

Fault Detection in Air Handling Units

The user-centered self-assessment methodologies for technical systems, energy components, and appliances are implemented in the SATO platform and are now being demonstrated and verified in the SATO use cases and pilots on real-life monitored data.

One of the implemented assessment methodologies focuses on fault detection in technical building systems – specifically, air handling units – and has been tested and validated in the Aalborg Office pilot. The method developed is quite versatile, making it possible to detect different faults in the air handling unit by selecting the relevant key performance indicators (KPIs) and explanatory variables to be included in the fault detection analysis. In the example shown in Figure 1, fault detection is related to the investigation of the difference between supply water temperature and the setpoint of the heating coil. Such faults could, for example, be due to poor control of the water mixing loop, causing the supply water temperature to be too low/high. The method was tested on a labeled faulty AHU dataset¹ and it was proven to have a correct rate of at least 95%, depending on the combination of explanatory variables and KPI.

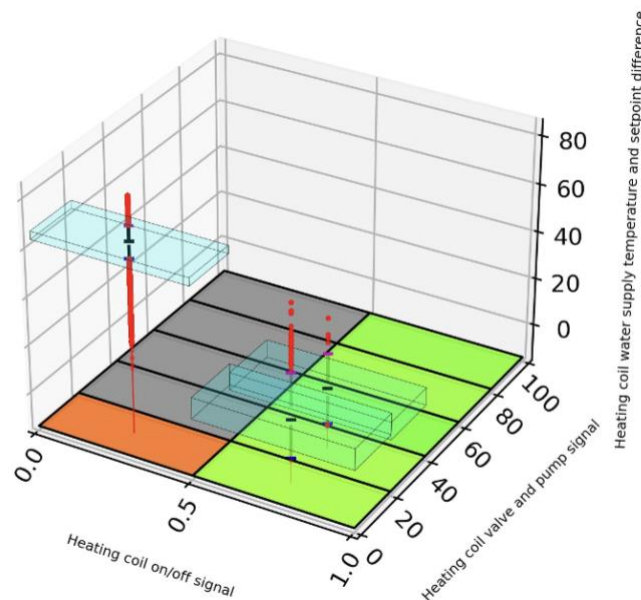


Figure 1: Example of initial idea for visualization of the fault detection method. The color on the bottom indicates the median performance, while the boxplot shows the spread of the KPI for each subdivision, along with the red dots for potential outliers.

¹ <https://doi.org/10.1016/j.enbuild.2021.110781>

The fault detection method takes offset in a combination of expert knowledge and two outlier detectors, a statistical method, and unsupervised clustering. Both detectors must indicate faulty performance for a fault to be detected. The main part of the expert knowledge needed is setting the combination of a KPI, explanatory variables, and subdivisions. These elements create a subset for the statistical and clustering techniques instead of searching the entire dataset. The advantage of this approach is that if the explanatory variables are set well, the subset should be more representative of the current data point than the entire dataset.

The visualization of the data is depicted in Figure 1, where color signifies the mean performance within the subdivision, and the 3D boxplot highlights subdivisions with excessive outliers. In this context, good performance (green) is when the KPI is as close to zero as possible, while any deviation from this indicates poorer performance. In terms of the boxplots, these appear once enough outliers are detected in a subdivision over a time period. In this case, it can be seen that only the low valve and pump signal subdivisions have many outliers, which may be caused by transitioning states, while the higher valve and pump signal subdivisions, show no current indications of faulty behavior. This underscores the importance of selecting appropriate explanatory variables, as transitioning states are not considered errors in this context.

Explanatory variable 1 is the 'Heating coil on/off signal,' which, due to its boolean nature, can only have two subdivisions. On the other hand, Explanatory variable 2, 'Heating coil valve and pump signal,' is a continuous value between 0 and 100, and, therefore, has been divided into five subdivisions in this example. As for the KPI, the difference between the heating coil water supply temperature and setpoint is chosen. This selection aims to investigate whether the heating coil can reach and maintain its setpoint and, if not, under which conditions it may fail.



About the project

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