# A Graph-based Sensor Fault Detection and Diagnosis for Demand-Controlled Ventilation Systems Extracted from a Semantic Ontology


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***Abstract*— Fault detection and diagnosis in HVAC systems such as demand-controlled ventilation system, is a crucial step to attain optimal user comfort and energy saving, through providing fast and accurate monitoring, control, and recovery solutions in buildings. This can be accomplished by increasing the number of the utilized sensors and actuators in each zone, which leads to an enormous increase in the complexity of the system, due to the need to capture these components' values and the interactions between them. To overcome the complexity issue, it is important to establish an accurate model of the system, which contains the system components like sensors and actuators, and the relationships between them. However, achieving an accurate model design of the building, its technical components and the relationships between them is rarely available. Especially, the lack of precision in technical measurements, which is needed in model-based diagnostic methods to develop precise thresholds and conditions that are required to make the decisions. In this paper a model was developed to overcome the previous challenges, by the following: 1) creating a simulated model for a building, to extract the missing sensors' thresholds, values and relationships between those sensors. 2) A semantic model represented by the building ontology, to model the relationships between sensors and their containing systems, created based on the diagnostic information provided by the simulated model. And 3) A novel diagnostic directed graph is extracted from the ontology to offer more automation to the diagnosis and lessen the complexity of the system, by providing a clear graph of the decision making process.**



***Keywords*— *DCV, fault detection and diagnosis; ontology; diagnostic graph; directed graph.***


## I. Introduction

Heating, ventilation and air conditioning (HVAC) systems, as any other system, are prone to fault occurrence all the time. Since, each of the installed pieces of equipment and their sensor components can fail or show some improper functionality due to breakdowns, degradation, sensor or equipment misconfigurations etc. Thus, taking an immediate action to detect the faults and recovering them as soon as they occur can ensure providing a comfortable environment for the occupants in the building, avoiding any unnecessary energy consumptions, as well as preventing any more discomfort to occupants or damage to the system components or occupants' belongings in the building, especially if one of the building zones is used for storage purposes for example.

Indoor air quality and thermal comfort in office rooms affect the health and the productivity of occupants. HVAC systems keep the thermal conditions in a comfort zone and indoor air quality in an acceptable range. Natural ventilation, a prevalent method in European countries which relies entirely on passive physical phenomena such as diffusion, wind pressure, or the stack effect, is an effective method to improve indoor air quality and to attenuate indoor carbon dioxide ($CO_2$) concentration in offices. HVAC systems are one of the largest consumers of energy, especially in office buildings [1]. The demand-controlled ventilation (DCV) is based on natural ventilation, which improves indoor air quality and increases the potential energy saving in heating systems by automatic adjusting the volume of air exchange (including inward flow of fresh air to the room and outward flow of polluted air from the room) using a damper actuator to the system's most optimum value. The automatic adjustment of economizer damper actuator is based on the $CO_2$ concentration sensor values, occupancy sensor values, the inside temperature, and the heating system's status. Studies demonstrate that 15% to 25% of the HVAC system's energy can be saved by setting the ventilation rates based on the occupants' fresh air requirement [2].

The study of DCV system in a huge building with many rooms and hundreds of components e.g. sensors and actuators is complicated, especially if some components fail. The existence of faults in a system can be disastrous, can cause performance degradation, or will increase energy consumption. A fault is an unpermitted deviation of at least one characteristic property of the system from its normal, acceptable, usual and expected behavior, which may trigger a failure or a malfunction of the system if it is not detected, contained and masked by fault-tolerance mechanisms [3]. Sensor faults such as wrong sensor readings or noisy sensors, and actuator faults such as actuator-stuck faults. These faults waste more than 20% of the energy consumed by HVAC systems, decrease occupant thermal comfort, as well as reducing productivity [4, 5]. A failure is a permanent interruption of a system's ability to perform a required function under specified operating conditions which result from one or more faults [3]. The key point is the identification of nature, locality, and value of the fault using diagnostic techniques at an early stage of fault appearance to put the appropriate recovery in action [6]. Based on the National Institute of Standards and Technology (NIST), fault detection and diagnosis (FDD) methods have a potential of 10% to 40% energy savings in HVAC systems [7]. The simulation environment, as a high potential tool, helps to study the system's behavior especially if one or more faults appear in the complex system and to develop a reliable fault detection and diagnosis technique.

