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TOWARDS SYSTEMATIC RELIABILITY MODELING OF SMART BUILDINGS

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ABSTRACT

Building Management Systems (BMS) monitor and control smart buildings. We are witnessing a trend of BMS becoming increasingly sophisticated and delivering more advanced services. The downside of this is that the complexity of BMS is also increasing, thus, making smart buildings vulnerable to various malfunctions and faults. We anticipate that reliability of smart buildings will be gaining in importance, especially for BMS of critical buildings, such as hospitals or buildings that host emergency services or store sensitive materials or technologies, whose unreliable operation could have catastrophic consequences. The assistance, however, is in the large amounts of easily available data that implies possibilities for development of highly accurate reliability models. Cloud computing can be also utilized to support collaborative sharing and benefitting from each other building's data. To utilize all of the above stated, we have developed a cloud-based BMS reliability analysis framework that we describe and illustrate in this paper.

1 INTRODUCTION

Building Management Systems (BMS) are Cyber-Physical Systems (CPS) that are utilized to run smart buildings. BMS are typically benchmarked against two performance measures: occupants' comfort and energy performance (Nicol and Humphreys 2004; Roetzel and Tsangrassoulis 2012). Both of these measures are highly relevant and, more importantly, have to be taken into consideration simultaneously. BMS are Cyber Physical Systems (CPS) that control and monitor a number of subsystems in smart buildings (Lazarova-Molnar et al. 2016a). Reliability is a measure of the ability of a system to perform as expected under predefined conditions for a predefined period of time. Reliability of BMS has not received an adequate span of attention. Reliability for general CPS has started to receive an increasing attention (Mitchell and Chen 2013; Lazarova-Molnar et al. 2017), however, BMS have not been targeted specifically. Reliability of BMS as a measure can affect a large number of decisions, starting from purchase decisions about components, up to configurations of systems and components. Furthermore, reliability of a smart building affects both occupant comfort and energy consumption. Reliability evaluation is especially important for critical buildings that should not compromise their correct operation, as discussed in Section 2.2 (Lazarova-Molnar et al. 2016b).

In one of our previous works, we emphasized on the evaluation of building's performance within its context (Lazarova-Molnar et al. 2015), e.g. performance goals of hosted organizations. We extend this context to also encompass reliability of BMS, as it plays a significant or even a critical role in supporting hosted organizations in performing their day-to-day operations. Thus, providing a methodology and tools to evaluate BMS' reliability is very much needed (Lazarova-Molnar 2017). In the following we address the issue of reliability in BMS, and detail a framework of how to avail quantitative reliability analysis of BMS. The aim of our approach is to be scalable and future-oriented by relying on and utilizing emerging new technologies, such as Cloud Computing and Internet of Things.

The paper is structured as follows. We begin by providing preliminaries in Section 2, by describing the specificity of Reliability of BMS. In Section 3, we describe the proposed framework for reliability modeling and analysis of BMS. We provide illustrative example in Section 4, and finally in Section 5 we conclude the paper.

2 RELIABILITY OF BUILDING MANAGEMENT SYSTEMS

Reliability is a measure of the ability that a system operates as expected under predefined conditions for a predefined duration of time. As BMS are ultimately composed of a number of components, reliability of BMS can be expressed through the reliabilities of each of the components. We begin by providing a background on reliability of BMS.

2.1 Reliability Modeling of Building Management Systems

BMS are CPS that control and monitor mechanical, electrical and electromechanical services in a smart building. Such services can include power, heating, ventilation, air-conditioning, physical access control, pumping stations, elevators and lights. With the emergence of new sensing technologies and other building intelligence solutions, BMS have grown to be very sophisticated and complex CPS (Zhao et al. 2013; Paulo et al. 2014). They are specific in that they carry a large burden in the global struggle for lower energy consumption (ca. 40% of total energy consumption is attributed to buildings) and they can serve various purposes, including highly critical ones. BMS are highly complex as they interconnect entities of different natures, such as occupants, weather conditions, sensing devices, building materials, etc., all exhibiting high uncertainty.

Reliability in BMS has not received the adequate span of attention, despite the frequent calls for its importance (Smith et al. 2004; Doukas et al. 2007). Reliability of BMS, however, is highly critical and goes hand in hand with maintenance cost. In other words, having an accurate reliability measure would enhance the potential for designing optimal preventive maintenance schedules. This, in turn, would both minimize maintenance cost, as well as improve the performance of the building, thus enhancing both comfort and energy consumption. In the following we provide a brief insight into the state of the art in reliability approaches for BMS, as well as the challenges associated with it.

