Fault Detection and Diagnostics in Ventilation Units Using Linear Regression Virtual Sensors

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***Abstract*—Buildings represent a significant portion of global energy consumption. Ventilation units are one of the largest components in buildings systems and are responsible for large part of energy consumption.**

Ventilation units are complex components, often customized for the specific building. Their faults impact buildings' energy efficiency and occupancy comfort. In order to ensure their correct operation, proper Fault Detection and Diagnostics methods must be applied. Hardware redundancy, an effective approach to detect faults, leads to increased costs and space requirements.

We propose to exploit physical relations inside the unit to create virtual sensors from other sensors' readings, introducing redundancy in the system. We created linear regression models for three sensors using other sensors related through physical laws as inputs. We use two different measures to detect when a virtual sensor deviates from the actual one: R^2 score and acceptable range.

We test our method on a real building at the University of Southern Denmark. Our method detected a fault in temperature sensor, where its readings had an abnormal trend and fell outside acceptable range for one day.

***Index Terms*—fault detection and diagnosis, virtual sensors, HVAC, smart buildings**

I. Introduction

In Europe, buildings account for 40 % of the total energy used and 36 % of the total CO2 emissions [1]. In the United States, the buildings' sector accounted for about 41 % of primary energy consumption in 2010, 44 % more than the transportation sector and 36 % more than the industrial sector. Total building primary energy consumption in 2009 was about 48 % higher than consumption in 1980, going from 1290 TW h to 2784 TW h [2].

Modern buildings consist of different subsystems such as Heating Ventilation and Air-Conditioning (HVAC) units, lighting and heating. Each subsystem contains in turn several components such as pumps, fans, ducts, sensors, lamps, wires etc. monitored and managed by a Building Management System (BMS). All these components are subject to faults, due to damage, wearing over time, misconfiguration and communication issues. Faults impact occupancy comfort, maintenance cost and particularly energy efficiency. It is estimated that in 2009 just 13 of the most common faults were responsible for over $3.3 billions in energy waste [3].

HVAC load varies depending on building type and location, but they are one of the heaviest subsystems and can make up to 50 % of the total energy consumption and, therefore, faults involving them cause large energy waste [4]. Research suggests that between 20 % to 30 % energy saving could be achieved by re-commissioning malfunctioning HVAC systems [5]. HVAC systems are often customized for their specific building and, therefore, lack quality system integration [6].

A. Problem statement

Building energy efficiency cannot be achieved without Fault Detection and Diagnostics (FDD) methods applied to ventilation units. Hardware redundancy is an effective approach to high quality FDD, however, duplicating sensors and other components inside every unit increases deployment and maintenance costs, necessary space and complexity. Commercial ventilation units are rarely shipped with hardware redundancy.

In this paper we propose a mixed model-based and data-driven technique to exploit spatial relations among different components in ventilation units to create *virtual sensors* and introduce redundancy in the system, which can be used to detect and diagnose faults. For each considered sensor we train a linear regression model to estimate it given other sensors in the unit. This allows us to detect and diagnose faults that cause actual and virtual sensors to deviate from each other. We apply this technique to a real world building and report the results.

The rest of the paper is organized as follows. The state-of-art is reviewed in Section II. The proposed technique is introduced in Section III. Section IV presents the case study and discusses results and implications. Finally, conclusions are drawn in Section V.

II. State-of-art

A. Fault Detection and Diagnostics

Kim et al. present a comprehensive review of recent FDD methods for building systems [7]. FDD methods are categorized in three groups depending on the approach: data-driven methods, model-based methods and rule-based methods.

In data-driven methods a black-box model of the system under test is trained over historical data using techniques such as artificial neural network or regression models. These methods require no detailed knowledge of the system and can be easily generalized. Historical labeled faulty and fault-free data are necessary to improve fault detection and to perform fault isolation and diagnostics.

