensor

The malfunction of the CO_2 sensor is not detected as depicted inFig. 11. The reason for that is again the poor prediction data. A false alarm appears for the illuminance sensor (Fig. 13) while the relative humidity sensor is between the limits (Fig. 12).

V. Conclusions

The proposed system is operating satisfactorily although it is fairly simple. Some shortcomings can be corrected if the influence of the outside disturbances is minimized. This can be achieved if they can be measured. Further improvements can be effected by a more appropriate training set for each sensor (persistent excitation).

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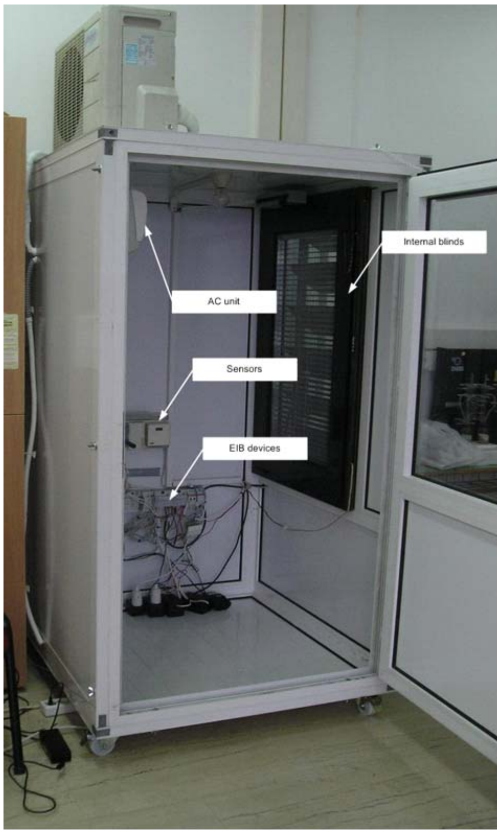

Fig. 2. The test bench

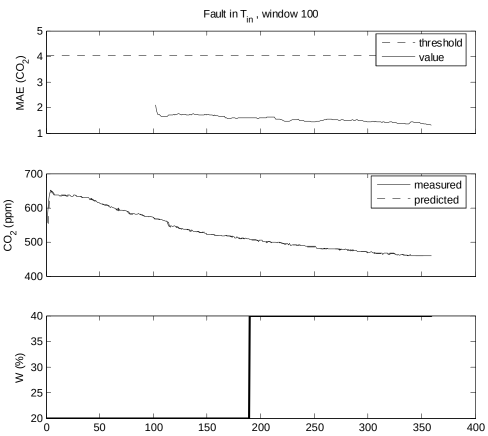

Fig. 3. Evolution of CO_2 for malfunction of the temperature sensor

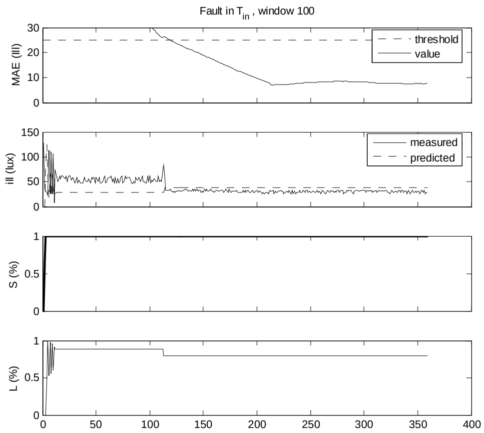

Fig. 4. Evolution of illuminance for malfunction of the temperature sensor

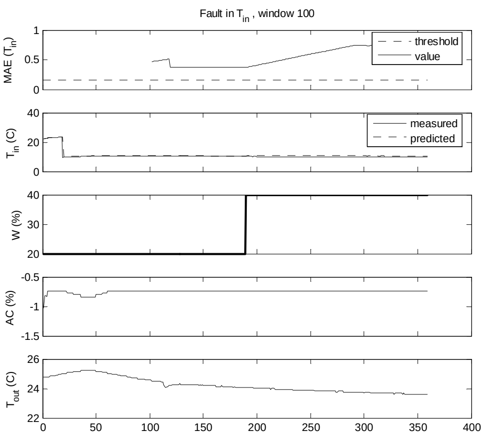

Fig. 5. Evolution of indoor temperature for malfunction of the indoor temperature sensor

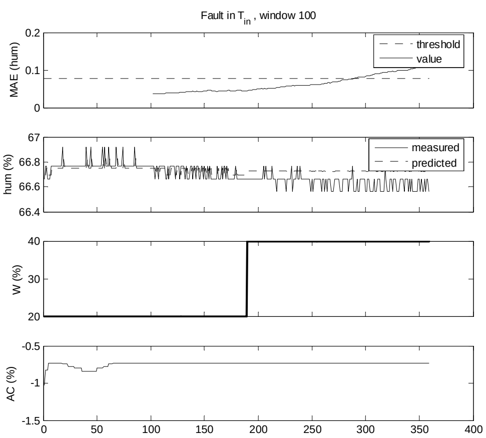

Fig. 6. Evolution of relative humidity for malfunction of the indoor temperature sensor