Hospitals are examples of buildings where the proper functioning of BMS is critical. Think of lighting failing during a surgery. Therefore, besides comfort and energy savings, reliability of BMS plays a critical role in assessing the performance of these BMS. One attempt to tackle reliability, although not as explicitly is presented in (Shohet 2003), where the authors describe a methodology of how to set maintenance priorities in hospital buildings based on performance indicators for building components and systems. The solution was successfully tested on 17 public health care facilities in Israel.

In one recent work on the topic of reliability (Peruzzi et al. 2014), authors state that "reliability, maintainability and availability are essential features if we want to define the quality that is the ability, of the plant to fulfill a specific requirement". This is one of the rare works that emphasizes on the importance of reliability in buildings.

In another work, focused on lighting systems (Salata et al. 2014), Salata et al. investigate the impact of reliability of lighting systems on the economy of a building. The authors of the paper further conclude that "the fact of choosing a system, consisting of LED sources only, can represent a convenient choice only under certain circumstances, that is as long as we talk about reliability and service life". Thus, having an accurate reliability measure is of paramount importance to estimating cost. We are confident that this conclusion can be extended to other types of systems, besides lighting.

Through comprehensive modeling of BMS fault dependency, and tracking of relevant data, which is now easier than ever before, reliability of BMS can be estimated at any given point in time. These models can be further used to provide decision support in purchasing components for a BMS, based on their reliability metrics. It can also provide support in their configuration.

In the following we observe the different purposes of buildings and relate that to the importance of providing reliability analysis correspondingly.

2.2 Importance of Reliability to Building Management Systems

Building management systems are multi-objective cyber-physical systems that are very domain specific and these domains also dictate their objectives and performance metrics definition. Reliability can range from "nice to have" to "extremely important" metric based on the purpose of a building. Buildings have been classified based on various properties (Nikolaou et al. 2011), such as airtightness (Zou 2010), or acoustics (Di Bella et al. 2012). However, up to now, there has not been a classification proposed to target importance of reliability of buildings. This has motivated us to investigate buildings specifications and purpose with respect to reliability and provide their classification with respect to reliability importance. We illustrate the concept of importance of reliability with respect to the various types of buildings in (Lazarova-Molnar et al. 2016a).

This classification is based on the cost of performing reliability evaluation and its justification. In some cases it is an unnecessary luxury, whereas in other cases the cost is in human lives, and that definitely justifies whatever the expense is. In Table 1 we show the meaning of each of the reliability importance levels in terms of its cost with respect to the benefits.

Table 1. Importance of reliability to buildings (Lazarova-Molnar et al. 2016a).

Reliability Importance	**Meaning**
nice to have	benefits do not justify the cost of reliability assessment
useful	benefits could exceed the cost of reliability assessment
necessary	benefits largely exceed the cost of reliability assessment
critical	benefits of reliability assessment concern human lives
highly critical	benefits of reliability assessment concern a large number of human lives

The first level of reliability importance, i.e. "nice to have" encompasses smaller buildings, such as one-family houses, where reliability assessment would be seen as an unnecessary luxury. However, in communal buildings, for example, assessment of reliability could be "useful", as some faults affect a large number of occupants, and also repairs can turn out to be quite costly. The third category of buildings, termed as "necessary" with respect to the importance of reliability evaluation, encompasses buildings where benefits from reliability evaluation have potential to largely exceed the cost of performing it. These are mostly commercial buildings, where the correct operation of a building largely influences the productivity of the hosted businesses. Examples of these types of buildings are shopping centers or factories. The last two categories, "critical" and "highly critical", encompass buildings where the lack of reliability could cost human lives, at two different scales. An example of a "critical" building is a hospital, where the correct operation of the BMS is crucial for the well-being of patients. A "highly critical" system is a nuclear power plant, where the inability of the building to operate as expected could have devastating consequences.

As of now, only reliability in highly critical BMS has been tackled more thoroughly, and it is usually improved through heavy redundancy (Verma et al. 2016). Generally, this could mean that the system incorporates redundant components having multi state systems with different maintenance policies. Among the significant work on this topic, although quite dated, Arueti (Arueti and Okrent 1990) presents a tool to assist scheduling and decision-making for performance of preventive maintenance for a nuclear power plant. The tool is based on data on failure rates, repair times, repair costs and indirect economic costs and utilizes probabilistic judgment and inference rules.

