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An Ontology-Based Framework for Building Energy Management with IoT

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Received: 30 March 2019; Accepted: 27 April 2019; Published: 30 April 2019

Abstract: In this paper, we develop an ontology-based framework for energy management in buildings. We divide the functional architecture of a building energy management system into three interconnected modules that include building management system (BMS), benchmarking (BMK), and evaluation & control (ENC) modules. The BMS module is responsible for measuring several useful environmental parameters, as well as real-time energy consumption of the building. The BMK module provides the necessary information required to understand the context and cause of building energy efficiency or inefficiency, and also the information which can further differentiate normal and abnormal energy consumption in different scenarios. The ENC module evaluates all the information coming from BMS and BMK modules, the information is contextualized, and finally the cause of energy inefficiency/abnormality and mitigating control actions are determined. Methodology to design appropriate ontology and inference rules for various modules is also discussed. With the help of actual data obtained from three different rooms in a commercial building in Singapore, a case study is developed to demonstrate the application and advantages of the proposed framework. By mitigating the appropriate cause of abnormal inefficiency, we can achieve 5.7%, 11.8% and 8.7% energy savings in Room 1, Room 2, and Room 3 respectively, while creating minimum inconvenience for the users.

Keywords: energy management; building energy management systems; ontology and inference rule based framework; building benchmarking

1. Introduction

Globally, buildings consume around 30% of total energy and 60% electrical energy every year [1]. Research and development interest in building energy management systems (BEMS) has, therefore, continuously increased in recent years [2–5]. The objective of BEMS is to improve energy efficiency of buildings as well as to reduce the inconvenience experienced by the building users. This can be achieved by controlling the operations of various energy consuming equipment such as HVAC, lights, elevators, etc. BEMS are complex systems comprising of various system components such as, sensors, energy meters, actuators, and communication devices, which are integrated together to achieve various goals. Furthermore, it is also important to note that BEMS require appropriate handling of all the information that is related to hardware, environment, users, context, services, as well as to make sense of them in a structured way. However, due to inherent heterogeneity and complexity of BEMS, structuring the information itself becomes quite challenging. Moreover, BEMS knowledge base is also diverse, distributed and growing.

Traditional building energy management techniques mostly evaluate the information coming from various sensors and then take different actions according to the objectives of the optimization framework (cost minimization, human comfort maximization, etc.) [6–10]. Such frameworks generally focus on specific building systems and fail to evaluate the complete scenario, and therefore, result in more energy wastage as well as more inconvenience. For example, if room temperature on a sunny day is detected to be on the higher side due to an open window, a traditional energy management system would further lower the thermal set point in order to maximize human comfort [10]. Such actions would result in more energy wastage. In this context, more structured ways of handling different information coming from diverse and unrelated building systems and sub-systems are required.

Ontology-based approaches can provide a higher level of abstraction, flexibility and implementation independence to attain a shared understanding of information across complex heterogeneous systems [11,12]. Ontology is related to the definition of common language and representation to structure information and knowledge and it provides a common vocabulary to express several properties, classes, and attributes of the components. There are some projects that investigate ontological-based approaches for BEMS [13–16]. In [13], authors present smart building ontology for ambient intelligence (BOnSAI), which extends and benefits from existing ontologies in different fields and also includes several concepts which are related to hardware, context, service, functionality, and Quality of Service in buildings. In [14] authors present ThinkHome, which uses Web Ontology Language (OWL) standard ontology for semantic representation of knowledge in homes. The unique feature of ThinkHome is the inclusion of energy related concepts such as energy supply, energy demand, energy tariffs, etc. In [15] authors use extended Semantic Sensor Network ontology (SSN) ontology and use heterogeneous data from different buildings with the objective to detect and diagnose abnormal building behavior. In [16], authors bring web technologies into building automation systems and propose building ontology as a schema for representing semantic data. Most of the existing literature however is focused on the development of common abstraction language for sensors and energy related concepts.

In this paper, we propose an ontology-based framework for energy management in buildings. To facilitate the development of our approach and in order to make it widely applicable for various building types, we divide the functional architecture of BEMS into three interconnected modules, which include, building management system (BMS), benchmarking (BMK) and evaluation and control (ENC). BMS module comprises of sensors, energy meters and actuators. Through BMS, real-time building parameters (temperature, humidity, occupancy, energy consumption) are measured. Moreover, with the help of actuators (such as, opening or closing of windows and changing thermostat settings), various control decisions are also implemented. The BMK module uses modeling-based, peer-to-peer (P2P)-based, and standard-based approaches to provide thresholds on various environmental parameters and energy predictions to evaluate and contextualized the appropriate behavior (energy efficient, energy inefficient, normal, abnormal, etc.) of building in various scenarios (modeling-based, P2P-based and standard-based approaches are defined Section 2.2). In the ENC module, real-time and predicted energy consumption and other parameters are compared, appropriate context is understood, cause of inefficiency and abnormal behavior is determined, and then appropriate control action is decided accordingly.

To make our approach widely applicable to various building types, we use the appropriate ontology for every module and provide various connectors and inference rules. Our approach makes it possible to easily identify inefficient and abnormal energy consumption states despite the system heterogeneity problems due to lack of standardization. The proposed approach can also result in more energy savings and less inconvenience for users because appropriate control actions are adopted due to benchmarking and context understanding. We explain the proposed approach with the help of simple examples. Moreover, a numerical study using actual data obtained from three different rooms in a commercial building in Singapore also highlights the advantages of the proposed framework. Development of ontology and inferred rule based design for energy optimization with the help of appropriate benchmarking to evaluate the context and cause of energy inefficiency and abnormality before taking appropriate energy optimization actions is largely missing in literature. Therefore, this paper is novel in providing a conceptual breakdown of functional architecture of BEMS into generalized and flexible modules, and development of simple inference rules for energy optimization in buildings.

The rest of the paper is organized as follows. In Section 2 we discuss our proposed functional architecture of BEMS. In Section 3 we describe our proposed ontology and inferred rule based methodology. In Section 4 we present a numerical case study. The paper is concluded in Section 5.