FDD for HVAC systems has attracted a lot of research attention, due to its importance and need throughout the years. Thus, the state of the art connected to such systems is so rich of resources, of different methods and approaches. The mentioned related work are just chosen based on the similarity in their approach to the one proposed in this work.

The FDD methods proposed by Katipamula and Brambley [8] shows the fundamental and most common fault detection and diagnosis approaches, and the advantages verses the challenges of each one of them. In [9], the FDD methods were categorized in three main categories: model-based approaches, data-driven approaches and rule-based approaches

Model-based approaches require some physical model of the building and its components, or a simulated model like in our case scenario, and in [10]. These methods can offer a lot of precision when it comes to the diagnosis, but only if the model created is detailed and correct enough. The main drawbacks of such FDD methods, is that the model development requires a lot of time and expertise, to create the physical model and to extract the diagnostic model precisely from the original physical model. Moreover, Model-based approaches are usually very rigid and difficult to change or adapt in the case of application for a different system or even a different building.

An example of data-driven approaches is shown in [11] and [12]. In this approach the diagnostic decision is taken based on observing the behavior and hidden patterns in the building's sensor data. A major advantage for such systems is the dynamic solutions it offers for the diagnosis, which provides an easy adaptability to different systems and different buildings. However, these systems focus only on accuracy of detecting the faults based on the hidden patterns or connectivity between the collected data, rather than their real, physical identification and relationships, because of their lack of knowledge in the system components relationships and connectivity in the real physical system. Which leads to the final FDD category, rule-based approaches category.

In practice, rule-based approaches are the most popular among others. In this approach, the domain knowledge is taken into account in the diagnosis process, so the characteristics and the symptoms of each failure is known and considered [13]. And they can also be transformed into a semantic graph [14], [15], [16]. With all the advantages of rule-based approaches, they still have some disadvantages that might put many researchers off using them. Such as, the enormous amount of effort needed to link the rules and their requirements with the system's components that the rules are applied on. In addition, the continuous need for changing the thresholds within the rules to fit the new building or system can be considered as another issue. Thus, configuring such systems can take a lot of time and effort [17], [18], [19].

This paper proposes the first stages of a bigger picture, to establish a new intermediate approach for sensor or actuator fault detection and diagnosis of DCV system that combines precise and detailed rules represented by the rule-based approaches, and the dynamic solutions, scalability and adaptability offered by the data-driven approaches. The rule-based approach is represented by the DCV semantic ontology and the diagnostic graph extraction from this ontology. The data-driven approach is still under progress and will be a future work as an extension to this work. The data-driven approach is used to convert the rule-based rigid graph, into a more dynamic one, based on the data-learned hidden patterns and relationships, and also the semantic information stored in the ontology. As a result, a dynamic diagnostic graph will be automatically created from the physical system, scaled, updated and applied to different systems, using both, the semantic rules stored in the ontology and represented by the original diagnostic graph extracted from it. As well as the ability to apply to different systems by learning the thresholds of each rule, symptom or node of the diagnostic graph using machine learning techniques.

In this paper, the rule-based approach is the one described and explained as the following:

1) A physical system and expert knowledge is needed to build the system, collect the data and generate the technical diagnostic rules, which is done by the simulated model created by our team of technical experts.

2) The diagnostic rules and the relationships between different system components, sensors and failures, are described in a semantically sophisticated method represented by the DCV system ontology.

3) The created ontology was translated into a diagnostic graph to add more automation and simplicity to our FDD system, and will ease the integration of the data-driven approach later on as, the future contribution to this work.

This paper is organized as follows: The next section reviews an overview of the simulated model. Section III provides the HVAC ontology. Section IV explains the diagnostic graph created. Section V shows the conclusion and future work.