In model-based methods a model of the system under test is created from first principles. These techniques are often accurate and can detect and diagnose unknown faults. Models can become complex and deep knowledge of the physical characteristics and relations of the system's components is required to create them.

In rules-based methods expert knowledge is used to design a set of rules describing the system's behaviour. No historical data or detailed knowledge from the system are necessary. Large rules sets are necessary to describe complex behaviours, which lead to conflicts and maintenance effort.

Yu et al. present a review of FDD techniques for ventilation units [6]. The authors focus on software redundancy techniques, classifying them in model-based, data-driven and rules-based categories as in general FDD methods, and define a list of desirable characteristics: 1) Quick detection and diagnostics, 2) Isolability, 3) Robustness, 4) Novel identifiability, 5) Classification error estimate, 6) Adaptability, 7) Explanation facility, 8) Modeling requirements, 9) Storage and computational requirements, 10) Multiple fault identifiability.

B. Virtual Sensors

Li et al. present a review of virtual sensing techniques in the context of buildings systems [8]. Virtual sensors have been successfully applied to other fields such as process control and automotive for more than two decades, and their usage would be advantageous in buildings systems. Virtual sensing techniques are categorized according to three criteria. Measurement characteristics, i. e., whether the sensors represents sensor at steady state or during transients. Modeling method, i. e., model-based or data driven, a similar characterization as general FDD techniques. Application purposes, i. e., whether the sensors are used for redundancy and FDD, or for monitoring additional unknown quantities.

Li et al. propose a method for FDD in air conditioners using features decoupling and virtual sensors. The authors create virtual sensors for several quantities, such as compressor power consumption, refrigerant flow, condenser exit pressure, exit air humidity and evaporation temperature. Virtual sensor performances are tested both at steady state and under transients [9].

Cugueró-Escofet et al. present an approach for sensors data validation and reconstruction and apply it to urban water distribution systems. Raw data undergoes several tests, from low-level tests checking elementary properties of signals to high-level tests exploiting *spatial consistency* between different sensors [10].

Cotrufo et al. develop a virtual sensor modeling exhaust airflow in ventilation units. Airflow sensors for exhaust duct are rarely present in ventilation units due to initial cost. They use energy balance equation to relate other sensors in the system with the airflow and propose two different models. While the local errors can be large, the authors show how the cumulative residuals are small and, therefore, the virtual sensor can be used to estimate daily averages [11].

Kusiak et al. propose data-driven models for virtual sensors for room level indoor air conditions, i. e., temperature, CO_2 level and relative humidity. The authors develop four data mining techniques, including artificial neural networks, support vector machines regression and Pace regression. The obtained virtual sensors can be used for validation and calibration of physical sensors [12].

Verbert et al. propose a multi-model FDD method for HVAC systems that exploits components interdependencies. They develop Bayesian networks for multiple operating modes, using both actual and virtual sensors created from system knowledge and historical data. The authors show how using virtual sensors significantly improves FDD performance [13].

III. Virtual Sensors in Ventilation Units

A ventilation unit is an aggregate of several components, working together to provide air exchange to the building. It is important that every component works correctly, otherwise performance of the unit will decrease, causing energy waste and reducing comfort level in the building.

Since all components work together they exhibit common patterns and shared phenomena. Even if there is no explicit redundancy in the system, i. e., no duplicated sensor or meter, many of the quantities in the unit are strongly correlated. In this paper we propose to exploit these relations and create models to predict a quantity from the surrounding ones, generating a set of *virtual sensors*. Given actual sensors available in the ventilation unit $S_1, S_2, \ldots, S_n$, a virtual sensor S'_i measuring the same quantity of S_i is created using a model $f(\cdot)$ that takes other sensors as input:

$$\begin{aligned} &S'_i = f(\overline{S}) \\ &\overline{S} \subsetneq \{S_1, S_2, \ldots, S_{i-1}, S_{i+1}, \ldots, S_n\}. \end{aligned}$$

For instance, consider a heating system where the following quantities are measured with sensors or meters: initial temperature T_0, heater energy M and final temperature T_f. We could create a virtual sensor for final temperature using a model of initial temperature and heater energy $T'_f = f(T_0, M)$.