2. Proposed Functional Architecture of BEMS

We divide the functional architecture of BEMS into three modules as shown in Figure 1. These modules include BMS, BMK, and ENC. In our model, these three modules are interconnected and they can collaborate with each other to provide a real-time energy management solution for improving energy efficiency of a selected building. In the following subsections we provide further details of these modules.

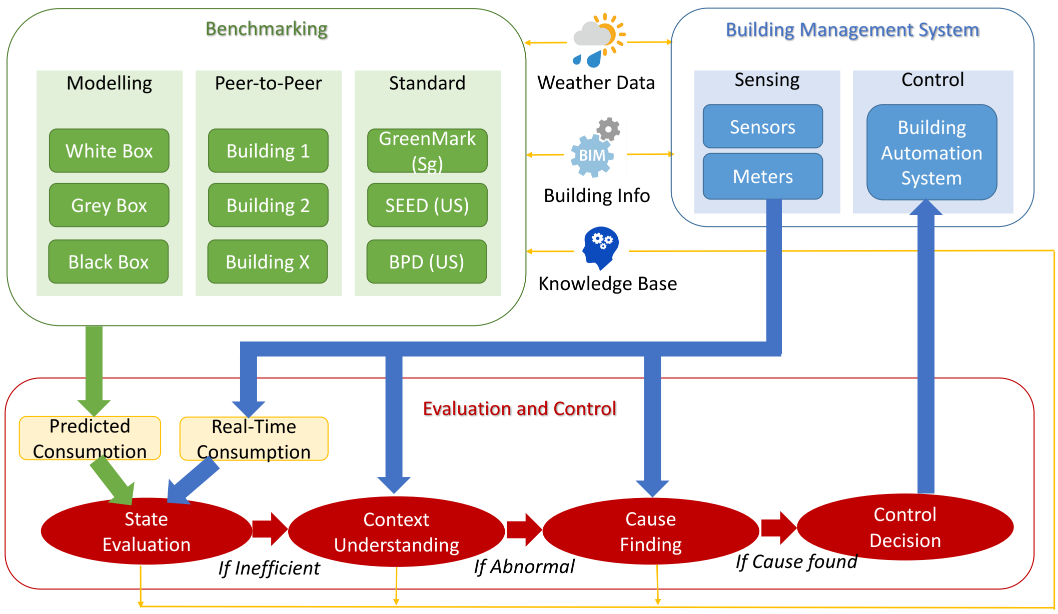

Figure 1. Proposed Functional architecture of BEMS.

2.1. Building Management System (BMS) Module

This module is responsible for measuring several useful environmental parameters as well as real-time energy consumption of the building. Necessary control actions required to maintain energy efficiency are also executed by this module. We further divide the functionality of BMS into two sub-modules i.e., sensing, and building automation system (BAS).

2.1.1. Sensing Sub-Module

Sensing sub-module provides the necessary capability to measure various environmental parameters (temperature, humidity, occupancy, noise), appliance states (ON, OFF), and energy consumption of appliances (air-con, lights, plug-loads). The information collected by the sensing sub-module is used to compute the real-time energy consumption of the considered building.

Any other information such as, building layout or weather data, can also be collected and utilized for the computation of energy consumption.

2.1.2. BAS Sub-Module

This sub-module provides the necessary capability to automate the control of various appliances. The automation can be achieved by installing smart relays, smart plugs, and other smart devices with various appliances and building infrastructure such as, windows, doors, etc. Through this sub-module, operational state of appliances (ON, OFF, temperature, light intensity) can be modified. Moreover, the state of some infrastructure can also be changed through this module. For example, window blinds or doors can be opened or closed through appropriate control commands.

2.2. Benchmarking (BMK) Module

In our architecture, BMK module provides the necessary information required to understand the context and cause of building energy efficiency or inefficiency and to further differentiate between normal and abnormal energy consumption in different scenarios. We can benchmark the performance of a building and its various systems (such as air-conditioning system, lighting system etc.) using different approaches. Through these approaches, we obtain the required assessment thresholds for comparing the real-time energy consumption of the considered building. We can use modeling-based, peer-to-peer (P2P-based) or standard-based approaches for benchmarking, and one or more of these approaches can be used to generate the required information for comparison.

2.2.1. Modeling-Based

In modeling-based approach, energy consumption of the selected building is predicted through data-driven and physical modeling approaches. Data-driven approaches include, black-box and gray-box modeling. For these data-driven approaches, only a limited amount of information about the building is used to develop perdition models. For example, machine learning algorithms can be used to predict the energy consumption of building in different scenarios based on temperature, humidity, and weather information. On the other hand, physical modeling approach such as white-box modeling requires complete information to build the models of energy consumption, energy efficiency, etc.

2.2.2. P2P-Based

In P2P-based approach, energy consumption data from other similar buildings is used as a basis to evaluate the energy performance of the selected building. Buildings with the same generic properties can be used for comparison and P2P data can also be exploited for the performance tuning of selected building. Several publicly available datasets that contain information about buildings and its various sub-systems can be used in the BMK module.

2.2.3. Standard-Based

Different existing standards to compute and assess the energy consumption of a building can also be used in the BMK module. Such standards set parameters and establish indicators to guide the design, construction, and operation of buildings towards increased energy effectiveness and enhanced environmental performance. Examples of such assessment benchmarks include, Green Mark standard, which is developed by the Building construction authority (BCA) of Singapore [17]. Standard Energy Efficiency Data (SEED) is also a US based benchmarking standard for building energy efficiency [18]. Furthermore, European Union has their own benchmarking standards for energy efficiency of buildings. The information provided in these standards can also be used to develop BMK module.

2.3. Evaluation & Control (ENC) Module

This module evaluates all the information coming from BMS and BMK modules. In this module, information is contextualized and cause of energy inefficiency (if it is detected) is determined. Appropriate control action is also decided by this module. Control action is then communicated to the BAS sub-module for implementation. The functionality of this module is divided into four sub-modules.