## II. Model Description

In this section, the model description of the overall simulated model is presented. For the implementation, test, and development of the semantic ontology and the extracted diagnostic graph. A framework, including a model and simulation tool for fault injection, or faulty and healthy data are needed.

The simulation environment in this study is MATLAB/Simulink version R2017a, using the Simscape toolbox of Simulink library. The model of six office rooms and one corridor includes all the thermal and physical dynamic during a typical winter day in February. Fig. 1 shows the overall office building sketch. Different types of faults, using a simulated dashboard with fault injection switches, including sensors' constant/noisy faults e.g. wrong sensor values with a constant value of 700 ppm for indoor $CO_2$ concentration or noisy fault values within the range of 550 ppm to 750 ppm for $CO_2$ concentration sensor, using the switch block, and a constant value of 15°C for the temperature sensor, and actuators' faults e.g. stuck in an open/close position of damper and on/off position of heater are modeled, simulated, and injected into the Simulink model.

In this model, the results can be stored in data sets including parameters e.g. the outside and inside temperature, inside $CO_2$ concentration, occupancy, heater status, and economizer damper status for each zone. The detailed description of the DCV model, its components, their functionality, and fault injection blocks by Behravan et al. are available [6, 19, and 20].

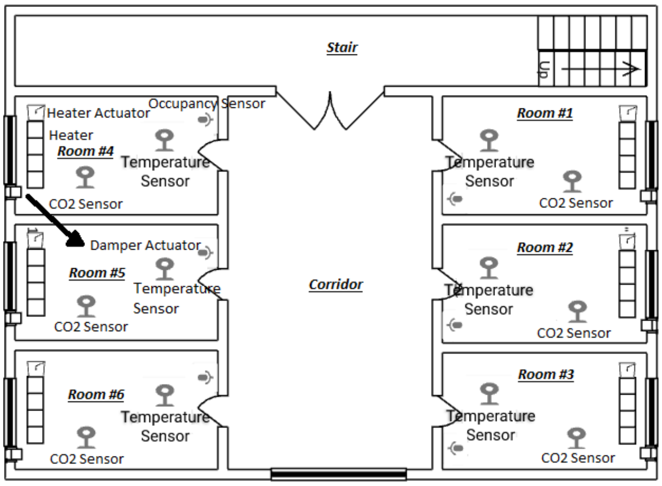


Fig. 1. Office building sketch for the model [21].

## III. DCV's Components Fault Detection and Diagnosis Ontology

Knowledge-based systems can be specified in two ways: implicitly or explicitly. In this paper, the explicit representation of the knowledge is applied using a common type of knowledge-bases called the ontology. The term Ontology is inherited from philosophy, more specifically from metaphysics [22], which symbolizes the existence and the nature of being in this context.

In computer science, the definition of ontologies was inspired by the philosophical term, which implies that, the ontology will only model the elements that exist in the domain system. The set of all elements in the domain are called the universe of discourse. Thus, the technical definition of the ontology in knowledge-based systems is a set of fundamental elements, which together represent the universe of discourse. Or in other words, our domain system e.g. entities or classes and relationships between those entities.

Ontologies can be either simple, consisting of few entities and their connecting relationships, or complicated filled with nested hierarchies, many classes and multi-connected relationships. Simpler ontologies are much easier to scale, learn and even understood by non-experts. However, larger ontologies tend to be more complicated, which adds up to the overall complexity of the system and the computational costs, due to the computational time required for querying and reasoning. Thus, the first point in mind while designing the ontology was, on one hand to keep it simple, and on the other hand to make sure it is detailed enough to represent an accurate reflection of reality and its components. Furthermore, the simplicity of the ontology plays an important role in reducing the complexity of the storage and retrieval of raw data such as, sensors types, values and thresholds of these sensors. As well as, the ability to keep records periodically of the sensors values at different points of time, which is a so important for the learning process and integrating the data-driven approach later in the future. The ontology design process is done as a collaborative work between two teams of experts, a knowledge-based experts and a field technician experts, which in our ontology scenario is an embedded system team of experts.