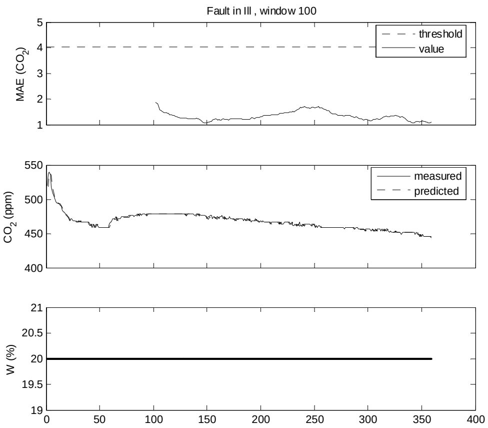

Fig. 7. Evolution of CO_2 for malfunction of the illuminance sensor

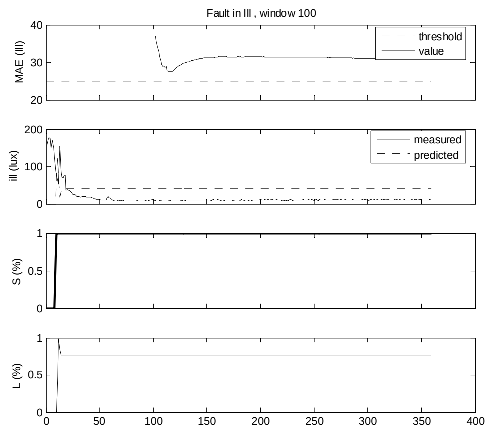

Fig. 8. Evolution of illuminance for malfunction of the illuminance sensor

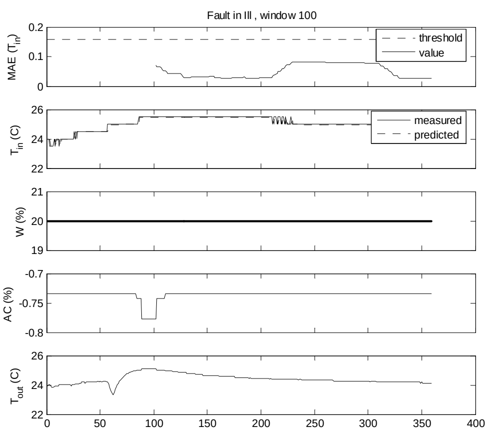

Fig. 9. Evolution of indoor temperature for malfunction of the illuminance sensor

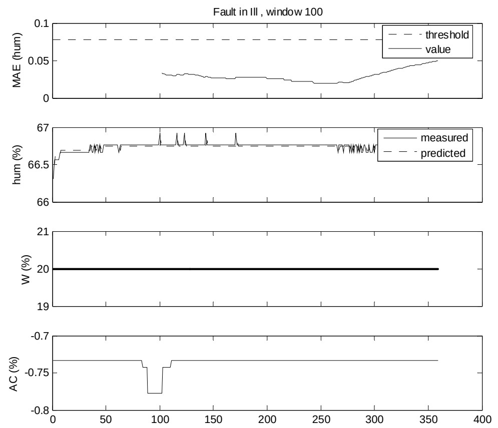

Fig. 10. Evolution of relative humidity for malfunction of the illuminance sensor

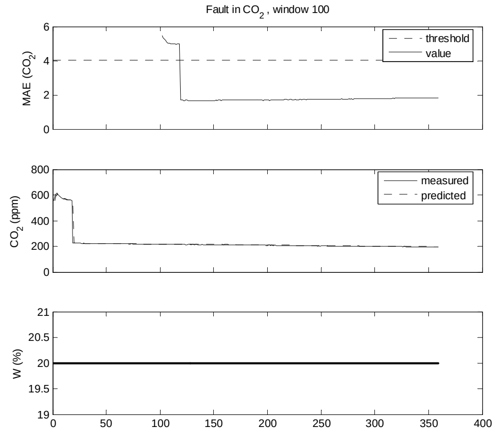

Fig. 11. Evolution of CO_2 for malfunction of the CO_2 sensor

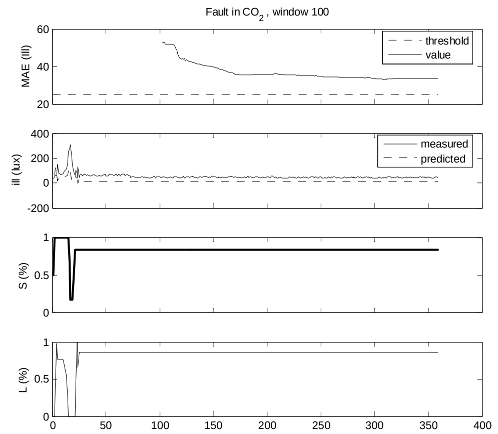

Fig. 12. Evolution of illuminance for malfunction of the CO_2 sensor

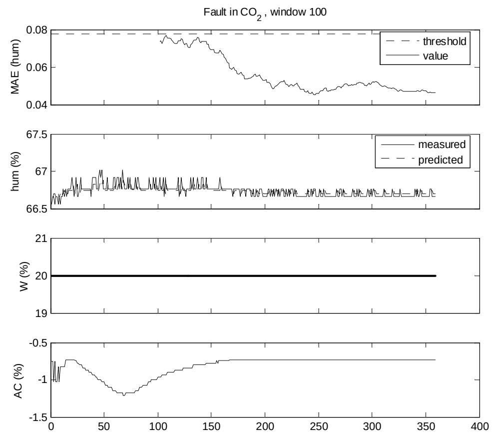

Fig. 13. Evolution of relative humidity for malfunction of the CO_2 sensor