2.3.1. Evaluation

This sub-module receives information on real-time energy consumption (or real-time parameters) of the selected building from BMS module, and the predicted and/or computed energy consumption information (or other parameters and thresholds) from the BMK module. Energy consumption values are then compared to evaluate the state of the building i.e., whether the building is efficient, inefficient or outperforming in terms of its energy consumption.

2.3.2. Context

This sub-module is responsible for identifying the reasons behind the evaluated state of the building. If the evaluated state is inefficient or outperforming, this sub-module would set a command (inference rule) to check whether the state of being inefficient (or outperforming) is normal or abnormal in the given context. An example would be higher energy consumption due to hotter outdoor temperature or over-crowding in a room.

2.3.3. Cause

If the state of the building is recognized to be abnormal, cause sub-module then sets different commands (inference rules) to identify the cause of building inefficiency. For example, it may check the status of windows, doors, thermal settings, etc., to identify the source of energy inefficiency.

2.3.4. Control

Once the cause (or causes) of an inefficient and abnormal behavior is (are) identified, control sub-module determines the necessary command (inference rule) to fix the cause (or causes) in order to resume the energy efficient consumption behavior of the building. The control commands are communicated to BAS, which implements the necessary actions.

3. Ontology for the Proposed BEMS

In this section, we discuss the ontology and inference rules for the three modules in our proposed functional architecture of BEMS. In order to develop an ontological modeling, we have to define appropriate concepts, sub-concepts, and attributes. For example, the possibility of having a 'sensor' in BEMS is a concept. Sub-concepts of this concept include sensor type (e.g., temperature, humidity, occupancy), sensor state (e.g., on, off, normal, faulty), etc. 'Building' is another concept, while building type (e.g., office, residential, commercial) is a sub-concept. In a similar way, equipment, zone, indoor environment, zone type, time zone, etc. are some other important concepts and sub-concepts in BEMS.

On the other hand, attributes define various properties of concepts and sub-concepts. The attributes are further classified into rule data, static data, and dynamic data. The rule data describes the relationship between concepts. For example, a rule would be required to define a relationship between building type, cooling system state, indoor temperature, and window status. To make these rules useful, we use static and dynamic data. The static data is unchangeable data such as, identification, label, name, and address of sensor. The constant threshold values defined in the BMK module are also some examples of static data. Dynamic data is variable, and keeps on changing. For example, indoor temperature value is a dynamic data. Similarly, outdoor temperature value is another example of dynamic data. Inference rules combine various concepts, sub-concepts and attributes. In the following, we describe the ontology and inference rule design for the three BEMS modules.

3.1. BMS Module Ontology

BMS module comprises of various sensors, energy meters, and actuators. This module also requires information about building layout, external weather, and all other building related data. To make the proposed framework more generic, it becomes essential to define appropriate ontology that provides a common information model and knowledge base. Moreover, interfaces and connectors are also needed to send or receive information from various external technologies. BMS ontology is therefore, divided into four parts, which are explained below.

- Generic Ontology: Generic ontology represents a common information model, which is the same for all the buildings. The ontology contains definitions, terminologies, and taxonomies. Several concepts, sub-concepts are defined for the sensors, energy meters, and other equipment. Generic ontology is also enriched with building specific knowledge and it provides a single access point for the configuration and maintenance tasks as well as automatic computation of building energy.
- Knowledge Base: Knowledge base is essentially a data storage. All the static and dynamic data is stored in the knowledge base and it can also be regarded as the center point of the ontology (alternatively called semantic core). Static building information includes building type (office, home, etc.), sensor type (indoor temperature, occupancy, noise, outdoor temperature etc.), while dynamic information may include time information (daytime, nighttime), occupant status (working, static, moving etc.), sensed values (temperature, occupancy, light, energy consumption, etc.). Further information on the range or type of dynamic values such as, acceptable temperature ranges, light intensity values etc., can also be included. Some dynamic data can also take binary values such as, true/false, yes/no, on/off etc. All this information is included in the semantic core.
- Interface: Knowledge base is surrounded by an interface. Information in knowledge base can be accessed through the interface. Similarly, information is also stored in the knowledge base through this interface. Interface specifications generally cover the communication between knowledge base and external systems.
- Connectors: External technologies and systems (such as air-con system, lighting systems, etc.) can be connected to the interface through various arbitrary software connectors. Message exchange within the connected systems is hidden by the connectors. Appropriate message exchange protocols are also required to enable communication between technology connectors and the interface.

For BMS module comprising of sensors and energy meters, concepts and sub-concepts can be defined with the help of W3C semantic sensor network (SSN) ontology [19]. This ontology can describe sensors and observations as states and events. It also provides a homogenous semantic model of sensors to the backend. There are 41 different concepts defined in SSN ontology. For the implementation of proposed ontology, Web Ontology Language (OWL) 2 can be used due to its superior expressiveness issues and syntax features [20]. For BAS sub-module, semantic web rule language (SWRL) can be used to develop appropriate rules for the control of various devices. Knowledge base, interface and connectors can be developed using Colibri, which is an open source software project specifically designed for BEMS [21].

3.2. BMK Module Ontology

The objective of BMK module is to provide appropriate basis for comparing the real-time energy consumption of the building for evaluation and contextualization of given information. We define or obtain appropriate thresholds for comparisons in various scenarios. In order to make our framework more flexible and generic (for use in different regions), our BMK model can obtain various thresholds using different approaches. These approaches can be selected according to the static and dynamic information available in the semantic core. For example, modeling-based approach can be used to define appropriate lighting conditions during daytime for specific type of buildings. Similarly, standard-based approach may be used to define appropriate energy consumption threshold of air-con in a given building at a certain indoor & outdoor temperature.

BMK module contributes in providing comparison data for various attributes in the ontological modeling. These attributes, which define the properties of various concepts and sub-concepts are then used to develop various inference rules. Standards such as Green Mark and SEED provide the most convenient way to obtain data for these attributes. It should be noted that modeling-based or P2P-based approaches are more helpful in developing attributes for scenarios that may not be available in existing standards. These approaches may also be adopted to customize the attribute data according to the unique operating conditions of the specific building. As a specific example energy efficiency factor (EEF) can serve as an important attribute in determining energy inefficient behavior of cooling equipment. If Green Mark standard is used in BMK module then the corresponding data for EEF attribute can be obtained. For example, EEF value less than 0.85 kW/RT defines energy efficient behavior of a cooling load with thermal capacity less than 500 refrigeration ton (RT).

