Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

A ZONING FRAMEWORK FOR ENHANCED SMART BUILDING AUTOMATION

Sanja Lazarova-Molnar
Elena Markoska

University of Southern Denmark
Campusvej 55
Odense, 5230, DENMARK

Nader Mohamed

Middleware Technologies Lab.
8010 Hinsdale Ln
Pittsburgh, 15057 PA, USA

ABSTRACT

Smart buildings are complex cyber-physical systems that typically involve a high degree of human interaction. This interaction, if controlled and utilized adequately, can provide a significant hint in fine-tuning and optimizing systems, as well as in diagnosing problems in systems in a timely manner. In this paper we define a Zoning Framework for enhanced and, potentially, optimal automation of buildings that utilizes the potential of human interaction and its multifaceted nature in optimizing on the various performance metrics of buildings. We, furthermore, present a workflow in which the framework can be utilized to optimize data collection processes, and, thus, aid in meeting performance goals of smart buildings.

1 INTRODUCTION

Smart buildings are complex cyber-physical systems that utilize Information and Communication Technologies (ICT) to enhance their performance on a number of metrics, such as occupant comfort, energy efficiency, etc. For this purpose, smart buildings' operations are typically monitored and controlled by Building Management Systems (BMS). Buildings in general are attributed to ca. 40% of the overall energy consumption (Atmaca and Atmaca 2015). Therefore, by the emergence of smart buildings, there is an opportunity to make buildings' operations more energy efficient, thus, having a substantial impact on the global struggle for reduced energy consumption. Occupants, however, are the main reason that buildings exist; thus, energy savings should not come at a cost for occupant comfort (Lazarova-Molnar et al. 2015). Furthermore, there are numerous studies that show the positive effect that energy-conscious occupant behavior can have on buildings' energy consumption (Lazarova-Molnar et al. 2015; Lazarova-Molnar and Shaker 2016). Thus, there is large potential in cooperating with occupants for enhancing buildings' performances.

Further to this, occupants can also make a difference in saving on buildings' operation costs through cooperating for timely and accurate fault detection and diagnostics (FDD), estimated at ca. 15-30% of building's energy consumption (Katipamula and Brambley 2005). One of the main challenges for FDD where occupants can help is obtaining meaningful data (Lazarova-Molnar and Mohamed 2016). Since occupants are the ones that interact with the system on regular basis and on a large scale, crowdsourcing occupants is an obvious way of obtaining useful data for FDD, as it has been shown in (Lazarova-Molnar et al. 2016, 2017). This data collection is, however, intrusive, and that is not always welcome and easy to perform as occupants need a clear incentive to participate in such initiatives. Therefore any non-intrusive collection of data would be very beneficial and supportive for the FDD processes. However, a non-intrusive data collection is already happening at a subtle level, although with the increased level of automation it will be happening less and less. Namely, occupants often interact with the system to match their comfort needs (i.e. increasing lighting level, reducing heating level, or opening a window), which is a significant feedback (and data) that needs to be utilized for optimizing BMS.

Buildings typically operate in one of two modes, fully manual or fully automated, and very sporadically and uncoordinated somewhere in between. We aim to provide a framework to enable more optimal differentiation and tuning of automation level, which would also support all data learning processes. For example, learning about occupant preferences needs data on what occupants prefer in terms of lighting, heating, etc. Therefore, enabling full interaction with the equipment for occupants for a certain length of time would be the thing to do. Once the system has learned occupant's preferences, it could gradually transit to fully automated mode, and perform everything automatically, thereby optimizing the building's performance also at the building level.

Therefore, in this paper we introduce a Zoning Framework for enhanced building automation that aims to make the most of occupants' interaction with the Building Management System, by introducing varying levels of granularity of automation of BMS, both in terms of space and time, thereby optimizing automation levels and interaction possibilities as calculated to be optimal for data collection and model building processes.