Different methods can be used to compute the value of a virtual sensor. When detailed knowledge about the unit is available it is possible to use physical models, e. g., computing airflow using fan speed and duct size and shape. Otherwise, it is possible to train black box models using data-driven techniques.

A. Fault Diagnostics

When two sensors, either actual or virtual, deviate, the only possible inference is that a fault is affecting one of them. In order to diagnose the faulty one a third sensor is necessary. Under the assumption of single simultaneous fault, when in a group of three sensors one deviates from the other twos, the former is identified as faulty.

Due to cost and space constraints, duplicated sensors are rarely available in ventilation units, and even less so are triplicated sensors. However, these constraints do not impact virtual sensors, which can be created without cost using data from other components. Some care is necessary when choosing the inputs: different virtual sensors should share as few inputs as possible, because a fault in an input impacts all its related virtual sensors.

For instance, consider a heating system with two initial temperature sensors T_0, T_1, a heater energy meter M and a final temperature sensor T_f, where two additional virtual sensors for final temperature were created:

$$T'_f = f(M, T_0), \qquad T''_f = f(M, T_1).$$

Assuming a single fault scenario, if T'_f and T''_f agree on their readings and T_f deviates from them there are two possible causes:

- Sensor T_f is faulty;
- Heater energy meter M is faulty.

This is due to the fact that heater energy meter M is used as input in both virtual sensors T'_f and T''_f, therefore, its fault impacts both their output.

B. Measuring Deviations from Actual Sensors

In order to automatically detect a fault, a measure of how much the virtual sensors deviate from the actual one is necessary. Several tools are available from statistical analysis, e. g., the maximal error or the norm of residuals. In this paper we use the coefficient of determination, or R^2 score, which gives an estimate of how much a model fit the data [14]. An R^2 score close to 1 indicates that the model is a good fit for the data, while values close to zero indicates the opposite. Negative values indicate that the model predicts data worse than a constant horizontal line.

We use the R^2 score both to verify that the trained models fit the testing data, i. e., that the designed model accurately follows the actual sensor, and to validate real-time data from the ventilation unit. For each period of interest, e. g., every day, the R^2 score for each virtual sensor against the actual sensor is recorded. When the measure is lower than a given threshold the pair virtual / actual sensors are flagged as faulty.

Another option for detecting deviations between actual and virtual sensor is to make the latter output an *acceptable range*. E. g., the predicted value plus the largest training error, or a confidence interval based on another training error statistics. When actual readings fall outside the acceptable range the two sensors are flagged as faulty.

With both approaches, in order to obtain accurate thresholds it would be necessary to have labeled faulty testing data.

IV. Case Study

A. Building OU44

In this paper we present Odense Undervisning Building 44 (OU44) as a case study [15]. It was built in 2015 at the University of Southern Denmark, campus Odense, and it is mainly used for teaching. It has three floors plus a basement and it contains classrooms, study zones, offices and auditoriums. It has four nearly identical ventilation units, each serving one corner of the building, or roughly 20 thermal zones.

A ventilation unit consists in a large air loop, as shown in Fig. 1. Inlet air enters the building, goes through a heat-exchanger (HX), then is heated to appropriate indoor temperature and pushed to the supply shaft, which is connected by Variable Air Volumes (VAVs) units to individual rooms. In the same way, exhaust air is collected from individual rooms in the extract shaft, it goes through the heat-exchanger and it is pushed outside. The heat-exchanger recovers heat from exhaust air and transfers it to inlet air, reducing the energy required by the heater. Air pressures in supply and extract shafts are kept at constant values 130 Pa and 40 Pa, which cause air to flow in the rooms. Two fans in the ventilation unit generate the required airflows to maintain the pressure setpoints.