3.3. ENC Module Ontology

In the ENC module, we combine all the information coming from BMS and BMK modules. Ontology for the ENC module comprises various generic and flexible inference rules. Several rules can be developed for evaluation, context, cause, and control sub-modules. Moreover, appropriate rules can be added as more information is gathered about building. In the following we explain how these rules can be designed. In these rules, a scenario is described with the help of a $\wedge$ symbol (representing the 'and' word in the English language). Static data, dynamic data, and benchmarking data are all used in the development of these rules. These rules can also be developed using SWRL language. Further details on developing rules in SWRL language can also be found in [22].

3.3.1. Evaluation Inference Rules

Let us assume that we have a building classified as Type-A. Inside the building we have a cooling system that is classified as Type-b. The first step is to develop rules through which we can determine if energy consumption of building or its sub-system is efficient or inefficient. An example of such rules for the evaluation sub-module is given in (1) and (2). Please note that inference rules are not classical equations. Instead they represent ways of combining diverse information coming from different building systems and sub-systems. In this paper, the method of representing these rules in similar to the one described in [12]. According to (1), if the thermal rating of a cooling system is less than X RT and EEF is less than Y kW/RT, the cooling system can be regarded as energy efficient. On the other hand, if EEF for the same cooling system is greater than Y kW/RT, then we regard it as energy inefficient (according to (2)). Please note that the value of EEF in these equations is computed by the BMS module, while the value of Y is provided by the BMK module. In a similar way, we can define evaluation rules for any other system or sub-systems in the building.

$$\begin{aligned}\text{Building(Type-A)} \wedge \text{Cooling-System(Type-b)} \wedge \text{Cooling load}(\leq X\ \text{RT}) \wedge \text{EEF}(\leq Y\ \text{kW/RT})\\ \rightarrow \textbf{Energy Efficient Cooling}\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Building(Type-A)} \wedge \text{Cooling system(Type-b)} \wedge \text{Cooling load}(\leq X\ \text{RT}) \wedge \text{EEF}(> Y\ \text{kW/RT})\\ \rightarrow \textbf{Energy Inefficient Cooling}\end{aligned} \tag{2}$$

3.3.2. Context Inference Rules

Once the energy consumption behavior is evaluated as inefficient, we further determine the context of this inefficiency. To understand the context, we consider more information from the BMS and BMK modules. For example, to develop a context rule for the previous example scenario, we also add the information about the indoor temperature and obtain the following context inference rules.

$$\text{Building(Type-A)} \land \text{Cooling system(Type-b)} \land \text{Cooling load}(\leq X \text{ RT}) \land \text{EEF}(> Y \text{ kW/RT}) \land \text{Indoor temperature}(\leq T_i) \rightarrow \textbf{Normal} \tag{3}$$

$$\text{Building(Type-A)} \land \text{Cooling system(Type-b)} \land \text{Cooling load}(\leq X \text{ RT}) \land \text{EEF}(> Y \text{ kW/RT}) \land \text{Indoor temperature}(> T_i) \rightarrow \textbf{Abnormal} \tag{4}$$

According to these rules (3) and (4), depending on the indoor temperature, we determine whether energy-inefficiency can be regarded as normal or abnormal. If the indoor temperature is less than or equal to T_i, we regard energy inefficiency as normal, otherwise we term it as abnormal. In this example, if additional power consumption (which is causing inefficiency) also results in further lowering of indoor temperature, we regard it as normal behavior. On the other hand, if despite additional power consumption, indoor temperature is on the higher side then it would mean that there is something wrong, which is preventing a drop in temperature. Please note that the value of T_i is set with the help of BMK module.

3.3.3. Cause Inference Rules

Once the context of energy inefficiency is classified as abnormal, it becomes important to determine the cause of abnormality. There could be different causes for an abnormal state. It is important to note that these causes can be added manually or automatically after data mining on the collected data. In order to develop inference rules for the cause sub-module, we further augment the context rules with additional information. For example, we can check the status of building windows with the help of following inference rule.

$$\text{Building(Type-A)} \land \text{Cooling system(Type-b)} \land \text{Cooling load}(\leq X \text{ RT}) \land \text{EEF}(> Y \text{ kW/RT}) \land \text{Indoor temperature}(> T_i) \land \text{Window status}(Open) \rightarrow \textbf{Cause(Window)} \tag{5}$$

By checking this rule (5), cause of abnormality can be detected as the opening of window. Similarly, for every possible cause available in the knowledge base, similar rules can be developed and checked.

3.3.4. Control Inference Rules

Finally, control sub-module has a list of appropriate action commands according to various causes. Once the cause of abnormal state is determined, suitable action is selected. For example, below we give a rule for the control module.

$$\text{Cause(Window)} \land \text{Window Status(Open)} \rightarrow \textbf{Control: Window Status(Close)} \tag{6}$$

It should be noted that multiple control actions could also be initiated depending on the causes. The control action is communicated to BAS for implementation.

3.4. Process Flow of the Proposed Framework

In the following, we list down various steps involved in our proposed framework.

1. Develop the ontology for the BMS module by defining concepts, sub-concepts, attributes etc.
2. Develop appropriate knowledge base, interface and connectors.
3. Collect real-time building information with the help of BMS module.
4. Select the approach or approaches (modeling, P2P or standard) for BMK module according to the region and building specifications.
5. Set the values of various thresholds and parameters in the BMK module for comparison.

6. Compare the data (parameters, energy, etc.) coming form BMS and BMK modules with the help of evaluation inference rules to classify the energy consumption behavior as energy-efficient or energy-inefficient.
7. If energy-efficient, no further action is required.
8. If energy-inefficient, use context inference rules to classify energy consumption behavior as normal or abnormal.
9. If energy consumption behavior is normal, no further action is required.
10. If energy consumption behavior is abnormal, determine the cause using cause inference rules.
11. If cause is found, decide appropriate control action.
12. Communicate the control action to BAS for implementation.