We begin by providing background on the complexity of occupant behavior and automation in buildings in Section 2, followed by the description of the Zoning Framework for enhanced building automation in Section 3. In Section 4, we provide a discussion of the framework, and finally in Section 5 we conclude the paper.

2 BACKGROUND

In the following we provide the background of the work that has motivated us in developing the Zoning Framework. More precisely, we discuss the complexity of buildings' occupants' behavior and the opportunity that lies in it for enhancing buildings' performance, as well as the state-of-the-art in building automation.

2.1 Complexity of Occupant Behavior

Occupant behavior, while being very complex and, at times, hard to predict, it can also be very revealing to problems and shortages in BMS (De Wilde 2014). The level of automation of a building is certainly one factor that limits the interaction of occupants with the building management system and, theoretically, it can range throughout different levels. There are buildings that do not allow occupants to even open a window, but also buildings that permit occupants to interfere with a wide range of components of the building management systems. Furthermore, there are zones in buildings with different levels of automation, dependent on their purpose and use. What is an optimal level of automation in a smart building? This is not a trivial question, and the answer is even less straightforward. It certainly depends on the goals of the concrete building management system, as well as on the occupants themselves, in terms of what kind of background they have, what are their tasks, or what kind of interaction can be expected from them. Apparently, the deciding parameters will differ from case to case.

To illustrate the complexity of occupant behavior, we use the example of an "open window". This is a scenario that can have a number of interpretations, some of them being the following:

a) A window is open due to high temperature
b) A window is open due to bad air quality
c) A window is forgotten and left open during night

Both cases (a) and (b) illustrate scenarios that communicate potential problems with the equipment, it could be that either of the temperature or CO_2 sensors are faulty, or a problem with the ventilation actuator, or some other unknown issues. Both events (a) and (b) have negative impact on the energy performance of the corresponding building. At the same time, both events are also significant feedback. If occupants were not allowed to open windows, this communication would have been omitted. Further factors in this scenario are whether there are sensors on the windows and whether an open window can be easily detected. Another beneficial factor is that occupant behavior should be quite straightforward to model due to the straightforwardness of reproducing it. The scenario (c), on the other hand, is not a feedback; however, it does need attendance, and it needs to be discovered as it could also pose a security threat. Furthermore, scenario (c) can also have a negative impact on the energy performance of a building as e.g. if it is in winter, due to the temperature drop the heating might be unnecessarily activated. Therefore, scenario (c) apparently carries a different message, compared to (a) and (b).

To further aggravate the issue, buildings' low automation levels coupled with inadequate occupant behavior can also pose a risk for the proper functioning of BMS equipment, as not all occupants interact with the equipment in its prescribed manner. Moreover, the increased penetration of advanced technologies makes interaction between smart buildings and occupants quite challenging for ordinary occupants; thus, increasing the likelihood of inadequate interaction, and, consequently, faults. Therefore, the automation/interaction levels need to be carefully studied and observed, as their optimization is far from trivial, and we expect that to even be a function of both space and time.

With respect to this, in (Lazarova-Molnar and Mohamed 2017b) we attempted classifying occupant behavior based on whether it was an opportunity or a risk to a building's performance, resulting into the diagram shown in Figure 1.

Each interaction is typically considered an opportunity (to collect data and learn about the system). Risk is typically a situation in which there is no feedback, but only loss. We define interactions with the system as events. Next, we need to distinguish between events and "lacking events". Examples of an event are "opening a window" or "turning on lights", and examples of *lacking events* would be "forgot to close window" or "forgot to turn off lights".

Figure 1: Occupant interaction classification.

We, furthermore, distinguish whether an interaction is intentional or unintentional. If it is intentional, then it can be considered a feedback, i.e. an opportunity, e.g. opening a window due to poor air quality or high temperature is a feedback from occupants that the system does not behave as expected, and it might as well signal that a component is faulty. Therefore, timely recognition of such events and directing attention to its diagnosis is an opportunity to improve the system's performance. Unintentional interaction is turning on a switch by mistake. E.g. when leaving an office, by mistake we might turn the light on. Typically, lacking-events cannot be intentional. However, there can always be exceptions to this.

