Adaptable Fault Identification for Smart Buildings

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Abstract
Malfunctioning HVAC equipment in commercial buildings wastes between 15% and 30% of energy. Many diagnosis approaches tackle this problem, but they either suffer from a lack of detailed fault information or a lack of adaptability to different buildings and equipment. Clearly, especially in the light of an ever increasing amount of sensor data that is available in heavily metered smart buildings, easily adaptable self learning in-depth diagnosis approaches are needed. This paper addresses the challenges of developing such approaches and describes the contribution artificial intelligence techniques like transfer learning, ontologies, knowledge representation or diagnosis can make in overcoming these challenges.

Motivation
There is an increasing need for automated fault identification tools in buildings. Almost 32% of the total energy consumption in industrialized countries is used for electricity, heating, ventilation, and airconditioning (HVAC) in buildings. This value could be significantly reduced if malfunctioning equipment could be identified quickly and numerous diagnosis approaches tackle this problem (Katipamula and Brambley 2005; Youk et al. 2008). However, these methods are generally highly specialized for specifically targeted fault behaviours (Katipamula and Brambley 2005), and thus limited to the diagnosis of well-understood faults. Due to the specialization of these technologies they are difficult to adapt to different equipment types and thus very costly to deploy.

On the other hand, more easily adaptable statistical techniques are used to detect faults in buildings (Jacoba et al. 2010). However, they only provide very limited fault information. Our vision is to develop a practical adaptable fault identification approach that addresses all of the above problems.

In particular such an approach should have the basic ability to discover characteristics of new faults for which there does not yet exist a diagnosis method. This is especially relevant in the context of smart buildings, i.e., buildings that have an automatic control system and that are heavily metered. Their rich sensor information could potentially be exploited for a more powerful diagnosis. The problems that need to be tackled are thus (i) how to identify and collect all relevant diagnosis information that might allow the characterization of new fault behavior, (ii) how to reuse this diagnostic information across different equipment and buildings and allow for an easy deployment of the approach, and, finally, (iii) how to efficiently exploit the gathered diagnostic information for a timely and optimal identification of faults?

This paper discusses the challenges of developing solutions to each of these problems and lists some Artificial Intelligence methods that are promising starting points for tackling these challenges.

Retrieval of Relevant Diagnostic Information
Smart buildings solutions can typically benefit from vast amounts of information that is available via different sources. A big challenge is to identify the relevant data and to develop the technologies that allow their timely retrieval.

For the task of fault identification in buildings there are at least three main sources of information and related technologies that need to be considered:

1. Metered data: data that comes from sensors in the building. It is often in the form of time series and can be exploited using statistical analysis tools like machine learning or time series analysis and forecasting techniques.

2. User feedback: data that comes from the feedback of occupants. This data is often written in free text and requires the use of natural language processing techniques along with well defined ontologies and taxonomies to be exploitable.

3. Domain expert knowledge: expert knowledge of the building’s behavior and functioning, generally represented using rule engines. The acquisition of these rules is often done manually leading to a huge work overhead. Rule engines are usually based on pure logic, fuzzy logic or Bayesian belief networks to make use of the knowledge induced by the rules.

Each of these sources of information requires the application of completely different technologies in order to retrieve and use them. Thus the collection of diagnostic information
could be significantly simplified if it were possible to avoid considering all of the above information sources. However, as the following use case demonstrates, this might limit the diagnostic capability.

Consider the case of a building where it is detected that a boiler is consuming an anomalous amount of gas. This boiler is supposed to provide heat to an office room and is controlled by a temperature sensor that makes sure that the target temperature is reached. This anomalous consumption might have (among others) the following explanations:

1. One of the building’s air handling units (AHUs) is not working properly leading to an inefficient transport of heat from the boiler to the targeted room.
2. One of the room’s windows has been left open leading to an important loss of heat in the room.
3. The temperature sensor is not working properly leading to a wrong report about the room’s actual temperature.

Thus, none of the different sources of information listed above can provide a full picture of the observed system:

1. Metered data is insufficient as it cannot capture all that happens in the building. For example, instrumenting each window of the building to know whether it is closed or to what degree it is open is too costly. Furthermore, some variables like the user’s thermal sensation are just impossible to measure directly. As it is not feasible to meter everything in the building, metered data provides a partial assertion of the building’s situation only.
2. User feedback is insufficient. If asked, users can give the information that a window is open; but they will not detect that the boiler is using much more gas to compensate for it. Users can also complain about the temperature in the room, but can not link it to a defective AHU.
3. Domain expert knowledge enables us to make the link between a boiler consuming too much gas and a defective AHU or a window open, but it is very difficult to apply that knowledge without having metered data and user feedback reporting about the state of the building.