A process flow chart explaining various steps in our proposed approach is also given in Figure 2.

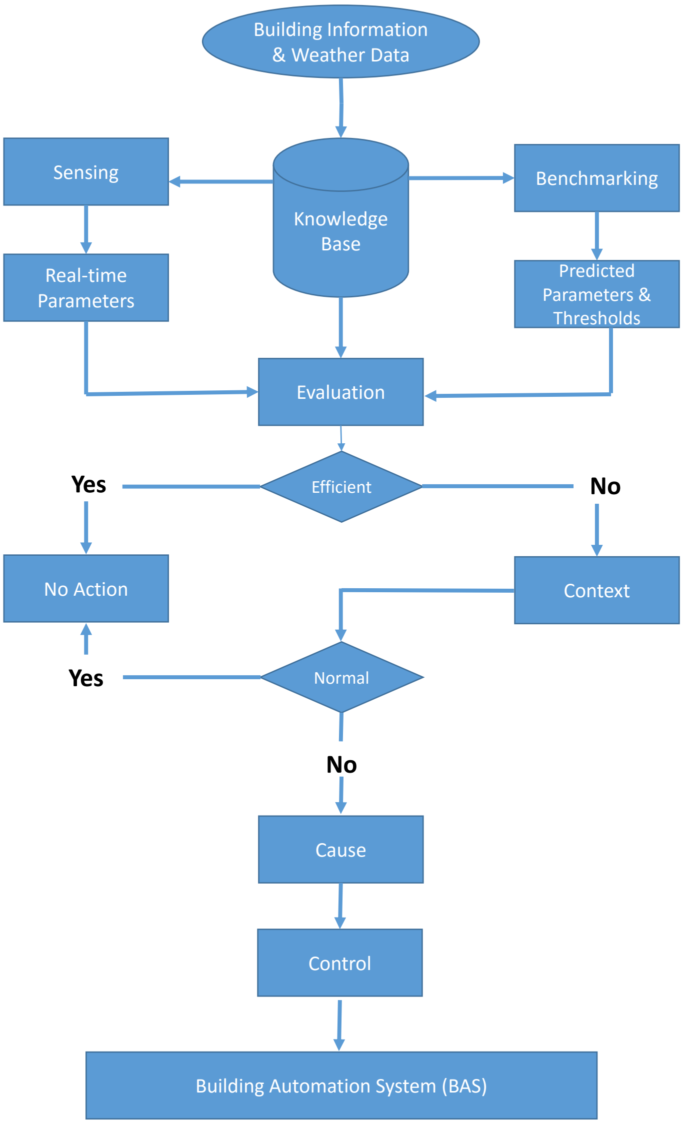

Figure 2. Process Flow Chart.

4. Numerical Results

In this section, we discuss the implementation of our proposed framework using experimental data obtained from a commercial building located in Singapore. We consider three meeting rooms in the building. The areas of Room-1, Room-2 and Room-3, respectively, are 6×8 m^2, 8×8 m^2 and

4×8 m^2. In this study, we only consider the air-con system, which is the major source of energy consumption inside buildings. We have installed sensors in all the three rooms that monitor the air flow rate of cool air in each room, which we used to estimate cooling power. A temperature sensor is also placed within each room to record changes in indoor temperature. The data is collected after every five minutes (or $\frac{5}{60}$ h). This activity was carried out for two months and in total we have 17,858 data points. BAS sub-module, which is required for automatic control of various appliances and infrastructure is not available in the meeting rooms. We use SSN ontology for the BMS module and we use standard-based approach for the BMK module. As the building is located in Singapore, we use BCA Green mark energy efficiency standard. This standard provides a comprehensive framework for assessing the overall environmental performance of new and existing buildings to promote sustainable design, construction and operations practices in buildings.

Using the sensor data, we estimate the actual power consumption (which varies) and thermal capacity (rated power) of the air-con load serving each room. These values are only computed when we sense the air-flow. The thermal capacity of air-con load is evaluated to be less than 1 RT. Power consumption and thermal capacity values are used to compute the EEF values. These values are plotted in Figures 3–5 respectively for Room-1, Room-2, and Room-3. Based on the Green mark standard, the value of EEF threshold to differentiate between energy-efficient and energy-inefficient behavior is 0.85. The inefficient behavior occurs at different times of the day. For Room-1, energy inefficient behavior is observed at 2.87% of data points. For Room-2 we observe energy inefficient behavior at 20.75% of data points. For Room-3, energy inefficient behavior occurs at 37.48% of data points. It should be noted that this difference in energy inefficiency in various rooms can be attributed to lot of factors such as room layout, room size and number of times room is used for meetings. For example, during the data collection period, Room-2 and Room-3 are more often used as compared to Room-1. When the number of occupants increases, the amount of energy required to cool the room also increases, hence, we observe higher number data points classified as inefficient.