This collaboration offers establishing the simulation model of the DCV system, and answers all the questions about the system components and the relationships between them from a technical point of view, that will be added to the ontology by the knowledge-based team, to guarantee achieving a high level of accuracy and reflection of the system's reality [23].

FDD for DCV systems is a complex decision making process, usually done manually by a team of mechanical and electrical experts, by monitoring and observing the behavior of the system to notice the symptoms that might lead to certain failures in the building. Creating an ontology to the DCV system can provide an extra stage of support, by defining specific symptoms to their associated failures that will indeed fasten and ease the fault detection process for technicians, as well as non-experts can detect faults directly without the need for system experts support all the time.

In this work, a DCV system ontology for an office building of six office rooms and one corridor is created, using the open-source editor protégé [24].

Our system ontology consists of four main entities or classes, *Office building*, *Sensory and control*, *Symptoms* and *Failures* classes. The *office building* class is divided into two main subclasses, *Rooms* and *Corridors*. Each of these subclasses contains the instances or individuals necessary to represent the simulated system accurately, which are six instances in the *Rooms* subclass, and only one instance in the *Corridors* subclass. The *Sensory and Control* class also contains two main subclasses that represent the two main sensory devices used in the simulation model, *Sensors* and *Actuators*. The *Sensors* subclass has six $CO_2$ sensor instances, six temperature instances and six occupancy sensors instances divided into the six rooms. While the *Actuator* subclass contains seven heater actuator instances and seven damper actuators distributed in the six rooms and the corridor. *Symptoms* class, contains all the symptoms that the system experts provided about the sensors and the symptoms that lead to their corresponding failures. Many instances are added to this class, these instances will be explained in details in the following section, when the diagnostic graph for each sensor is proposed. Finally, the *Failures* class contains all the sensory devices failures which are six $CO_2$ sensor failures for each $CO_2$ sensor in each room, and the same thing for temperature sensors, six failures are added to each one of them, seven heater actuator failures and seven damper actuator failures to cover all the actuators in each room and the corridor. Which make them 26 main failures added to this system. Fig. 2 shows the main concepts of the ontology along with their associated relationships.

Here are the main relations between the classes in the diagnosis ontology:

- *Located_in(Sensory and control, Office building):* This relation states that the sensory and control devices are located in the office building components, either in one of the rooms or corridors.
- *Failure_in(Failures, Sensory and Control):* this relation connects the failures and their sensory components that contains these failures.
- *Lead_to(Symptoms, Failures)*: this relation shows the symptoms and their associated failures, where the *Symptoms* class is the domain of this relation, and the *Failures* are the range of this relation.
- *Can_Cause(Symptoms, Symptoms):* For this relation, the domain and the range are the same entity, both are the symptoms class, which indicates that some Symptoms *Can_Cause* other symptoms, and a series of symptoms can lead to a specific failure instead of one symptom directly.

  The described ontology is scripted in the Web Ontology Language (OWL) [25]. It is so important to highlight here, that the ontology is not a fixed dictionary of terms, but a model with semantic representations, which will offer more dynamic solutions comparing to other syntax-only models.