2.2 Automation in Smart Buildings

Building automation has been developed alongside with building intelligence, in an attempt to achieve higher efficiency for smart buildings as well as lower their energy consumption. The symbiosis between the instrumentation in the buildings, as well as the software installed in them, yields opportunities for continuous monitoring of behaviors of buildings. This instrumentation incudes sensors, meters, as well as hardware utilized to control subsystems in buildings. As this instrumentation allows for both monitoring and control, it in turn provides easier maintenance of all systems too.

Especially with heating and ventilation systems (HVAC), being able to provide a stable indoor climate at all times without notice of occupants, while also optimizing the electricity consumption, is achievable through smart automation. To this end, it is worthy to note that occupant comfort often comes at the cost of higher electricity consumption, and thus finding a balance between the two goals is of paramount importance. To tackle this issue, attempts at multiple objective optimization solutions have been created in which the tradeoff between the different goal is weighed and thus an informed decision can later be made (Yang and Wang 2012).

Given the documented benefits of building automation, the market for these systems has been evaluated extremely highly. The very increase of demand for energy-efficient solutions has fueled the growth of the market, as well as propel forward research questions that improve building automation as well as improve it. Furthermore, the predictions for the growth and application of building automation systems seem to show a tremendous positive trend as a continuous process in the future (Report 2017).

The benefits that building automation and control can bring to a building are quantified in various capacities and using various metrics. Measurements, such as comparisons between the operation of buildings before and after installation of automation systems are used to discover improvements of the energy efficiency, as well as building's maintenance processes (Ippolito et al. 2014). To add an additional layer to building automation, it is also possible to examine behavior of occupants, as well as learn typical behaviors of heating or ventilation systems based on weather conditions. Based on this knowledge the systems are able to predict the needs of a building in the incoming period, thus allowing the automation system enough time to make the necessary calculations to discover an optimal course of automation and control (Gwerder and Tödtli 2005).

Building automation is also addressed vastly in various research questions. There are many attempts to explore the possibilities and challenges of building automation. Some of these involve frameworks that combine classical approaches with more intelligent data mining, often in novel workflows, to discover the optimal way to automate building processes (Wicaksono et al. 2010; Fan et al. 2015). More palpable studies cover comparisons between the automated behavior and the occupant behavior (Meerbeek et al. 2014). Focused on motorized exterior blinds, the study compares the output from an automation system and its own triggers for the change of the position of the blinds, with the user-triggered changes. The most prominent result from this study concludes that a large majority of the occupants preferred to not have any automation at all, for various reasons such as conflicting preferences, and interest in the control of their own working environment. Given the insights this type of study delivers into differences between automation and user behavior, the application of similar studies to subsystems which consume more energy, such as heating or ventilation, might yield additional benefits.

As buildings are highly complex cyber physical systems which often are a host to a large number of occupants, the aspect of their security often comes in question. In particular, the fact their automation systems are comprised of several modules usually hints at various potential security threats. Security of the automation system comes particularly in question when the building is posed as a safety-critical system. Paper (Granzer et al. 2010) discusses the interactions between the devices that instrument the buildings, their appliances, as well as the networks that they must communicate through in order for automation to occur successfully. The study in the paper shows with confidence that security mechanisms need to be in place, as a multitude of building automation system technologies lack state-of-the-art security features.

Though the general trend of building automation systems is so that they are more applicable and the demand for them is higher, they can still be applied to various degrees in any given building. Based on the level of instrumentation of the building as well as its purpose, various variables of building behavior can be set as constants and vice versa. It is important to study the buildings' individual needs as well as its occupants' requirements, so that the installation of an automation system can yield the highest benefits and an agreeable compromise between energy consumption and occupant comfort.

3 FRAMEWORK FOR USE OF AUTOMATION LEVELS TO OPTIMIZE DATA COLLECTION AND INTELLIGENCE IN BUILDINGS

Motivated by the above-described findings related to the potential of fine-tuning automation levels of smart buildings to enable more controlled and useful participation of occupants, thereby also increasing their own comfort, we have designed the Zoning Framework that we describe in the following.