It is therefore necessary to cross-correlate these different information sources in order to develop smart systems for fault identification.

However, each of the information technologies (statistical analysis, rule engines, taxonomy based natural processing engines) needed to process data from different sources is very costly to deploy and maintain. Another difficulty arises from the infeasibility to predefine all fault behavior in advance and from the diversity of the fault concept. A fault might be a drift in energy consumption, a sudden drop in water consumption, or a combination of those. Each of these faults concerns different systems and should be triggered using different data analysis methods on different subsets of variables. Currently, the predefinition of methods and variables is an entirely manual process (Seem 2007; Li, Bowers, and Schnier 2010; Yang et al. 2011).

Techniques are needed that allow a user to incrementally explain to the system how it could identify faults by defining which subset of variables and learning methods the machine should use to detect it.

Summary of Challenges
To summarize, the identification and retrieval of diagnostic information is a challenging problem due to:

- the need to analyze data from three different sources,
- the need of integrating data from three different sources,
- the infeasibility of predefining all information required to make complete fault identification and
- the diversity of the fault concept when learning new diagnostic information.

An approach capable of overcoming all these challenges has not yet been developed.

Promising Artificial Intelligence Methods
Techniques from the field of machine learning are promising to meet these challenges. For instance, active learning techniques capable of enabling a domain expert to guide the system in its learning could be considered. In particular the work of (Gervasio, Yeh, and Myers 2011) that presents a metalearning approach could serve as a promising starting point for learning how to define the learning problem based on relevant variables and analysis methods. While the experiments of the above approach were conducted on a synthetic domain and relied on exhaustively generated data, we have to tackle the metalearning challenge by resorting to available data only.

Automatic Reusability of Diagnostic Information
The core problem with reusing the diagnostic information is that it is not straightforward to transfer the different sources of information without considerable effort. In most smart building scenarios metered information is the most readily available information source. It is retrievable via a computer-based control system, the Building Management Systems (BMS). An individual BMS typically monitors and controls a large range of different types of equipment. Thus, each BMS has a large set of variables that represent measurements taken by physical sensors. The use of mark up languages to aid interoperability has already begun, e.g., use of SensorML (Liscano and Kazemi 2010) for sensor systems or PMML for statistical models (Guazzelli, Lin, and Jena 2010). These detailed descriptions can allow an operator to understand similarities between the components of different BMS. However, components of the diagnostic information from one building may still be labeled differently in another building. For example, in one system the term ‘Back-end temperature’ may be used while in another ‘boiler return temperature’ may be used to describe the same type of measurement.

Much care must also be taken to transfer diagnostic information retrieved from domain experts. This is often in the form of rules and subtle changes to these rules can have large effects. An example of a simple rule is: \( T_{oa} - T_{ma} > \epsilon_t \). This same rule appears in (Schein et al. 2006) and (Han and Chang 2009). It essentially looks at the difference between outside air and mixed air temperature under a particular operation condition. However, a simple change in the
thresholds for this rule ($\epsilon_t$) could have a large impact on the
efficiency of the building. More generally, transferring sta-
tistical information is highly challenging. This is due to the
source of information that statistical models are based on: metered data are often very specific to their metered system
and it is challenging to segment what statistical knowledge
might be common across two buildings and what knowledge
from the metered data is specific to the observed system and
should not be transferred. Even if the information that can
be transferred has been identified, defining how to perform
the actual transfer is far from trivial: complex multivariate
normalization factors might be needed to apply statistical
knowledge from a building with 200 people and 1000 m$^2$
to a similar building with only 10 people and 200 m$^2$.

**Summary of Challenges**

The following problems arise in relation of the transfer of the
diagnostic information:

- An ontology based on the reports of users will require
techniques to extract the terms and relationships while one based on information supplied by expert users must
be built using interactive tools.
- The diagnostic information will not be exhaustive and re-
quires the potential to discover new rules and integrate
knowledge from other information sources.
- Even the diagnostic information for the same building can
become redundant over time as equipment in the building
is changed, zones of use change, etc.
- Different buildings will have different physics, i.e. differ-
ent termo-dynamic properties, different equipment; and
so the diagnostic information will require much adjust-
ment to transfer properly. This adjustment will be expen-
sive in terms of time and man-hours (thus requiring an
automatic or semi-automatic approach).