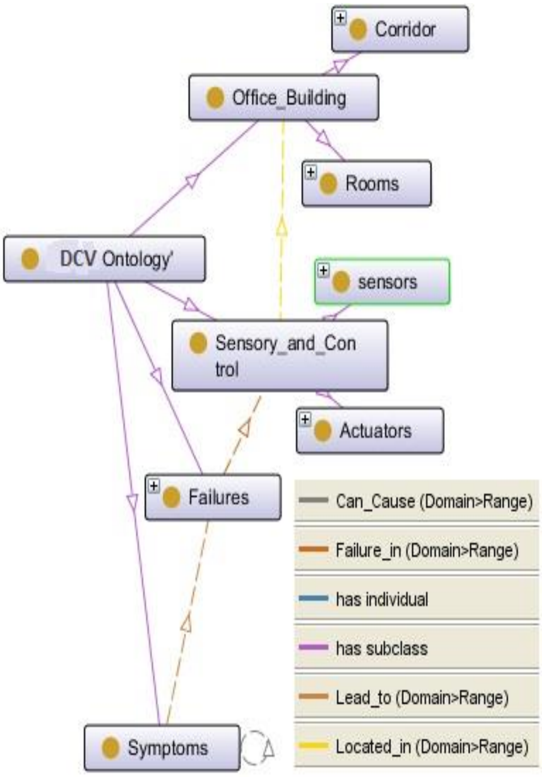


Fig. 2. Office building sensor fault detection and diagnosis ontology architecture.

The created ontology was evaluated and reasoned using HermiT 1.3.8 reasoner for consistency checking [26]. HermiT is a very popular reasoner used to check the consistency of ontologies scripted using the OWL language.

## IV. A Graph-Based Sensor Fault Detection and Diagnosis

In this step, the semantic information provided by the domain experts, and stored in the building ontology are translated into a directed graph. Some might underestimate the importance of this stage for the rule-based diagnostic approaches, where such methods rely on IF-Then statements most of the time, which makes it so much time and effort inefficient. By representing these rules using a clear graph, the time and effort required for the detection and diagnosis process is reduced dramatically, as well as using the graph representation of the diagnostic information provides a clear and easy platform, which can be used by any individual including experts and non-experts of the domain system or the ontology.

Mapping the semantic information from the system ontology to the diagnostic graph is done manually by the knowledge-based experts, to ensure that all the needed information was translated precisely and completely.

Table 1 shows the main symptoms of the $CO_2$ sensor failure, and how these symptoms are nested to one another. Each sensor and actuator added to the system has its own symptoms table. These symptoms are provided by the embedded systems team and modeled into the ontology by the knowledge-based experts. For more information about the symptoms for the sensors and actuators used in this study, check [20].

Fig. 3 shows the diagnostic directed graph for the $CO_2$ sensor as an example of sensory and actuation component. This graph is duplicated as a sub-graph for each room or corridor that contains a $CO_2$ sensor in it. The overall diagnostic graph contains all the sub-graphs of all sensors in the entire building. Each sensor and actuator in the system will have a similar structured graph with different features and symptoms, based on the semantic information stored in the ontology by the system experts.

The directed graph created in this paper, shows the connection between the diagnostic features extracted from the inserted instances in the ontology and their data properties. These features are connected to some corresponding symptoms, extracted from the semantic relationships added to the ontology. The added symptoms can lead to another symptom, or directly cause the component failure. A single diagnostic graph is created for each sensory and control device stored in the ontology, that is located in each and every component of the building ontology, regardless it is a room or a corridor. Thus, if each room has four sensory and control devices that might have a failure, and their information stored in the ontology, then the diagnostic graph of this room, contains four main sub-graphs connected to each sensory device. Keep in mind that our office building simulated and used to create the ontology has six rooms and one corridor, which means the overall diagnostic graph represents all the sub-graphs of each sensory device from all the office building rooms and corridors. As a result, the overall diagnostic directed graph can be so complex and computationally challenging for bigger systems. To overcome this challenge, the integration of date-driven approaches to support this rule-based graph representation is needed. Applying machine learning as an example of the data-driven techniques will provide more dynamic solutions to this graph, by adding the possibility to