Several sensors, shown as arrows in Fig. 1 are available inside ventilation units and heating loops: air temperature at several positions, airflows trough the two fans, supply and extract pressure, incoming and outgoing water temperature, and water flow through the pump. In addition to that, several meters measures the activity of fans and water pump: fan speed, fan current and voltage, fan power and electrical consumption, and pump electrical consumption.

Ventilation units are only working during working hours, i. e., from Monday to Friday from 7am to 6pm in local time. At any other time, at night and during the weekends, the systems are shut down.

B. Results

Three sensors were considered for monitoring in a ventilation unit: post-heat-exchanger temperature, airflow and fan speed. For each of them two different models were constructed using other sensors as inputs, as shown in Table I. Linear regression models were used under the assumption that inputs and outputs obey linear relations, at least locally [16]. Models were trained over a week long historical data from Monday 13th March 2017 to Sunday 19th March 2017, and tested over two weeks from Monday 27th March 2017 to Sunday 9th April 2017.

Another virtual sensor was also constructed, i. e., *Effort*, which is proportional to an estimate of the power requested to the ventilation unit and, therefore, to the airflow. By design fans produce airflow to maintain constant shaft pressure, which in turn depends on how many VAV units are open in the building. Effort is an aggregate count of those units, which makes it effectively a virtual sensor for an unknown quantity in the ventilation unit.

For each sensor two models were used, in order to perform fault diagnostics and not only fault detection. Table II shows the R^2 score of the models' predictions over each day, which measure how much actual and virtual sensors agree. Low R^2 scores, indicating that models deviate from the actual sensors, are highlighted in boldface.

For temperature two models are used, one exploiting knowledge about the heat-exchanger interactions, and another one which relies on similar but less structured relations between air temperature and heater (Model B). The former predicts

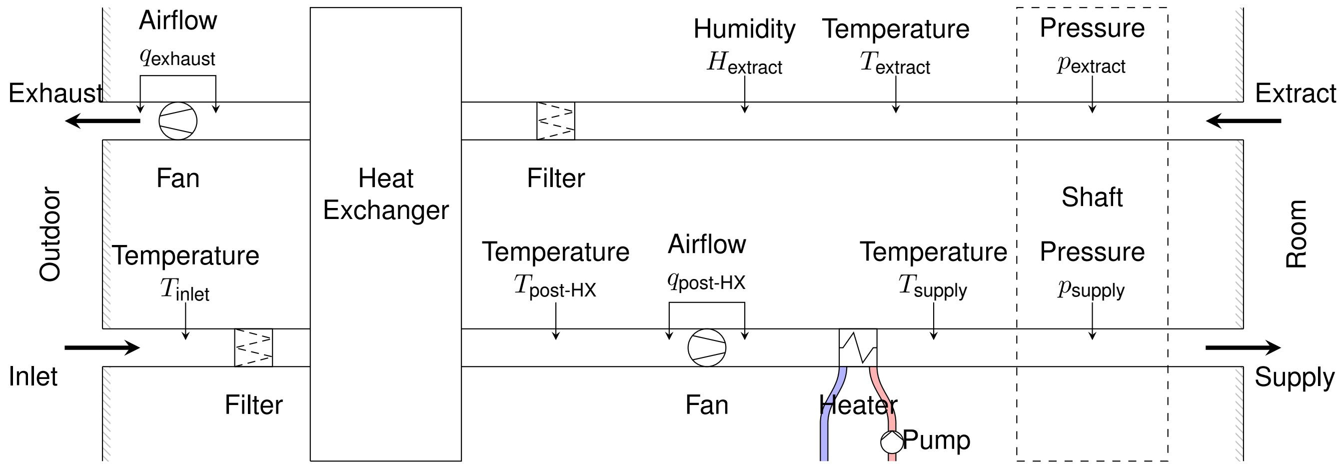

Figure 1. Diagram of a ventilation unit in building OU44. Inlet air enters the unit from bottom-left, passes through the heat-exchanger and through the heater, before entering the main shaft and supplying individual rooms. From the rooms it enters again the main shaft, goes through the heat-exchanger to heat up inlet air, and finally is pushed outside the building. Several sensors, shown by arrows, are available in the unit.