**Promising Artificial Intelligence Methods**

Ideally a method to automatically transfer the diagnostic in-
formation is needed and this may require descriptions which
are structured and rich enough to allow for a more seamless
transfer of the diagnostic information. The major difficulty
here is that there are no freely available domain ontologies
and there is no single solution available to create the ap-
lication ontology. However, there are methodologies that
can aid ontology creation: (1) lexico-syntactic patterns to
detect hyponymy relations (Hearst 1992); (2) exploiting the
internal structure of phrases to derive taxonomic relations;
(3) exploiting hierarchical clustering algorithms to automati-
cally derive term hierarchies from text (Grefenstette 1994;
Cimiano, Hotho, and Staab 2005). Deploying the axioms
and rules in a real-word setting requires automated vari-
able mapping from the ontology onto the BMS. Ontology
mapping is the process of finding semantic correspondences
between similar elements of different ontologies. The cor-
respondence can be based on lexical similarity, e.g., (Seco,
Veale, and Hayes 2004), among other methods.

A domain ontology for smart buildings must also ac-
count for the types of knowledge from all the information

<table>
<thead>
<tr>
<th>Table 1: Ontological layers for a smart building scenario.</th>
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<tbody>
<tr>
<td>∀x (chilling(x) V heating(x) = fault(x))</td>
</tr>
<tr>
<td>cool(dom.CHILLER-COIL, range: WATER)</td>
</tr>
<tr>
<td>is-a(FUEL-LINE, PIPE)</td>
</tr>
<tr>
<td>FAULT := &lt; I.E.L &gt;</td>
</tr>
<tr>
<td>(regulator, control, controller)</td>
</tr>
<tr>
<td>HVAC, boiler, chiller</td>
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sources. Thus in the building management domain there is
a great deal of formal knowledge already represented, e.g.,
in fault detection and diagnostic rules. The ontology builder
must reconcile the existing formal knowledge with knowl-
edge from the users (expert or otherwise). Table 1 shows
an example of ontological layers for the building manage-
ment area based on a non-building management (Buitelaar
and Magnini 2005). Rather than building an ontology just
from the base (term level) an integration with a top-down
approach is needed that can exploit existing expert knowl-
edge like rules and axioms.

For tackling the problem of transferring statistical knowl-
edge methods from the field of transfer learning, in par-
ticular the work of (Hu, Zheng, and Yang 2010), provide a
promising starting point.

**Optimal Diagnosis based on iteratively acquired diagnosis information**

Given the knowledge that becomes iteratively available there
are many different ways of representing it. A major aim is to
ensure that the resulting representation allows for easy up-
dates and efficient diagnostic reasoning. Numerous diagno-
sis approaches for fault identification in buildings have been
developed but they are highly specialized for particular fault
behaviors (Katipamula and Brambley 2005). Thus, a good
understanding of the anticipated fault is needed for selecting
an efficient diagnosis approach. In our context this assump-
tion does not necessarily hold. When discovering new fault
behaviors one cannot resort to existing specialized diagno-
sis methods. Therefore, diagnosis algorithms are needed that
most efficiently exploit the available knowledge about fault
behaviors.

The latter is defined over events from different sources consist-
ing for instance of:

- user feedback, e.g., ‘lamp broken’,
- results from statistical analysis, e.g., ‘fault pattern in time
series data of illumination sensor’, or
- domain expert input, e.g., ‘alert if light switch is on and
illumination level below 200 lux’.

The same fault could be identifiable based on any of the
above information sources or based on a combination of the
latter. Furthermore, some information might require a
costly action to obtain it, e.g., request user feedback, and
these actions might fail. Thus, in contrast to most diagnosis
algorithms that aim to identify faults based on a set or se-
quence of readily available observations, we face the addi-
tional challenge here of obtaining the necessary observations
at minimal cost.
Summary of Challenges
For tackling the above mentioned problems a unified diagnosis framework is needed that can
- handle missing sensor information and incomplete system models,
- associate action costs to (observable) events, and
- compactly represent diagnostic information.
Such a framework has not yet been developed.

Promising Artificial Intelligence Methods
Methods from knowledge representation, reasoning and diagnosis have the potential to address these challenges. In fact, parts of the above problems have been tackled before, like the one of missing sensor information and incomplete system models (Bonarini and Sassaroli 1997; Chatain and Jard 2004; Zhao and Ouyang 2008), the one of considering action costs (Torta, Dupre, and Anselma 2008) or the one of compactly representing probabilistic models (Darwiche and Marquis 2002; Dechter and Mateescu 2007). However, these approaches were partially applied to toy systems only and significant advances are necessary in order to integrate them and use them for diagnosing complex building systems.

Conclusions
Properly functioning HVAC equipment is the basis for many challenges in the smart living domain, like reduced energy use and increased occupant comfort. Thus, the problem of developing an easily adaptable self learning fault identification approach for smart buildings is one of great practical significance. This paper has described some of the main challenges that need to be tackled in order to approach this development task and has identified a number of artificial intelligence techniques that have the potential of addressing these challenges.

References
Gervasio, M.; Yeh, E.; and Myers, K. 2011. Learning to ask the right questions to help a learner learn. In IUI ’11.