A NEW ALGORITHM FOR SENSORS VERIFICATION AND CORRECTION
IN AIR HANDLING UNITS

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ABSTRACT

The use of trend data from Building Automation Systems (BAS) is a cost-effective strategy for ongoing commissioning in HVAC systems. Quality of measurements, thus, is essential for the effectiveness of commissioning process. This paper presents an approach to verify, and correct if necessary, the outdoor air temperature and relative humidity measurements in an AHU economizer. The proposed iterative algorithm solves an optimization problem that maximizes the goodness of fit, in terms of coefficient of variation, CV-RMSE, between a directly measured variable, and its value derived from an air energy balance. This approach has been verified with data from an institutional building in Montréal, proving its capability to highlight errors in the measurements of outdoor air relative humidity and temperature. Corrected values have been finally validated through comparison against spot measurements with calibrated sensors.

INTRODUCTION

The implementation of ongoing commissioning for HVAC systems is a cost-effective strategy to overcome the rise of faults and decrease in energy performance over the entire building systems life cycle (Roth K. et al., 2008). Faults and degradation can affect both equipment and sensors, causing decrease in equipment performance, energy wastes and occupancy discomfort. This paper focuses on faulty sensors detection in Air Handling Units (AHU), and presents a new algorithm to automatically adjust the measured air temperature and humidity. Faults in sensors may be often considered as soft failures, and thus they may produce small persistent waste of energy and/or discomfort for occupant, and remaining unrevealed for a long time (Haves P., 1999). Although numerous methods and algorithms for HVAC Automatic Fault Detection and Diagnosis (AFDD) have been developed during the last decades (Breuker M. S. and J. E. Braun, 1998, Jia Y. and T. A. Reddy, 2003, Cui J. and S. Wang, 2005), the same attention has not been given to self-correction algorithms, making the human intervention in commissioning strategies still crucial (Padilla M. et al., 2015). Four different types of faults are identified in sensors: bias faults, drift faults, complete failures and precision degradation (Chen Y. and L. Lan, 2010). Adding self-correction algorithms to systems control codes allows to minimize fault effects until the human action fix the fault (Fernandez N. et al., 2009). Self-correction algorithms could consist of virtual sensor measurements which replace values from sensors detected as faulty. Several virtual sensors algorithms have been developed for HVAC equipment and components: Nassif et al. (2003), Song et al. (2012), McDonald et al. (2014). Fernandez N. et al. (2009b) presented algorithms for sensors fault detection, isolation and correction in AHU. Algorithms implement rules based on physical principles coupled with knowledge of the AHU components configuration. Brambley M. R. et al., 2011 presented a study on self-correction strategies for AHU: 26 algorithms have been based on models developed during commissioning in order to simulate the correct system operation. Ten of those algorithms were integrated in the code of a prototype software for automated sensors fault detection and correction. Padilla M. et al. (2015) proposed a sensor correction algorithm for supply air temperature and pressure in an AHU, developing grey box models using variables usually measured for control purpose by the Building Energy Management System (BEMS). Whether a fault in sensors is detected, faulty measurements are replaced by values derived from those models. Finally, Padilla M. and D, Choiniere (2015) developed an algorithm for sensors fault detection and isolation in an AHU. The authors developed the algorithm coupling Principal Component Analysis (PCA) and Active Functional Tests (AFT).

This paper presents a new algorithm for sensor self-correction without need for human intervention or
additional measurements at additional cost. Results from testing the algorithm in an AHU economizer are presented as well.

**ALGORITHM**

The algorithm proposed in this paper aims for the self-correction of measurements of outdoor air temperature or relative humidity entering the AHU economizer. Only one of these two sensors might show abnormal measurements. Measurements from a BAS trend data are used in this study. The reference value of outdoor air temperature is predicted at each time step from the air energy balance at the mixing box of the economizer (assuming that all other sensors give accurate measurements). The measurements are corrected with a constant optimal value identified through an iterative procedure, and compared with the correspondent reference value. Short term measurements with calibrated sensors are used for validation purpose only.