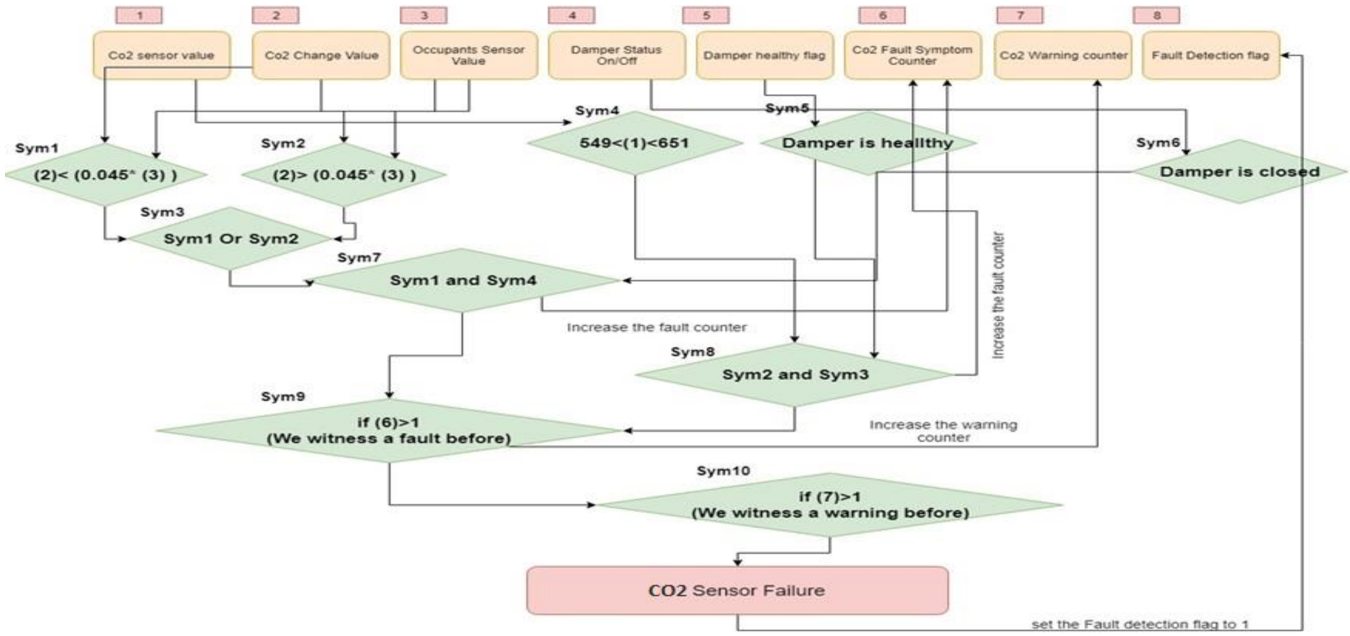


Fig. 3. $CO_2$ Sensor Diagnostic Directed Graph

Tabel 1. Symptoms Associated to $CO_2$ Sensor Failure

| **Failure Type** | **Symptoms** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***Sym1*** | ***Sym2*** | ***Sym3*** | ***Sym4*** | ***Sym5*** | ***Sym6*** | ***Sym7*** | ***Sym8*** | ***Sym9*** | ***Sym10*** |
| Failure in $CO_2$ Sensor | $CO_2$ change< (0.045 X occupancy sensor value) | $CO_2$ change< (0.045 X occupancy sensor value) | Sym1 Or Sym2 | 549< $CO_2$ value<651 | Damper is healthy | Damper is closed | Sym1 AND Sym4 | Sym2 AND Sym3 | $CO_2$ fault counter> 1 | $CO_2$ warning counter>1 |

prune, add some branches or learn the values and thresholds stored in each feature and symptom node in the diagnostic graph.

## V. Conclusion and Future Work

This work shows the initial stages of a full project framework, to build a new fault detection and diagnosis approach as an intermediate method between rule-based and data-driven approaches, to gain all the advantages of both approaches and eliminate their challenges as possible. The data-driven approach is still under examination and evaluation, and will be published later on as a future extension to this work.

The contribution of this work is added to the rule-based approach in the current stage. Which can be summarized as follows: 1) Create the simulated model of the office building system using expert's knowledge, to collect the data and generate the technical diagnostic rules. 2) Design a knowledge-based representation of the simulated model that contains the diagnostic rules and the relationships between different system components, sensors and failures. All these were described in a semantically sophisticated method represented by the HVAC Office building ontology. 3) Build a diagnostic graph to add more automation and simplicity to our diagnostic system, by using the information stored in the created ontology. This diagnostic directed graph is essential to our project framework. Because of its role in facilitating

the integration of the data-driven approach later on, in this project.


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