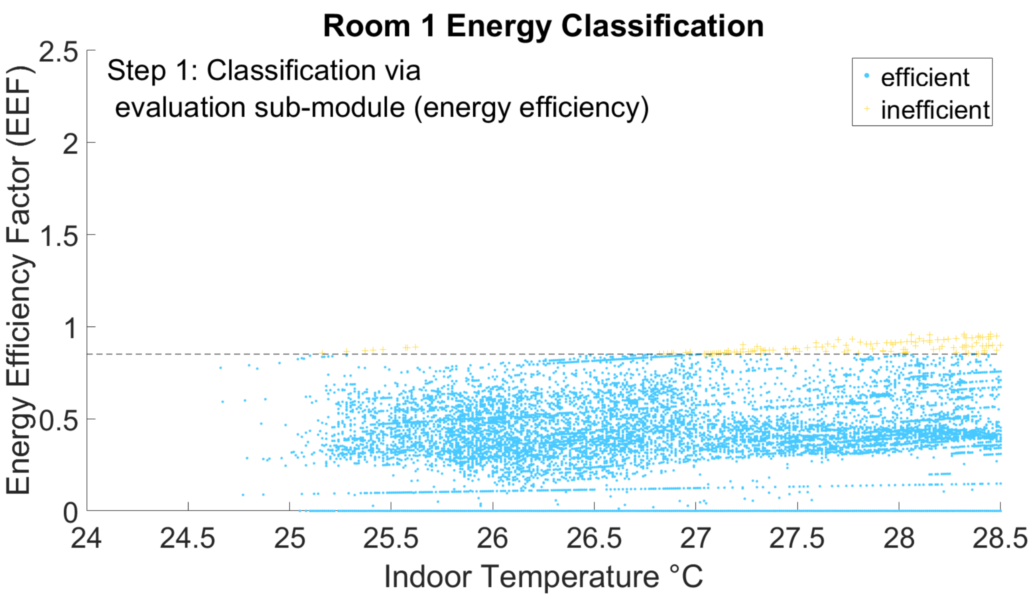

Figure 3. Classification of energy-efficient and energy-inefficient behavior based on inference rules in the evaluation sub-module for Room-1.

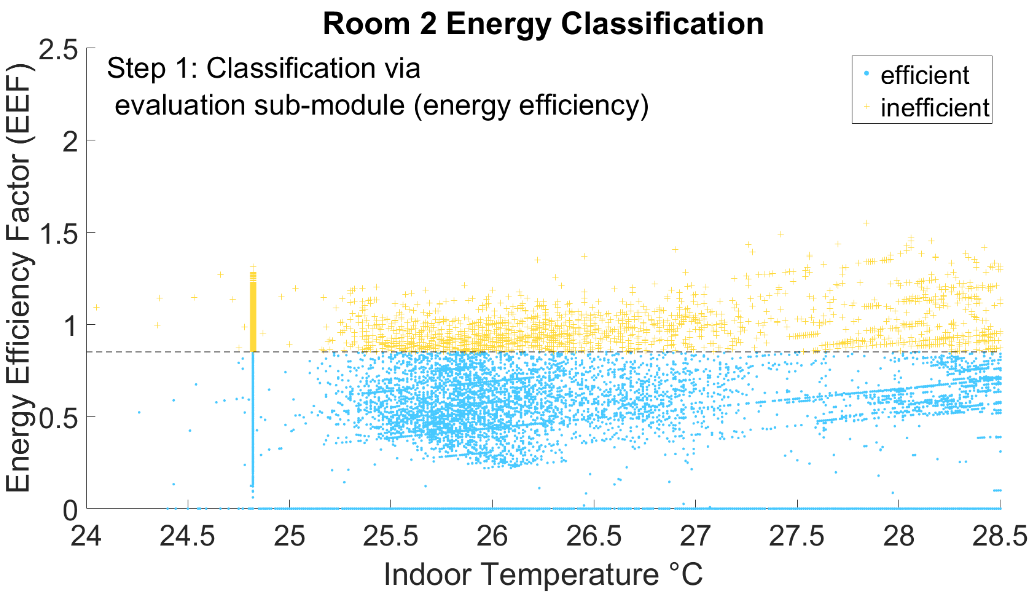

Figure 4. Classification of energy-efficient and energy-inefficient behavior based on inference rules in the evaluation sub-module for Room-2.

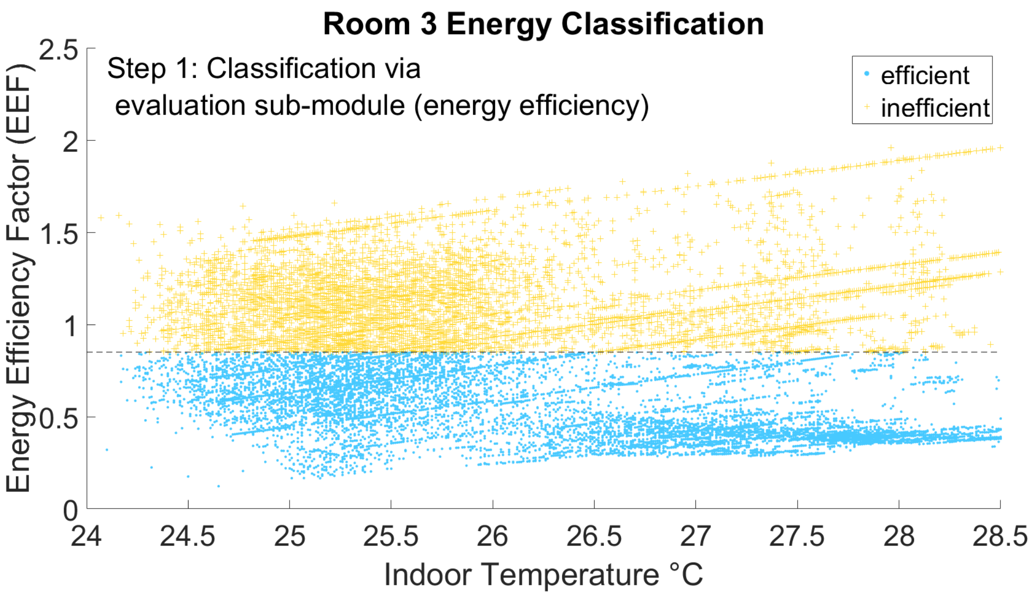

Figure 5. Classification of energy-efficient and energy-inefficient behavior based on inference rules in the evaluation sub-module for Room-3.

In Figures 6–8, we further classify the energy inefficient behavior into normal and abnormal categories for Room-1, Room-2, and Room-3. For this classification, based on the local climatic conditions and the number of occupants in the room, we set the value of T_i in various inference rules as 27 °C. For Room-1, 97.08% energy inefficient points are also classified as abnormal. For Room-2, 39.63% energy inefficient points are classified as abnormal. For Room 3, we also observe that only 26.63% energy inefficient points can be termed as abnormal. In terms of overall data, 2.79% of energy inefficient points are abnormal in Room-1, 8.22% of energy inefficient points are abnormal in Room-2, and 9.98% of energy inefficient points are abnormal in Room-3. It should be noted that classical BEMS apply control actions at all the energy-inefficient data points. This indiscriminate strategy can result in user inconvenience as well as erosion of trust and confidence in BEMS technologies. On the other hand, our proposed approach intelligently applies control action only when the context is classified as abnormal, while at all the normal energy-inefficient points, no control action is taken.