3.1 Description

The basic idea of the Zoning Framework is to enable keeping track of, and controlling automation levels of a building to the benefit of the data collection processes, and ultimately, enhancing building's performance in terms of various metrics, such as occupant comfort, reliability or energy efficiency. This is achieved through partitioning the building into building zones that are abstract units that do not necessarily need to be compact and connected physical spaces. The actual mapping of physical space to building zones, thus, is meant to be changed dynamically, and it can, as well, be optimized based on the specific building and its properties and functionalities. Occupants' properties and needs can also affect the mapping of physical space to building zones. Each building zone is then a unit that can have various levels of automation, as calculated to be adequate for data collection and model building purposes. The whole idea of the Zoning Framework assumes a smooth feedback loop between the Building Management System and building's occupants, such that occupants are always aware of the level of control that they have, and vice versa, occupants can always inform the system when their needs are not being met by the automated control and they need to be in charge of some parts of equipment. In the following we provide the formal description of the framework.

3.2 Basic Elements

A building B is formalized as a set of n building zones Z_i, for which there are a number of applicable automation levels. Note that a zone is not necessarily a compact physical space, and it is more of a functional zone. Not all building zones have the same set of applicable automation levels, as this depends on the equipment in each building zone. This configuration converts into following description for a building B:

$$B = \{Z_i\}, i = 1, 2, \dots, n$$

Automation level is a set of equipment that is unable to be controlled by and interacted with building occupants, and an equipment that is instead controlled automatically, either through set points or through more sophisticated approaches. Examples of such sets of equipment could be lights, heating, cooling, etc. Formally, we define an automation level, A, as:

$$A = \{E_i\}, where\ E_i\ is\ a\ set\ of\ zone\ equipment$$

Consequently, we denote $\varnothing$ to be the lowest level of automation, i.e. the automation level in which the occupant can interact with and control all of the equipment in her/his building zone. This automation level ($\varnothing$) is useful for learning about building occupants' preferences and model building. Building zones' automation assignment, BZA, is a set of tuples that match building zones with sets of applicable automation levels:

$$BZA = \{(Z_i, \{A_j\})\}, i = 1, 2, \dots n;\ j = 1, 2, \dots, m;\ A_j\ is\ applicable\ to\ Z_i$$

Building configuration, BC, is an automation configuration of a building, i.e., a description of one possible coupling of building zones and automation levels. Formally, it is a set of tuples that match building zones Z_i with automation levels A_j, i.e.:

$$BC = \{(Z_i, A_j)\}, i = 1, 2, \dots n;\ j = 1, 2, \dots, m.$$

This formal description allows for optimizing and fine-tuning building automation levels with respect to space and time, which implies that the building configuration is a function of time t, i.e.:

$$BC(t) = \{(Z_i, A_j)\}, i = 1, 2, \dots n;\ j = 1, 2, \dots, m.$$

In the following we provide the application and workflow of this formal framework. The goal is to enable a more granular automation of buildings, such that it would enhance the data collection, learning and model building processes, and, in turn facilitate optimization on a number of performance metrics of smart buildings.

3.3 Workflows

The workflow of the Zoning Framework is illustrated in Figure 2. The idea is that each building zone Z_i in a building with n building zones gets initiated with the lowest automation level, i.e.:

$$BC(0) = \{(Z_i, \varnothing)\}, i = 1, 2, \dots, n,$$

denoting the beginning of the Learning Phase, in which the building management system learns about occupants' preferences and habits. Once *sufficient* data has been collected, the system gradually transits into a Stable Phase, by progressively increasing automation levels of building zones. From the Stable Phase, the system then transits to different automation levels for separate zones on demand only, i.e. by discovering discrepancies between occupant comfort and automation levels, or anomalies in the system's performance. This phase is indicated as Refinement Phase. From then on, the system switches only between the Stable Phase and the Refinement Phase. In the lower part of Figure 2, an illustrative abstract example of a building with four building zones is shown, the green color codes the lowest automation level, the orange codes the intermediate automation level, and the red color codes the highest automation level.