Table I
VIRTUAL SENSORS DEFINITIONS

Model Name	Output	Inputs
Model A	post-HX Temperature	Inlet temperature, extract temperature, airflow
Model B	post-HX Temperature	Inlet temperature, water flow, water loop temperature difference
Model C	Airflow	Effort
Model D	Airflow	Fan speed
Model E	Fan speed	Airflow
Model F	Fan speed	Fan current, fan voltage

temperature value much more accurately than the latter. The R^2 table shows that both models deviate significantly from the actual sensor on 31st March 2017, and Model B deviates also on 4th April 2017. Readings from the actual sensors are shown Fig. 2 with respect to the two models' error ranges, which corresponds to the predictions plus the maximal training error.

On 31st March 2017 the actual sensor's readings oscillate strongly, in contrast with the two virtual sensors which have a smoother behaviour, and fall outside the models' error ranges. Since the two models share an input variable, i. e., inlet temperature, this situation could be caused by a fault in the actual post heat-exchanger temperature sensor or in the inlet temperature sensor.

The situation on 4th April 2017 is less extreme. Model B consistently overestimate the actual sensor's readings, but the overall trend is similar and, moreover, all the readings fall inside the model's error range. Therefore, this event could be classified as a false alarm. Using a more accurate model instead of Model B could reduce the frequency of false alarms.

For airflow two models are used, one using only effort as input (Model C) and one using only fan speed as input (Model D). Airflow and fan speed follow the fan laws and are proportional to each other [17], and as expected predictions for this model are nearly exact.

Model C is less accurate, and its R^2 score on Tuesday 28th March 2017 is very low, which suggests a fault in the virtual sensor's input, i. e., ventilation effort, since Model D agrees with the actual sensor on the same day. Ventilation effort is produced by aggregating several independent streams with frequent periods of missing data, which can indeed cause the model to deviate from the actual sensor. Moreover, ventilation effort does not take into account the size of each room and the corresponding VAV dampers, which reduces the model's accuracy. Readings from the actual sensors are shown Fig. 3 with respect to the two models' error ranges, which corresponds to the predictions plus the maximal training error.

For fan speed two models are used, one using airflow as input (Model E) and one using fan current and voltage as inputs (Model F). Fan speed is proportional to airflow due to fan laws, and also to the fan power consumption, which in turn depends on current and voltage. Both models predict the actual sensor nearly exactly.

V. CONCLUSIONS

We proposed a technique to exploit relations between physical quantities inside a ventilation unit to create virtual sensors, introducing, therefore, redundancy, which can be used to perform FDD. We applied our technique to ventilation units in a real building, creating two virtual sensors for each of three existing sensors: temperature, airflow and fan speed, using linear regression models. We noted how on a particular day both virtual sensors for temperature deviated from the actual sensors, which suggests a fault has happened.

We used simple linear regression model to generate virtual sensors and predict physical quantities based on other sensors. Some virtual sensors were accurate, but some others were not. Better performance could be achieved by using more advanced methods, such as artificial neural networks, statistical machine learning algorithms or energy models of the ventilation