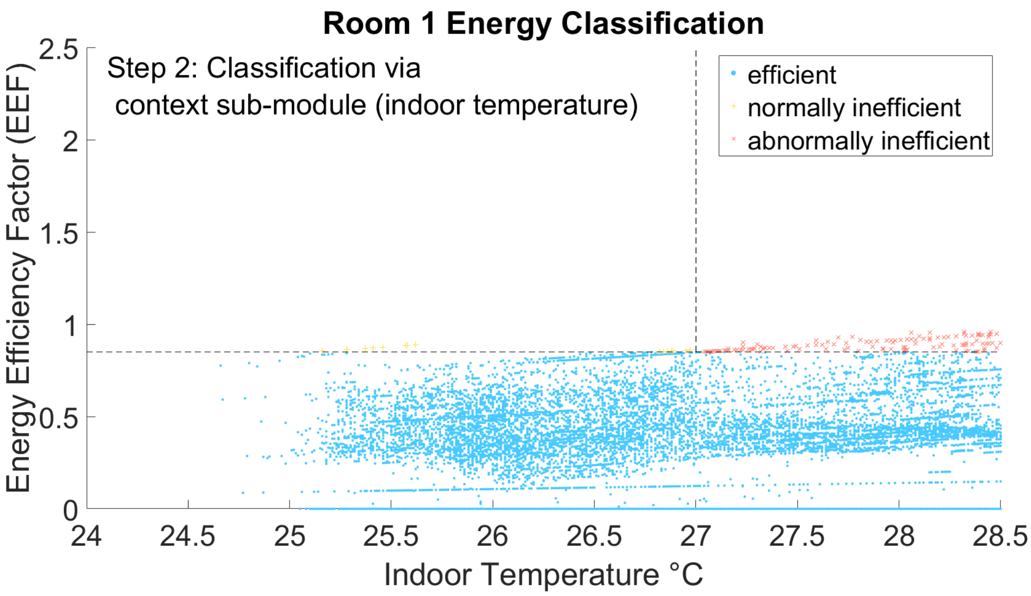

Figure 6. Classification of normal and abnormal behavior based on inference rules in the context sub-module for Room-1.

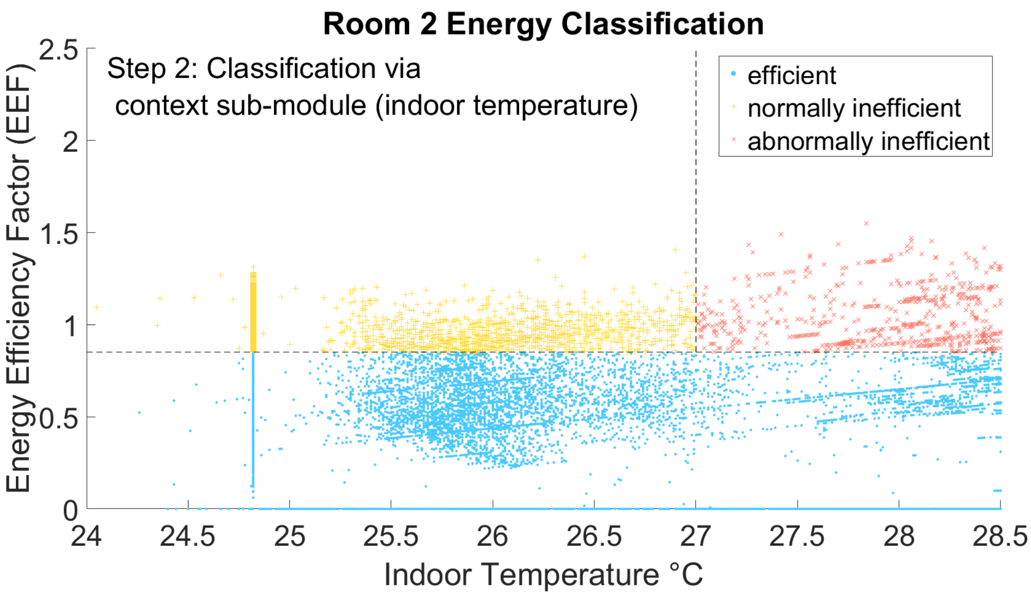

Figure 7. Classification of normal and abnormal behavior based on inference rules in the context sub-module for Room-2.

For all the abnormal points, we further have to determine the cause and then implement appropriate control action. In our experiments, we do not have the embedded actuators and limited sensors, which restrict our ability to determine the cause and control actions. However, we assume that the abnormal scenarios are primarily due to the opening of the room windows. To restore normal, energy-efficient behavior, control action would simply consists of closing the window. With this assumption, we now provide an estimate of energy savings due to our proposed energy optimization framework. To highlight the advantages of our framework, we also make a comparison with HVAC energy management scheme proposed in [10]. In [10], authors use traditional energy management scheme to reduce HVAC energy consumption, while maintaining the thermal set point temperature and user thermal comfort within some threshold limits. Control actions in the reference paper are only based on the environmental sensor data without any contextualization and proper determination of cause. For comparison, we generate the results for the scheme developed in [10] on the data used in this study. The results are summarized in Table 1. In this table, total energy consumption, energy consumption at inefficient data points (normal & abnormal), energy consumption at abnormal data points, and percentage energy savings by our scheme and the reference scheme are provided. The power consumption of each data point (kW) is converted into average energy consumption (kWh) by multiplying it with data sampling interval, which is equal to $\frac{5}{60}$ h. In Room-1, average energy consumption at abnormal data points in 5 min intervals is 0.0364 kWh and there are 499 such instances. In Room-2, average energy consumption at abnormal data points in 5-min interval is 0.0414 kWh and there are 1469 such instances. In Room-3, average energy consumption at abnormal data points in 5-min interval is 0.0452 kWh and there are 1783 such instances. Normal average energy consumption of each room in 5 min intervals is at 0.0114 kWh, 0.0137 kWh, and 0.0201 kWh, respectively.