As mentioned previously, the system lowers the automation levels once there are discrepancies between what the system provides and what the occupants' needs are. The system can also lower the automation level when it detect anomalies in the behavior, and it is in need of occupants' feedback in terms of interaction. One example is an anomaly with data from CO_2 sensors, in which case the system will notify specific occupants that they can operate (open and close) the windows for the system to obtain significant hints in terms of interaction data for better identifying the cause of the problem.

Transition of building zones between the various automation levels need to be performed by informing the occupants. Therefore, as one of the triggers for shifting between phases, we envision a feedback loop in which occupants inform the system of their comfort levels. Thus, occupants can share if their comfort if being reduced, as well as also periodically inform the system that they are content, which would be evaluated as a sign that the developed models are accurate.

Finally, as an example we can use a new office building *B* that hosts multicultural staff, as this is very common nowadays. The building is divided into *n* building zones, mostly mapped to offices and common spaces. We assume the equipment that the building features that can be automated is as follows: lighting, heating, ventilation, windows and window blinds. Once the employees have been moved in, the building is set to the lowest automation level, i.e.

$$BC(0) = \{(Z_i, \varnothing)\}, i = 1, 2, \dots, n,$$

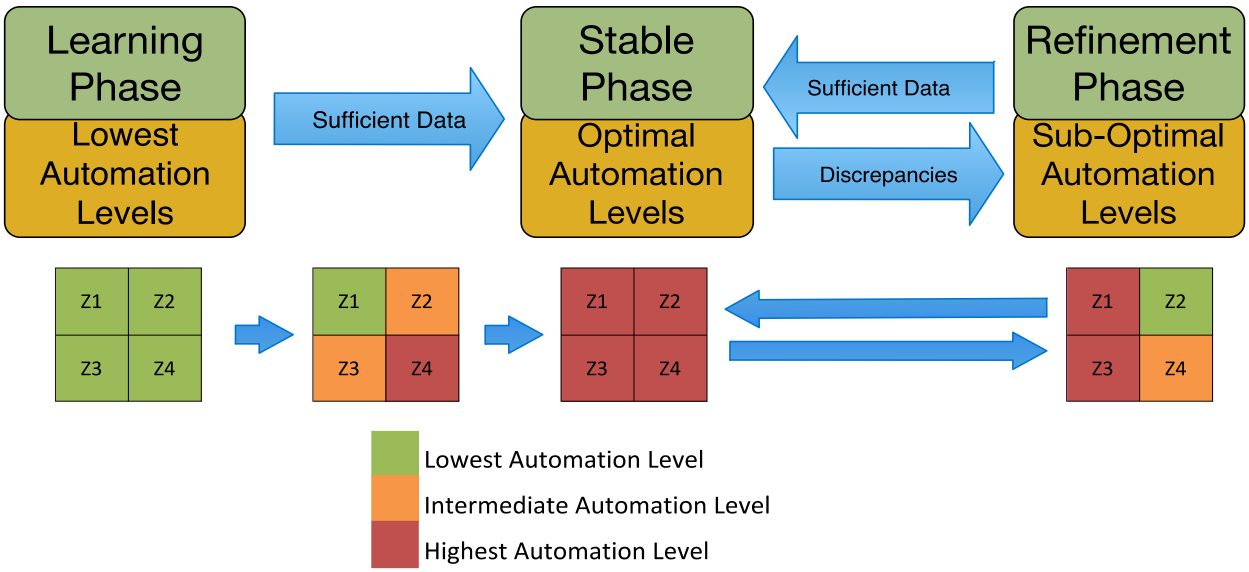

Figure 2: Buildings zoning framework and its workflow.