Table II
PREDICTION R^2 SCORE FOR VIRTUAL SENSORS

Date	Temperature Model A	Temperature Model B	Airflow Model C	Airflow Model D	Fan Speed Model E	Fan Speed Model F
2017-03-27	0.955	0.782	0.371	0.987	0.988	0.997
2017-03-28	0.989	0.804	**0.04**	0.98	0.977	0.997
2017-03-29	0.839	0.217	0.368	0.992	0.992	0.995
2017-03-30	0.894	0.729	0.681	0.956	0.956	0.996
2017-03-31	**−1.162**	**−1.995**	0.572	0.852	0.908	0.996
2017-04-03	0.86	0.442	0.87	0.967	0.968	0.997
2017-04-04	0.886	**−0.474**	0.644	0.983	0.984	0.997
2017-04-05	0.774	0.57	0.8	0.944	0.953	0.996
2017-04-06	0.73	0.654	0.622	0.988	0.989	0.997
2017-04-07	0.802	0.537	0.772	0.904	0.932	0.996

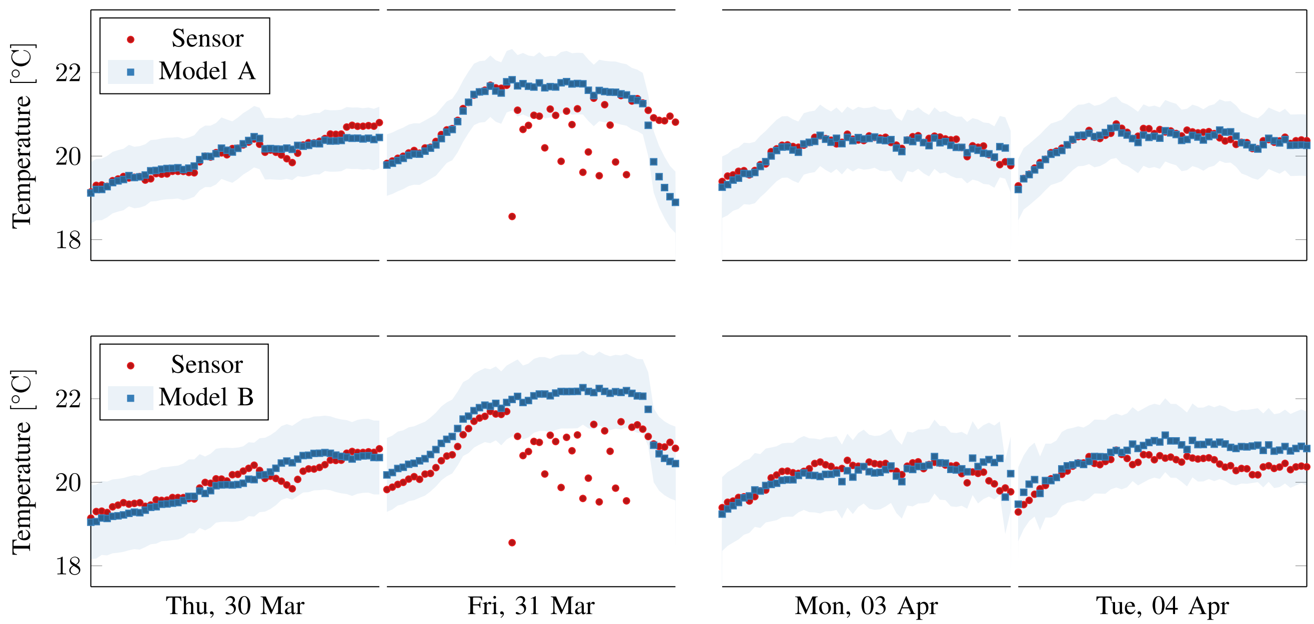

Figure 2. Comparison between actual sensors and acceptable ranges obtained from model-based virtual sensors for post heat-exchanger temperature during working hours (from 8am to 5pm) for selected days. The sensors readings fall inside the acceptable ranges except on Friday 31st March 2017, when they deviate significantly. On Tuesday 4th April 2017 Model B consistently overestimates the actual sensors, but their trends are similar.

units [18]. Assuming to have a training period of fault-free historical data it would also be possible to adopt methods from time-series analysis, such as Auto Regressive Moving Average with eXogenous variables (ARMAX) predictors, to create a virtual sensor using its past actual sensor as input.