The "critical" category of buildings, such as hospitals, have had various isolated reliability approaches targeted at different parts/aspects of the BMS (Shohet 2003). However, we were not able to discover an integral solution that targets the reliability of the BMS as a whole.

Future reliability solutions have to be scalable and flexible, as the speed with which new technologies emerge imposes this as a basic requirement for solutions to be sustainable. If this is not fulfilled, we will have reliability approaches that would become obsolete as BMS get updated, or tightly linked to specific buildings. Therefore, a robust and scalable framework for reliability assessment of BMS is essential.

3 FRAMEWORK FOR RELIABILITY MODELING OF BUILDING MANAGEMENT SYSTEMS

To streamline reliability and availability evaluation of BMS, we have developed a framework that we detail as follows. To begin with, we illustrate the general concept and idea in Figure 1. The idea is based on the development of what we term as Reliability Diagram Blueprint (RDB), which models both hardware and software parts and components, as well as their data flows and physical connections from the BMS collected data and a basic class diagram of the building management system that captures the main relationships. This RDB is further specified and fine-tuned from the ongoing data collection, and finally utilized for reliability evaluation, and also, potentially, for Fault Detection and Diagnostics (FDD) and generation of preventive maintenance schedules.

3.1 Description of the BMS Reliability Framework

Our reliability analysis approach is based on exhaustive modeling of BMS using a modeling formalism inspired by class diagrams, with Fault Tree elements. This class diagram is what we term as Reliability Diagram Blueprint (RDB), used for each concrete building management system to be instantiated with the actual components, their features and their relationship, yielding an Instantiated Reliability Diagram (IRD). In the RDB, every component (both software and hardware) is represented by a class. Each class is a template for instantiating the actual components in a concrete building management system. It is important to note that IRD tracks all data relevant to reliability. To illustrate our idea, we provide an illustrative example for a lighting system in Section 4.

Our BMS reliability approach, as further illustrated in Figure 1, utilizes data collected through the building management system and tracked through its IRD to learn reliability relevant connections among faults of components. Note that components refer to both physical components and software components and applications, which we intend to model and represent in the same way as physical components, and collect data relevant to their reliability as well. This collection of data from both parts of the system is an especially important issue when one deals with cyber-physical systems (CPS) such as BMS. Once an actual IRD is generated and relationships are learnt from data, using state-of-the-art machine learning methods and root cause analysis approaches, reliability and availability assessments can be performed by using probability algebra. This model, along with the reliability evaluation functionality, can be further utilized for detection and diagnosis of faults, as well as generation of preventive maintenance schedules. Namely, in order to assess a quality of a given maintenance schedule, reliability measure has to be introduced as an objective function. This is an added benefit of our approach.

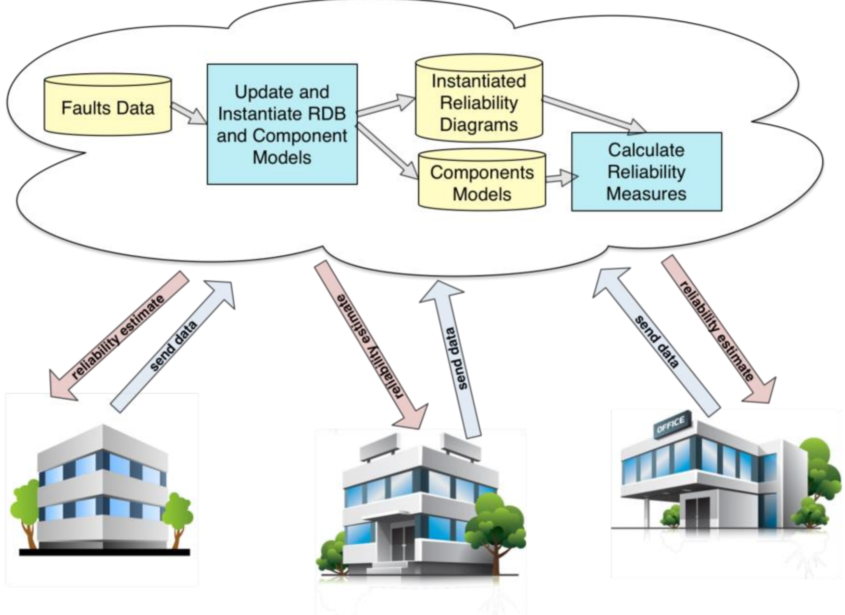

Figure 1. Framework for reliability evaluation of BMS.