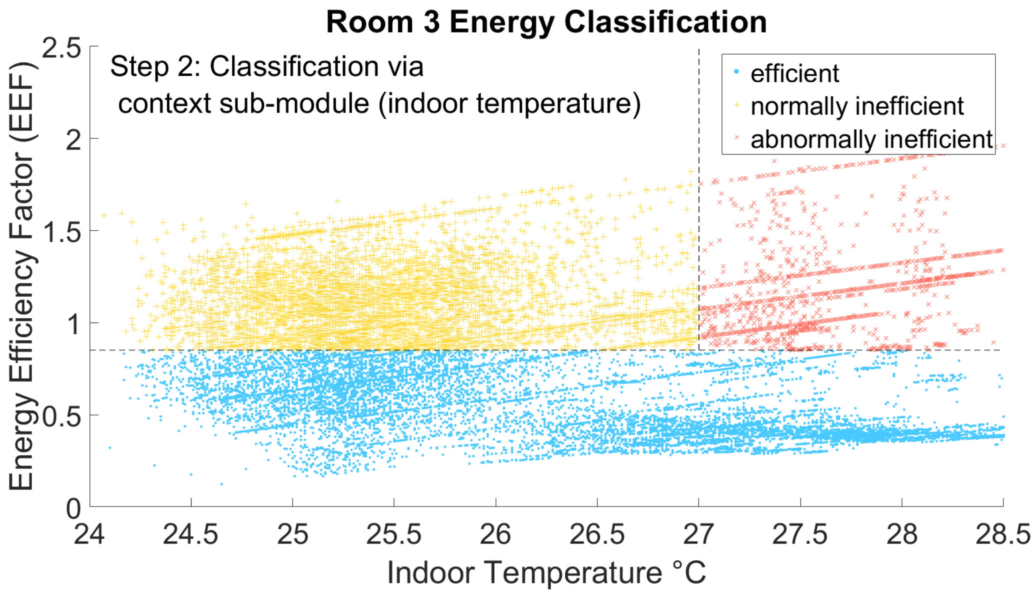

Figure 8. Classification of normal and abnormal behavior based on inference rules in the context sub-module for Room-3.

Total energy savings provided by our framework is the energy saved by converting abnormal energy consumption points to normal energy consumption points. The difference between average energy consumption at abnormal data point and average energy consumption at normal data point is multiplied by the total number of abnormal data points to arrive at the total energy savings in each room. With this method, the percentage energy savings by our framework is 5.7%, 11.8% and 8.7% respectively in Room-1, Room-2, and Room-3. On the other hand, percentage energy savings provided by the reference scheme are 4.3%, 5.6%, and 4.1% respectively for Room-1, Room-2, and Room-3. The reference scheme tends to take sub-optimal decisions at several data points that are classified by our framework as inefficient but normal. At these data points, in order to maintain thermal comfort, room temperature is further lowered, which results in increased energy consumption and, hence, increased energy wastage. On the other hand, our scheme only takes corrective actions when the cause of inefficiency is determined to be abnormal. It is also important to note that our proposed framework achieves these savings while also creating minimum inconvenience to users.

Table 1. Energy Saving Comparison of our proposed framework with a reference scheme proposed in [10].

Room	Total Energy Consumption (kWh)	Average Energy Consumption at different data points (kWh)		Total number of abnormal data points	Estimated %age Energy Savings of Our Framework	Estimated %age Energy savings of Reference framework
		Abnormal	Efficient			
Room-1	216.6	0.03643	0.01140	499	5.7%	4.3%
Room-2	342.4	0.04143	0.01375	1469	11.8%	5.6%
Room-3	513.1	0.04526	0.02013	1783	8.7%	4.1%

5. Conclusions

In this paper, we proposed a framework for energy optimization in buildings, which is based on appropriate ontology and inference rules. For the development of our framework, we divided the functionality of BEMS into BMS, BMK, and ENC modules. The data from the BMS and BMK modules are compared and evaluated. Appropriate inference rules are developed for various ENC sub-modules. These rules help in the evaluation and contextualization of information, and classification of energy consumption into efficient and inefficient categories. Inefficient consumption is further classified into normal and abnormal categories. For abnormal energy consumption, cause is determined and control actions are communicated to the BAS module. We demonstrated the implementation of proposed framework and its advantages with the help of a numerical case study and some experimental data from a commercial building in Singapore. Compared to traditional energy management schemes our proposed framework provided significantly better results. By mitigating the appropriate cause of abnormal inefficiency, we also achieved 5.7%, 11.8% and 8.7% energy savings in Room 1, Room 2, and Room 3, respectively, while creating minimum inconvenience for the users.

The developed framework is flexible and in future could be enhanced by adding more inference rules for various building systems and sub-systems. The framework could also be enhanced by developing a benchmarking module that can combine standard-based, P2P-based and modeling-based approaches for better prediction and thresholds for comparison. These directions would probably be explored in the future.

Author Contributions: Initial conceptualization was done by C.L., V.C., C.Y., W.T., N.U.H., X.W., and X.L. Methodology and core part of the framework were developed and refined by C.L., Y.C., N.U.H., X.W., and X.L. Manuscript was largely written by C.L., W.T. and N.U.H. Figures were prepared by C.L., V.C. and B.K.K.N. Simulation results were carried out by C.L. and V.C. Sensors for experimental data collection were deployed by B.K.K.N. Final paper review, editing and figure correction was performed by Y.C., X.W. and X.L.

Funding: This work was supported in part by the National Research Foundation (NRF) Singapore and administered by Building and Construction Authority (BCA) – Green Building Innovation Cluster (GBIC) Programme Office, and in part by the SUTD-MIT International Design Centre (IDC; idc.sutd.edu.sg), NSFC 61750110529, and in part by Higher Eduction Commission (HEC), Pakistan, through grant number NRPU P#5913. Any findings, conclusions, or opinions expressed in this document are those of the authors and do not necessarily reflect the views of the sponsors.

Conflicts of Interest: The authors declare no conflict of interest.

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