We highlighted how during one day the R^2 score between actual and virtual temperature sensors changed abruptly and significantly and actual sensors' readings fell outside the acceptable range, which suggested a fault. However, a proper threshold system must be set up to achieve automatic FDD. This can be achieved by using expert knowledge and a training set of labeled faulty historical data or by generating faulty data using simulations. Moreover, the temperature sensor exhibited faulty behaviour only for a single day during the first week, while it appeared to work correctly in during the second one. Therefore, a threshold system should also be used to decide whether a significant but short-lived deviation is a fault.

Finally, we used regression models to predict data during a period close to the one used for training, under the assumption that the system's behaviour did not change significantly. When extending the prediction to other periods, this assumption might not hold anymore, and seasonal variations must be taken into account.

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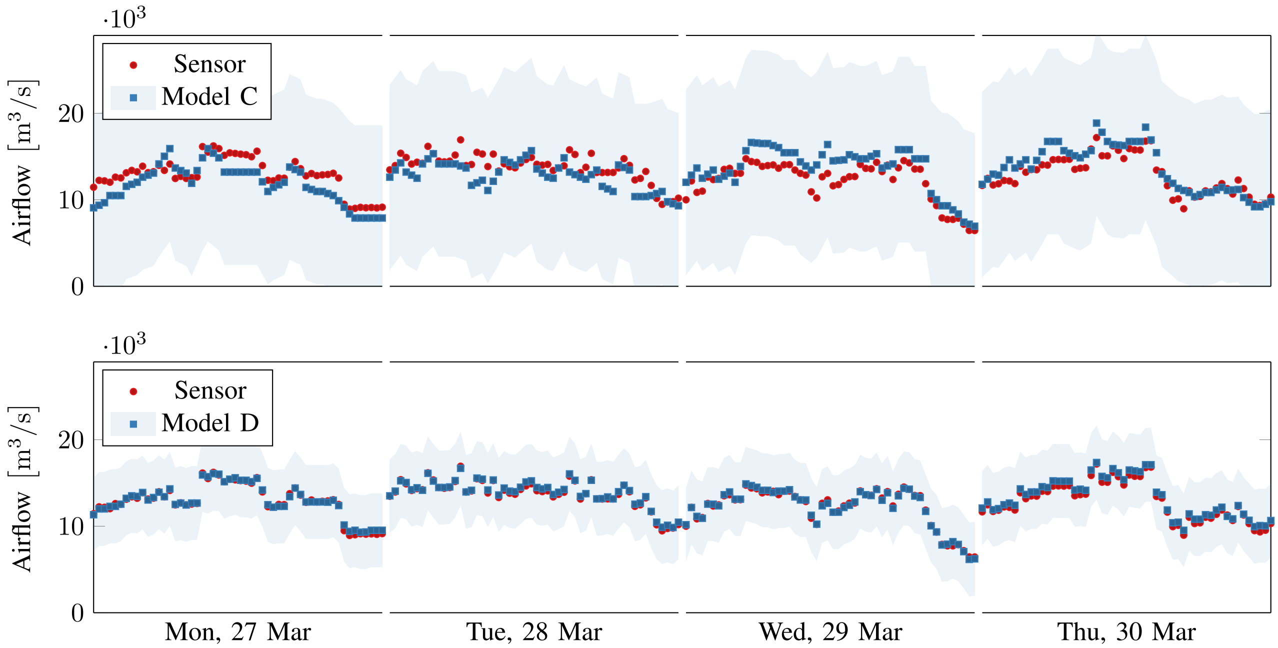

Figure 3. Comparison between actual sensors and acceptable ranges obtained from model-based virtual sensors for post heat-exchanger airflow during working hours (from 8am to 5pm) for selected days. On Tuesday 28$^{\text{th}}$ March 2017 Model C deviates significantly from the actual sensor, but readings always fall inside the acceptable range for the entire period.

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