Everything that is known about general BMS is modeled, in the RDB, including physical connections and data flows among components. RDB can also incorporate expert knowledge, as well as knowledge from physics and knowledge obtained through BMS modeling and simulation. This model, resembling and inspired by fault trees, needs to capture, among other things and most importantly, fault dependencies of all components and subsystems.

To support reliability analysis, among other variables, each of the nodes in the RDB contains the following reliability-related variables:

- Age, that keeps track of the age of a component,
- Number of failures, that keeps track of the number of failures that have occurred during the specified age of the component,
- Link to a faults and failures table that keeps details about the faults and failures, their nature, their repair times, etc.,
- Time since last repair, which keeps track of the duration of time during which a component has operated undisturbed, and
- Fault model that is either derived from expert knowledge and further refined from data, or built completely from collected data.

In addition to these, IRD also stores reliability metrics for each component, always updated and fine-tuned according to the latest statistics. These include, among others: MTTF (mean time to failure), MTBF (mean time between failures), MTTR (mean time to repair), failure distribution and repair distribution. Tracking of faults and failures would enable fine-tuning failure/repair probability distribution functions and fault/failure dependencies among software and hardware components.

A Petri net or a state-transition diagram can be used to represent the fault model of a component, which can be built and updated as new data becomes available. An example of such a state-transition diagram with three states is shown in Figure 2. In this example, the component can exhibit a fault that would degrade its performance, or a failure that would bring it to a “stand by” mode. Each of the states can be exited through corresponding repairs. In a more realistic model, the state "degraded performance" can be a continuous state, thus yielding a hybrid model. All of the fault models information needs to be formalized and associated with components in the IRD. In Figure 3 we provide a description of the object that would be used to store the fault model. As shown in the figure, the fault model contains a set of all faults, where each fault is described by its failure distribution function (FD_i), its repair distribution function (RD_i), and a set of causes (C_i). A cause can be a set of circumstances (e.g. values of certain parameters within certain ranges) or other faults of other components. A cause can also include a temporal dependency between the cause and the fault, which can be described either by a deterministic value or by a probability distribution function. Furthermore, the fault model contains the set of states of the component (S), as well as the transition matrix (T) that for each pair of states holds the set of faults that transition the system from the first state to the second one.

Based on the described fault models, there could be three basic calculation modes for reliability evaluation of a given building management system:

- Probability algebra based, for a quick estimate with lower accuracy, based on the assumption of memoryless and constant failure rates,
- Discrete-event simulation, allowing for complex descriptions of failure rates, but limited in the quality of the reliability estimate result, or
- Proxel-based simulation, allowing also for complex distributions of failure rates, and allowing for smooth transient reliability solutions (Lazarova-Molnar 2005).

The choice of reliability calculation mode can be also accompanied by an automated decision support, guided by answers of a set of questions that target the purpose, the efficiency and accuracy of the reliability calculation.

Set of Faults

$$F = \left\{F_1, F_2, \cdots, F_{n_f}\right\}, F_i = (FD_i, RD_i, C_i)$$

Set of States

$$S = \left\{S_1, S_2, \cdots, S_{n_s}\right\}$$

Transition Matrix

$$T = \left[t_{ij}\right], t_{ij} \subseteq F$$

Figure 3. Fault model object, as represented in the RDB.

As fault tree relationships that capture dependencies among different faults and failures, are sometimes far from trivial to derive, the plan is to use statistical machine learning algorithms to learn a fault tree structure and dependencies from data, on non-critical BMS, and utilize this knowledge (as much as possible) for critical BMS. Such a learning algorithm would capture the patterns and association rules, and utilize this knowledge to determine fault and failure relationships. For example, from sufficient data on Fault X followed by Failure Y, it would be possible to build a probability distribution function that models the time distance between Fault X and Failure Y. For each rule lift and support would be kept (Hipp et al. 2000). As causation would be sometimes difficult to derive, Root Cause Analysis (RCA) could be utilized (Zawawy et al. 2010). RCA will enable to derive a causation that e.g. Fault X influences Failure Y and not vice versa. This can be across components of both hardware and software nature.

To further enhance the accuracy of the derived models, as well as the efficiency of the learning phase, we intend to build the framework utilizing the cloud, so that many buildings can share their data for collaborative and more accurate components' and faults' modeling. There is a significant advantage in the learning processes when having many, large and diverse datasets that cover more scenarios, as opposed to leaning from a single building (Lazarova-Molnar and Mohamed 2017). This implies that there has to be clustering in place to group together buildings, systems and components in groups based on their similarities, in order to benefit from common knowledge and models.