According to weather changes and properties of occupants, for some building zones it might take longer, and for some shorter to build accurate models of occupants' preferences, therefore, from then on, the system will gradually transform to the Stable Phase, during which transition, the system will also consider global system goals, such as, e.g., reduction in the energy consumption, and utilize this in the overall tuning of the system. During the transition, occupants are constantly being informed about the exact level of automation of their building zone. Once everything has been automated, we state that the system in a Stable Phase. However, occupant's preferences change, and also occupants change. Furthermore, new weather conditions may occur. This can affect occupants' comfort, as well as system's performance, such that either the system may need to impose new limitations (e.g. lowered heating) and needs occupants' feedback, or occupants may not be content with current configuration. Alternatively, the system may have exhibited anomalous behavior and may need additional input to diagnose the cause. In either of those cases, the automation levels would be lowered for the adequate set of equipment, and occupants will be informed of that. Then the system will move into the Refinement Phase to make the necessary learning for the new adjustments, and again, gradually transit back to the Stable Phase.

4 DISCUSSION

While the full automation of energy management for smart buildings can provide good energy efficiency, it is very difficult to reach optimal levels. There are many reasons for this limitation including:

1. Smart buildings are usually heterogeneous in terms of usage, equipment, conditions, designs, operational requirements, resources and occupants behavior. Therefore, it is very difficult to design, deploy, and configure general BMS that minimizes energy consumption while maximizing occupants comfort levels for all smart buildings types and situations.

2. Although machine learning techniques can be applied to enhance the operations of BMS through learning the situation of a building, this may take significant time to collect and analyze enough data to effectively optimize the energy efficiency and enhance occupants comfort.
3. Smart buildings are usually equipped with many sensors that report their observations to different energy subsystems and the BMS. These sensors after some time could degrade or fail, which may result in faulty observations that may negatively impact the energy efficiency.

A smart building can be considered as one large zone or a collection of several small zones. Dividing a building into zones can relax some of the discussed limitations and offer additional benefits:

1. It is easier to manage and optimize energy efficiency and occupants comfort levels in small zones compared to a large zone since smaller zones have less parameters, equipment, conditions, and requirements to deal with.
2. It is easier to learn from small zones and find all possible situations and conditions. In addition, it will take less time to apply learning methods and reach usable results.
3. Having multiple buildings and dividing them to multiple small zones increases the chances of having multiple similar zones. These zones similarities can be utilized in transferring the experience gained in managing energy efficiency in one zone to other similar zones. In addition, new observations can be found faster from these similar multiple zones.
4. Multiple similar zones in multiple buildings can be also utilized to find new faults faster. For example, data analytics can be applied to the observations from the similar zones to find new faults faster (Lazarova-Molnar and Mohamed 2017a). As a result, general solutions can be applied faster to solve these new faults and less energy will be consumed.

The zoning approach for smart buildings can provide better understanding for different issues in smart building to better address their energy efficiency aspects. One of these issues is about the BMS-occupant interactions. Occupants behavior in buildings and interactions with BMS have high effect on the energy efficiency for different aspects such as cooling, heating, ventilation, and lighting. It has been found that careless behavior can increase an added of one-third of energy consumption to the building while careful behavior can save a third (WBCSD 2009). Automation with ambient intelligence can substantially enhance energy efficiency in buildings (Arens et al. 2005; Nguyen and Aiello 2013). Nevertheless, there are some risks and opportunities included in accomplishing the important BMS' role of improving energy efficiency while maintaining occupants comfort. These risks and opportunities can develop based on the type and level of automation applied in the BMS and the type and level of interaction permitted between the BMS and the building's occupants (Lazarova-Molnar and Mohamed 2017b). Low levels of automation in BMS can usually increase the risks and reduce the opportunities of realizing a BMS' goals while higher levels of automation can usually reduce the risks and increase the opportunities of realizing the needed goals for careful behavior. Simultaneously, permitting low occupant-BMS interaction levels is good for careless occupants as they will not have a strong influence on impacting the BMS' goals negativity, thus lowering the likely risks in realizing the goal of energy efficiency. In contrast, permitting high occupant-BMS interaction levels is good for careful occupants as this will offer opportunities that can be employed to realize the goals of BMS in improving energy efficiency and occupant comfort levels in buildings.