The algorithm could also be applied to the return or mixed air stream, assuming as correct the measurements from the other air temperature and relative humidity sensors.

i) **Energy Balance**

The energy balance of mixing of two air streams in the adiabatic mixing box of the AHU is written as presented in Equation 1 in terms of α-factor. The α-factor is intended as the ratio of the outdoor air flow rate to the supply air flow rate (Eq. 2) (ASHRAE. 2001).

\[
\alpha = \frac{h_{ma} - h_{rec}}{h_{oa} - h_{rec}} \tag{1}
\]

\[
\alpha = \frac{m_{ma}}{m_{a}} \tag{2}
\]

where \(h_{ma}\) is the mixed air enthalpy, \(h_{rec}\) is the recirculated air enthalpy, and \(h_{oa}\) is the outdoor air enthalpy, \(m_{oa}\) is the outdoor air mass flow rate, and \(m_{a}\) is the supply air mass flow rate.

The outdoor air temperature entering the mixing box is predicted from the energy balance in terms of α-factor by using the sequence of Equations 3, 4 and 5 at each time step.

\[
x_{oa,a} = \alpha (x_{ma} - x_{rec}) + x_{rec} \tag{3}
\]

\[
h_{oa,a} = \alpha (h_{ma} - h_{rec}) + h_{rec} \tag{4}
\]

\[
T_{oa,a} = \frac{h_{oa,a} - h_{fg} x_{oa,a}}{c_{pa} + c_{pv} x_{oa,a}} \tag{5}
\]

where \(x_{oa,a}\) is the outdoor air specific humidity estimated with α-factor, kg/kg; \(x_{ma}\) is the mixed air specific humidity, kg/kg; \(h_{oa,a}\) is the outdoor air enthalpy estimated with α-factor, kJ/kg; \(T_{oa,a}\) is the outdoor air temperature estimated with α-factor, °C; \(h_{fg}\) is the water vaporization enthalpy, kJ/kg; \(C_{pv}\) is the water vapor specific heat at constant pressure \(P = 101,325 \text{ Pa}\); \(C_{pv} = 1,875 \text{ kJ/(kg K)}\), and \(C_{pa}\) is the dry air specific heat at constant pressure \(P = 101,325 \text{ Pa}\), \(C_{pa} = 1,006 \text{ kJ/(kg K)}\).

Values derived from eq. 5 for each time step compose a vector of temperatures, which are compared to the outdoor air temperature measurements from the BAS. The results of comparison are reported in terms of Coefficient of Variation of the Root Mean Square Error (CV-RMSE (%)). If high CV-RMSE values are obtained, we conclude that the measurements of the variable of interest (in this case the outdoor air temperature) might contain abnormal values. We assume CV-RMSE values higher than 10% to be indicative of the presence of abnormal values. Investigation on the presented algorithm using laboratory data should be conducted in order to identify an optimal CV-RMSE limit value for abnormal values detection. In this case, the measurements of outdoor air temperature need to be corrected and, for this purpose, a self-correction algorithm is proposed to be used. Certainly, the scope of this correction should be limited in time until the maintenance team make the physical corrections or replacement of sensors.

ii) **Iterative Procedure**

The measured value of outdoor air temperature at each time step is modified (Eq. 7). A delta vector \((dT(j))\) of 38 air temperature corrections, containing values from -5.0°C up to +5.0°C, increased by 0.25°C, is used (Eq. 6). For each \(j\)-correction, a new α-factor vector of values \((\alpha_{cor}(j))\) is derived through Equations 8 and 9.

\[
dT = [-5.0, -4.75, -4.50, \ldots, +4.50, +4.75, +5.0] \tag{6}
\]

\[
T_{oa,cor}(j) = T_{oa} + dT(j) \tag{7}
\]

\[
h_{oa,cor}(j) = T_{oa,cor}(j) \cdot C_{pa} +
\]

\[
+ x_{oa}(h_{fg} + T_{oa,cor}(j) \cdot C_{pv}) \tag{8}
\]

The algorithm is proposed to be used. Certainly, the scope of this correction should be limited in time until the maintenance team make the physical corrections or replacement of sensors.
\[ \alpha_{cor}(j) = \frac{h_{ma} - h_{rec}}{h_{oa,cor}(j) - h_{rec}} \]  