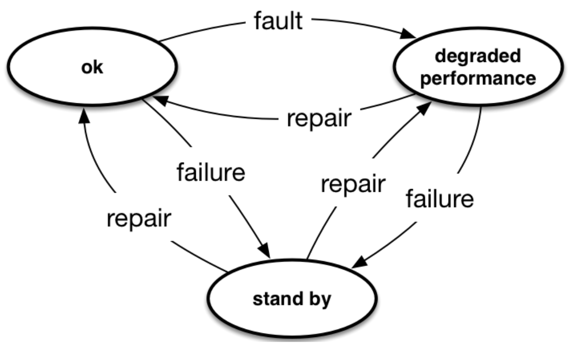

Figure 2. State-transition fault model of a component..

3.2 Implications

The idea behind the presented reliability framework is motivated by the amount of data from buildings that is continuously getting collected. This automatically collected data coupled with crowdsourcing could provide a significant input to extract association rules and calculate reliability metrics that would enable constructing of a Fault Tree-like model that would be to a great extent derived from data, and some parts from expert knowledge.

The association rules that can be extracted also encompass temporal features, through which distribution functions of the time needed for one fault to affect another fault can be derived. Association rules can also encompass trends and ranges, as causes for faults and failures, meaning that more information can be contained than in a traditional fault tree. This data would be also utilized to derive failure and repair distribution functions, or if they are already specified, to further fine-tune them. Furthermore, this data will be also utilized for modeling degradation of components, as well as degrading performance of the overall system. We see the proposed BMS reliability assessment framework as scalable and reusable, as the information obtained can be shared in a collaborative manner, such as to enable similar buildings and systems to learn and benefit from each other's experiences.

4 ILLUSTRATIVE EXAMPLE FOR RELIABILITY DIAGRAM BLUEPRINT

In the following we provide an illustrative example to demonstrate the concept of the proposed BMS reliability framework in terms of creation of an RDB. For this purpose we decided to use the example of a lighting system. Figure 4 depicts an RDB that consists of the majority of the components that make up a lighting system within a building. The diagram is built resembling a UML class diagram, with some additional elements. The diagram is a simplified representation of a lighting system, along with the software components that manage the interaction with the hardware itself. The diagram consists of two major parts, displayed in different colors. All white boxes display classes of components that are related to the hardware of the lighting system, while all of the yellow boxes show classes that are related to the software components of the system. In the following subsections further explanation will be provided for each of the groups of components.

4.1 Hardware Components in the Lighting System

In the diagram, the hardware components are depicted with white color. Classes Measurement and Actuator act as superclasses, from which other classes then inherit. Measurement is a class that represents any component that is used for measuring, namely sensors and meters; hence the subclasses LuminositySensor, PIRSensor and ElectricityMeter. A luminosity sensor is a device that measures the amount of light in the area where it is placed. Its measurement is lux. A PIR device that detects the presence of occupants in the area where it is placed, and its output is a Boolean value. Electricity meter is a device that measures accumulated electricity consumption in kWh. Actuator is a class for components that are used for actuating other components, mainly through the building control. Two components of this kind are ActuatorLight and ActuatorShades. Light actuator is a manual light switch that occupants can use to turn lights on or off. Shades actuator is a device responsible for closing, opening or turning shades of a window. Components LightEmitter and Shades are independent components that represent sources of light such as light bulbs, as well as curtains and other forms of physical shading, respectively. All presented components have references to their respective faults data and models as a part of their class in the diagram. Faults could be of different types, and can be added on-the-fly as they are being discovered. Along with the data on faults, a fault model is being built that represents the behavior of the corresponding component.

In general, faults that may occur with these components are related to physical damage of the hardware or their wear-out. These faults have exclusively to do with the components themselves, their wear and age, as well as their physical health.