The main goals of BMS can be achieved effectively if the risks related with the careless occupants are lessened while increasing opportunities in finding new observations from careful occupants to improve the automation in BMS (Lazarova-Molnar and Mohamed 2017b). High levels of BMS automation are normally beneficial to apply. Yet, the best allowable level of occupants-BMS interaction levels is based on the occupant's types. Based on these observations, a high-level of BMS automation allied with adaptive allowable levels of occupant-BMS interactions can offer the worthiest solution in achieving BMS' goals. This adaptive level is determined based on the carefulness of occupants. By means of an adaptive level of occupant-BMS interaction can decrease the risks allied with careless occupants and will increase the opportunities allied with careful occupants in discovering and applying found feedback and observations to improve BMS' operations. As a smart building can be very large while the occupants behaviors can be a mix of careful and careless interactions; using a uniform adaptive level will not result in an effective approach for energy efficiency. However, the smart building can be divided into several zones based on the types of occupants' behaviors as well as other factors to have more effective results.

5 SUMMARY AND OUTLOOK

We presented a Zoning Framework that features a model to enhance building automation levels, and, therefore, to enhance on a number of performance metrics of a smart building. The main purpose of the Zoning Framework is to enable higher granularity, both space-, time-, and level-wise in automation of smart buildings. One of the significant enablers, however, for our Zoning Framework is the presence of a feedback loop, which would ensure that building occupants are aware at all times about the details of the automation levels that apply to them. Furthermore, the feedback loop would ensure that occupants have a systematic way of expressing their discomfort with certain aspects of the equipment, which would then send the framework into a Refinement Phase.

We believe that a zoning framework, such as the one we presented, would enable a more controlled approach to improving performance of smart buildings, as well as assist all processes related to achieving it, such as timely and accurate fault detection and diagnosis or better understanding of the way a building operates. Moreover, the Zoning Framework actually provides a model to better integrate building occupants and benefit from their participation.

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AUTHOR BIOGRAPHIES

SANJA LAZAROVA-MOLNAR is an Associate Professor with the Faculty of Engineering at the University of Southern Denmark. Her current research interests include: modeling and simulation of stochastic systems, reliability modeling, decision support for decentralized energy systems, energy informatics and data-based approaches to fault detection and diagnosis. Sanja obtained her Ph.D. in Computer Science from the University "Otto-von-Guericke" in Magdeburg, Germany, where she was also a member of the Simulation Group at the Institute of Simulation and Graphics. Contact her at slmo@mmmi.sdu.dk. See also http://www.lazarova-molnar.net

NADER MOHAMED is an independent Computer and Information Research Scientist. He obtained his Ph.D. in Computer Science from the University of Nebraska-Lincoln, Nebraska, USA in 2004. His current research interest focuses on middleware, cloud and fog computing, cyber-physical systems, unmanned aerial vehicles, and data analytics. He worked at The College of Information Technology, UAE University, Al-Ain, UAE as an Associate Professor from September 2009 to August 2015 and as Assistant Professor from August 2006 to August 2009. Between August 2004 to August 2006, he was an Assistant Professor of Computer Engineering at Stevens Institute of Technology in New Jersey, USA. He can be reached at nader@middleware-tech.net

ELENA MARKOSKA is a PhD research fellow at the University of Southern Denmark. Her background is in computer science and software engineering, acquired through a BSc and an MSc from Ss. Cyril and Methodius University in Skopje, Republic of Macedonia. Her research involves performance testing for smart buildings. The framework developed studies the benefits from the interactions between metadata models and performance tests in an approach which continuously tests the real time behavior of the building. The methodology is adaptable to a wide variety of buildings and is applicable with minimal human effort. Her email address is elma@mmmi.sdu.dk.