(9)

where \( j \) varies from 1 to the 38, \( T_{oa,cor}(j) \) is the \( j \)-th corrected outdoor air temperature measurement, \( h_{oa,cor}(j) \) is the \( j \)-th corrected outdoor air enthalpy, and \( \alpha_{cor}(j) \) is the \( j \)-th corrected \( \alpha \)-factor. For each \( j \), the corrected vector of \( \alpha \)-factor values is used with equations 3, 4 and 5 to obtain a new predicted value of \( T_{oa,\alpha}(j) \). For each \( j \), the CV-RMSE between \( T_{oa,\alpha}(j) \) and \( T_{oa,cor}(j) \), over the entire sample, is calculated. The \( dT(j) \) correction value that gives the minimum CV-RMSE is retained as the best correction value \( dT(j^*) \) of outdoor air temperature.

Finally all measurements of outdoor air temperature \( T_{oa} \) recorded by the BAS are replaced with the corrected outdoor air temperature \( T_{oa}^* \) (Eq. 10).

\[ T_{oa}^* = T_{oa} + dT(j^*) \]  

(10)

In addition to the correction of measurements of the outdoor air temperature, this iterative procedure allows for the correction of \( \alpha \)-factor. As a result, we obtain a better estimate of the outdoor air flow rate, if there is no air flow meter on the outdoor air intake. The effectiveness of the overall algorithm is verified by comparing the corrected outdoor air temperature measurements with short term measurements with calibrated sensors.

The flow-chart of the overall algorithm implementation is showed in figure 1.

**CASE STUDY**

This study uses two AHUs installed in parallel in a new university building in Montréal, QC. The outdoor air and recirculated air flows are mixed in two mixing boxes, installed in parallel, before the air is treated and supplied to the conditioned space (Figure 2). Four variable speed fans are used to supply the conditioned air to the building, and two fans for the returned air. Two heat recovery coils are installed at the outdoor air intake for pre-heating or pre-cooling.

![Figure 2 – Schematic of the Air Handling Units.](image-url)

The recirculated air temperature (\( T_{rec} \)) and relative humidity (\( RH_{rec} \)), are derived from the return air conditions, considering that the air specific humidity does not change through the return fan, and the outdoor air temperature increases by 1.8°C (Zibin N., 2014). Table 1 lists variables used in this study from the BAS trend data that contains measurements recorded at 15-min time step.

Moreover, short term measurements with calibrated sensors have been taken from September 2 to September...
19 in 2015 in order to preliminary verify the accuracy of measurements from the BAS. Short term measurements of the mixed air relative humidity have been taken, since this variable is not recorded by the BAS. Measurements from BAS trend data taken when the heat recovery coils were working have been excluded from the data set.

Table 1 – Variable used in this study for sensors self-correction.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outdoor air temperature</td>
<td>°C</td>
<td>(T_{oa})</td>
</tr>
<tr>
<td>Outdoor air relative humidity</td>
<td>%</td>
<td>(RH_{oa})</td>
</tr>
<tr>
<td>Return air temperature</td>
<td>°C</td>
<td>(T_r)</td>
</tr>
<tr>
<td>Return air relative humidity</td>
<td>%</td>
<td>(RH_r)</td>
</tr>
<tr>
<td>Mixed air temperature</td>
<td>°C</td>
<td>(T_{ma})</td>
</tr>
<tr>
<td>Mixed air relative humidity</td>
<td>%</td>
<td>(RH_{ma})</td>
</tr>
</tbody>
</table>

From the comparison with short term measurements, we concluded that the BAS measurements of outdoor air relative humidity and temperature show abnormal values (Figures 3 and 4). Statistical indices from comparison confirm the occurrence of abnormal values from the BAS: Mean Absolute Error MAE = 30.8% and CV-RMSE = 45.7% for relative humidity, MAE = 1.3°C and CV-RMSE = 9.1% for air temperature. As the proposed algorithm considers the failure of only one sensor, and for the purpose of presenting the proposed algorithm, the short term measurements have been used to replace the measurements from one of the two outdoor conditions sensors.

RESULTS

The proposed algorithm has been applied to available measurements from September 2 to September 19, 2015. The two following sub-sections give results from those two data sets: i) \(T_{oa}\) faulty data set; and ii) \(RH_{oa}\) faulty data set.