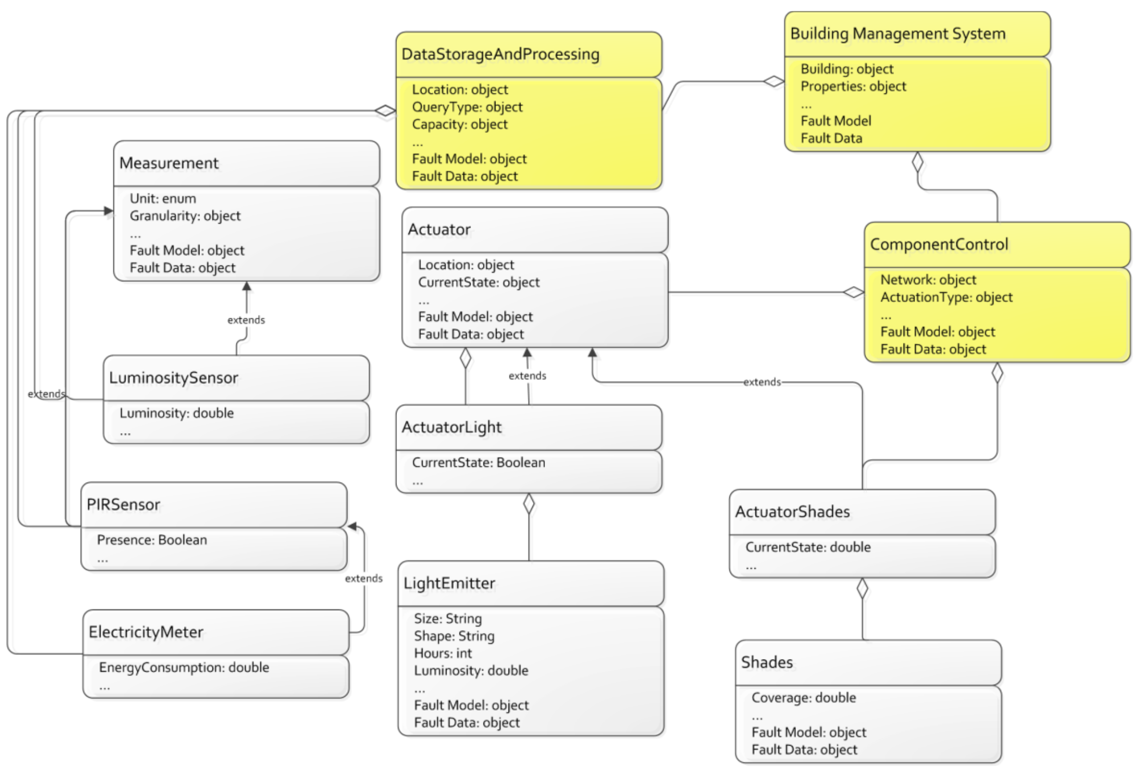

Figure 4. Example BRD for a lighting system.

4.2 Software Components in the Lighting System

Software components along with all of their interactions with other components, on the diagram, are depicted in yellow color. In the diagram, the class BMS (Building Management System) is composed of the classes ComponentControl and DataStorageAndProcessing. The BMS class represents the software component that is in management of all of the control and data of the building. Within this software component, all of the data from meters or sensors is stored, processed, and monitored. In addition to this, the class BMS contains software functionality to access actuators in a building and control them according to various algorithms and demands.

As these two aspects of the BMS are separate and contain different functionalities, they are depicted as separate classes. The class DataStorageAndProcessing is responsible for the data collection from sensors and meters, as well as applying necessary calculations. The class ComponentControl, on the other hand, deals exclusively with the access and control of the actuators installed within the building. Even though these components are very complex in their own right, they have been simplified for the benefit of the illustrative example.

4.3 Instantiation

RDB is instantiated with the concrete components, yielding IRD, and for each component a record is kept for its faults and failures, which is also utilized for building the fault model. The list of faults and failures is not exhaustive, meaning that it can always get extended with newly discovered faults. In addition, from expert and a priori knowledge, the model will be instantiated with a portion of the faults/failures relations based on the actual wiring and data flows. Reliability of the system is then evaluated using one of the three proposed methods. The calculated reliability estimate could then help in various decision-making processes, such as, for instance, deciding if it is a good idea to exchange all light bulbs or any other type of component are by another model. It would allow to instantly see the effect of that change on the overall reliability of the system.

5 SUMMARY AND OUTLOOK

Reliability needs to be one of the objectives when BMS are being designed, and this is not the case now, as it is seen as a very complex issue. The goal of this paper is to raise the importance of addressing reliability of BMS, as well as propose a framework for evaluating reliability of BMS from the data that is being collected. Our proposed framework relies on data sharing and collaborative data analytics, as supported by Cloud computing and Internet of Things. It utilizes data collected through the various devices and occupants of buildings, and builds models from it.

The benefits from having such reliability evaluation framework in place would be very significant. It would enable assessing various what-if scenarios for purchasing components, it would enable generation of preventive maintenance schedules (as schedules need to be assessed), and it can also assist in the Fault detection and diagnosis processes by utilizing the modeled relationships and faults.

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