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An Automatic Detection of Anomalous Energy Consumption by Leveraging BEMS Big Data Analytics

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Abstract

Over the past few decades, there is an increased global concern about energy saving to prepare for depletion of fossil fuels and to cope with global warming and climate change. Concerns over energy and environmental issues around the world have led to the worldwide focus on energy use reduction. Recent field studies have shown that commercial and residential building sectors consume more energy than other sectors such as transportation, industry, agriculture or service sectors. Moreover, it is predicted that the total energy consumption in the building sectors will be continuously increased in future in both developed and developing countries. A recent case study of energy consumption in building sectors, which occupy the largest portion of total energy consumption, has reported that energy savings of 10 to 30% can be achieved by detecting and analyzing anomalies in energy usage patterns in real time. Thus, recently there is a growing attention to apply fault detection and diagnosis (FDD) technologies to the domain of building energy consumption, with the aim of detecting abnormality of building energy consumption pattern. However, although substantial research works have been done on automatic fault detection on building energy usage, there has been little attempt to investigate this issue by analyzing high volumes of data collections produced by Building Energy Management System (BEMS). Thus, in this paper, we propose a middleware platform for automatically detecting abnormal energy consumption by leveraging BEMS big data analytics. Experimental results show that with the proposed approach, it is possible to accurately detect anomalous patterns in building energy consumption.

Keywords: Fault detection, BEMS, Big Data Analytics

INTRODUCTION

Recently, as energy issues become a global issue, there is a growing interest in the Building Energy Management System (BEMS) [9] which efficiently manages and controls the energy used in commercial and residential buildings. BEMS is an optimal control system that can rationally manage building energy use to create a pleasant indoor environment, while minimizing energy consumption. BEMS achieves energy efficiency by collecting and monitoring data from operation sensors (eg. temperature, humidity, and illumination), data collected through sensors attached to energy management facilities (eg, cooling / heating, water, gas) and life pattern data of residents.

In developed countries, commercial and residential building sectors are consuming more energy than other sectors, such as the transportation, industry, agriculture, or service sectors. For example, in the United States, energy consumption by buildings accounts for more than 40% of total national energy consumption. Moreover, it is predicted that the total energy consumption in the building sectors will be continuously increased in future, in both developed and developing countries.

Over the past few decades, global concerns over energy and environmental issues around the world have led to the worldwide focus on energy use reduction. Considering that the building sectors consume more primary energy than other sectors in most countries, it is important to reduce energy use from these regions. In the building sectors, it is well known that malfunctioning controls and operations of building equipment are a primary cause of energy leakage, which leads to inefficiencies in energy usage. A recent case study of energy consumption in a building has reported that it can achieve energy savings of 10 to 30% by detecting and analyzing anomalies in energy usage patterns in real time. In this regard, technologies for detecting and diagnosing anomalies in building energy use patterns (FDD: Fault Detection and Diagnosis) have recently attracted much attention. FDD is considered to be a technology capable of realizing optimal control of building energy by automatically analyzing data. However, although substantial research works have been done on automatic fault detection on building energy usage, there has been little attempt to investigate this issue by analyzing high volumes of data collections produced by BEMS. Therefore, in this paper, we propose the technique which aims to automatically detect abnormal energy consumption by leveraging BEMS big data analytics.

FADECT: A MIDDLEWARE PLATFORM FOR DETECTING ABNORMAL ENERGY CONSUMPTION

Figure 1 provides an overview of the proposed middleware platform, FADECT (Fault Detection of Building Energy Consumption), for detecting abnormal energy consumption by leveraging BEMS big data analytics. Note that the proposed FADECT is built on the top of BEMS. As shown in the figure, the proposed FADECT is mainly composed of (1) BEMS data modeling, (2) BEMS data storage, (3) fault detector. We now explain and describe each of these components in detail.

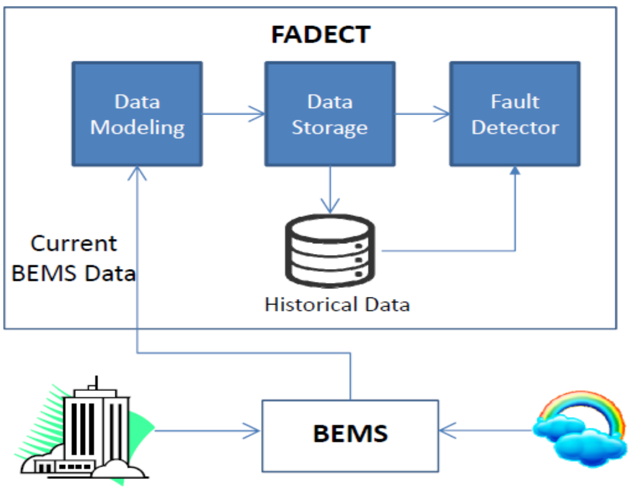

Figure 1. An overview of the proposed middleware platform, FADECT, for detecting abnormal energy consumption

A. BEMS Data Modeling

In general, BEMS collects large amounts of data, such as operational data (eg, temperature, electricity, lighting, ventilation, and air conditioning), energy usage pattern data, and weather data. These data sets have temporal characteristics of time series. Therefore, FADECT uses the temporal database model to effectively model the data set collected by BEMS (Figure 2).