(i) \(T_{oa}\) faulty data set

Figure 5 highlights some differences between measured and derived \(T_{oa}\), suggesting the occurrence of faulty values affecting one of the variables involved in the energy balance equation (Eq. 1). The statistical indices support also the same conclusion: MAE = 3.1°C and CV-RMSE = 34.5%. Although normally the temperature difference is not reported as percentages, for the consistence with the reporting of difference in relative humidity, we preferred to use the percentage in reporting the CV-RMSE of air temperature difference. The remarkable difference between measurements and derived values showed in figure 5, thus, comes from inaccurate evaluations of the \(\alpha\)-factor, which derive from faulty values involved in eq. 1, and which finally
cause incorrect outdoor air temperature derived values (eq. 5).

Through the iterative procedure, the best correction value of outdoor air temperature has been found to be \(dT^* = -2.0°C\). Figure 6 shows the variation of CV-RMSE with \(dT\). The corrected outdoor air temperature values have been thus evaluated: \(T_{oa}^* = T_{oa} - 2.0°C\). The corrected outdoor air temperature, thus, replaced the values collected by the BAS creating a corrected data set.

To evaluate the effectiveness of the propose algorithm, the derived outdoor air temperature \(T_{oa,\alpha}^*\) (Eq. 3, 4 and 5), are compared with the corrected \(T_{oa}^*\) measurements. Comparison is showed in figure 7. Statistical indices show an improvement in the data set due to the correction procedure on outdoor air temperature values: MAE = 2.7°C (from 3.1°C) and CV-RMSE = 20.6% (from 34.5%). Thus figure 7, compared to figure 5, shows a slight improvement in comparison between measurements (corrected) and correspondent derived values. Statistical indices reflect this improvement.

Statistical indices used for the comparison between spot and corrected measurements show improvement in CV-RMSE but a worse MAE value: MAE = 1.8°C (from 1.3°C) and CV-RMSE = 6.9% (from 9.1%). Figure 8 shows the outdoor air temperature profiles from spot measurements, corrected values and measurements from the BAS.
(ii) \( RH_{oa} \) faulty data set
Implementing the algorithm on the \( RH_{oa, faulty\ data\ set} \), \( RH_{oa} \) values are derived from the \( \alpha \)-factor through Equations 11 and 12. Within the algorithm steps, this correspond to what have been done for the outdoor air temperature along Equations 3-5.

\[
x_{oa,\alpha} = \frac{x_{ma} - x_{rec}}{\alpha} + x_{rec}
\]

\[
RH_{oa,\alpha} = \frac{P_{voa}}{P_{saoa}} \cdot 100
\]

where \( x_{oa,\alpha} \) is the outdoor air specific humidity derived from the \( \alpha \)-factor, kg/kg; \( P_{voa} \) is the outdoor air partial pressure of water vapor, \( Pa \), function of the outdoor air specific humidity; \( P_{saoa} \) is the outdoor air saturated vapor pressure, \( Pa \), function of the outdoor air dry temperature, \( Pa \).

Figure 9 highlights the significant difference between measured (\( RH_{oa} \)) and derived (\( RH_{oa,\alpha} \)) outdoor air relative humidity. The statistical indices support also the conclusion of a large difference between those relative humidity values: Mean Absolute Error (MAE) = 92.4%, and CV-RMSE = 410.6%. Similarly to the previous section (\( T_{oa} \) faulty data set), the large variation between measured and derived outdoor air relative humidity values depend on the inaccuracy of estimated \( \alpha \)-factor, and thus, on the correctness on measurement values used in \( \alpha \)-factor calculation.

Through the iterative procedure, the best correction value of air specific humidity was obtained \( dx^* = 0.0035 \) kg/kg. The corrected outdoor air relative humidity (\( RH_{oa}^* \)) values have been thus obtained from the corrected outdoor air specific humidity (\( x_{oa}^* \)). The corrected outdoor air relative humidity values replaced the values collected by the BAS, creating a corrected data set.

In order to verify the effectiveness of the algorithm, the outdoor air relative humidity (\( RH_{oa,\alpha}^* \)) have been derived from \( \alpha \)-factor (Eq. 11 and 12), along the corrected data set, and compared to \( RH_{oa}^* \).

The comparison between the corrected \( RH_{oa}^* \) and derived \( RH_{oa,\alpha}^* \) values (Figure 10) shows a remarkable improvement with reference to values from before the optimization. The statistical indices show also a good agreement: MAE = 3.6% (from 92.4%) and CV-RMSE = 4.7% (from 410.6%).
Figure 10 - Comparison between corrected measurements from the BAS and correspondent values derived from α. A perfect correlation reference line is plotted in red.

Statistical indices used for the comparison between spot and corrected measurements of outdoor air relative humidity confirm the effectiveness of the proposed algorithm: MAE = 5.5% (from 30.8%) and CV-RMSE = 6.0% (from 45.7%). Figure 11 shows the outdoor air relative humidity profiles from spot measurements, corrected values and measurements from the BAS. The missing values in Figure 11 correspond to those records, removed for the analysis, when the heat recovery coils worked.

Table 2 summarizes the statistical indices from the comparison between measurements and derived values, before and after the use of correction algorithm. Table 3 summarizes statistical indices from the comparison between spot measurements and measurements from the BAS (before the correction algorithm), and between the spot measurements and corrected measurements (after the correction algorithm). For this case study, the proposed algorithm improved significantly the estimates of outdoor air relative humidity; as the CV-RMSE was reduced from 45.7% to 6.0%. For the outdoor air temperature, the effectiveness of the algorithm is not clear; the CV-RMSE was reduced from 9.1% to 6.9%. However, both CV-RMSE values are acceptable as they are less than 10%.

### Table 2 – Statistical indices from comparison between measurements and derived values

<table>
<thead>
<tr>
<th></th>
<th>Before the correction algorithm</th>
<th>After the correction algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>CV-RMSE</td>
</tr>
<tr>
<td>$RH_{oa}$</td>
<td>92.4%</td>
<td>411.0%</td>
</tr>
<tr>
<td>$T_{oa}$</td>
<td>3.1°C</td>
<td>34.5%</td>
</tr>
</tbody>
</table>

### Table 3 – Statistical indices from comparison of the spot measurements with uncorrected measurements from the BAS (before the correction algorithm), and with the corrected measurements (after the correction algorithm).

<table>
<thead>
<tr>
<th></th>
<th>Before the correction algorithm</th>
<th>After the correction algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>CV-RMSE</td>
</tr>
<tr>
<td>$RH_{oa}$</td>
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</tbody>
</table>

### CONCLUSIONS

The *self-correction* algorithm presented in this paper can be applied to measurements from the BAS trend data, when abnormal values are noticed. The algorithm
validation have been done using short term measurements.

The proposed algorithm proved to be more effective, in this case study, for the correction of measurements of outdoor air relative humidity then of outdoor air temperature. The difference between spot measurements of the outdoor air temperature and BAS trend data have not constant high variation (Figure 4) due to some physical factors such as the influence of solar radiation on the sensor. As a consequence the use of a constant correction value for the entire data set does not allow for a larger reduction of the CV-RMSE value. However, the CV-RMSE values are less than 10% (Table 3), which can be accepted for practical purposes. The reduction of CV-RMSE between the spot measurements and corrected BAS trend data is larger for the outdoor air relative humidity because the difference between the spot measurements and the uncorrected BAS trend data is almost constant over the entire data set (Figure 3), due to the constant bias error of the sensor.

The proposed self-correction algorithm could be integrated into AHU control strategies implemented by the BAS. If faulty measurements are detected, the proposed algorithm would produce corrected values, which would be used by the BAS instead of the directly measured faulty ones. At the same time, information on eventual detected abnormal values would be sent to building operators, supporting them in scheduling maintenance and calibration strategies and inspections. Until the human intervention would not recalibrate the faulty sensor, the proposed algorithm would supply corrected values to the BAS.

In conclusion, the proposed self-correction algorithm proved to be effective in the case study for the correction of measurements of outdoor air relative humidity and temperature.

Results presented in this paper concern a 17 days long data set of measurements during the fall season (September 2015). Future investigations should use larger data sets from different periods of the year. The algorithm should be tested with other case studies. Also, the effectiveness of using variable correction values instead of a constant correction values, as presented in the paper, should be tested. For instance, correction values could be evaluate independently per each hour of the day or bin of values, depending on the sensor error profile.

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