We use the temporal database concept to model the BEMS data and define the Sensor Trace Matrix (STM) as follows. Suppose that S_1, S_2,..., S_w are sensor trace data related to the building energy usage data or building operational data collected from w different sensors. The sensor trace S_r collected from the r-th sensor can be represented as a m-dimensional vector $<d_{r,1}, d_{r,2}, d_{r,3},..., d_{r,m}>$. Here, $d_{r,i}$ $(0 \le i \le m)$ denotes the value observed through the r-th sensor in a particular time stamp i. Given w sensor traces S_1, S_2, ..., S_w, the Sensor Trace Matrix (STM) is defined as a $w \times m$ matrix, where the values of the r-th row and the i-th column of STM is as following

$$\text{STM[r][i]} = d_{r,i}$$

We note that due to the nature of the continuously collected BEMS data, it is not possible to store and manage the entire sensor tracking matrix as a whole. Thus, STM needs to be generated on a daily basis.

B. BEMS Data Storage

The proposed FADECT uses the NoSQL database, MongoDB, to store and manage the entire BEMS data. As you can see in Figure 3, the database used in FADECT consists of two collections: environmental data collection and energy usage data collection.

The environmental data collection stores data related to both the building environment (eg, weather data such as temperature, humidity, illumination, rainfall, snowfall, sunshine hours, etc.) and the building operations collected from building operation sensors (eg, temperature, humidity, and illumination). On the other hands, energy usage data is stored in the energy usage data collection. Note that both collections store data in the STM format defined in the previous subsection.

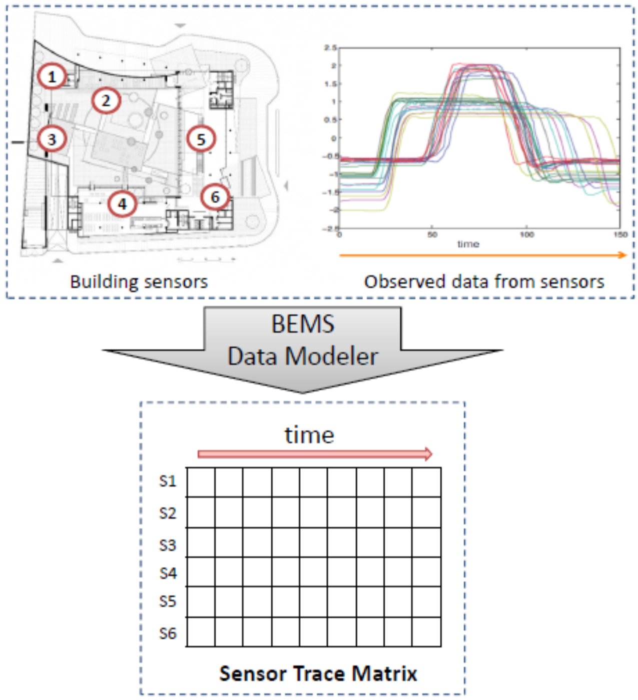

Figure 2. BEMS data, including the building energy usage data and building operational data, is modeled by using the concept of time series database.

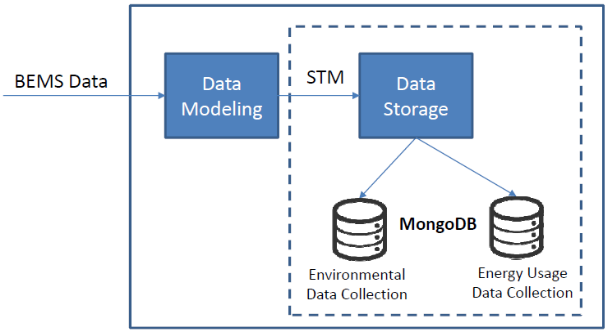

Figure 3. An overview of the BEMS Data Storage

C. Fault Detector

Figure 4 illustrates the fault detector which is the key component of the proposed FADECT. As shown in the figure, the proposed method takes two sets of input data, the current BEMS data and the past BEMS data, and calculates similarities between them to determine if there is an abnormality in the current building energy usage pattern. Therefore, the proposed error detector consists of two subtasks that (1) extract *k* historical data from the database and (2) calculate the similarity between the current BEMS data and the past BEMS.

Building systems behave very differently in different weather and operating modes. In order to effectively detect anomalous patterns in building energy consumption, it is necessary to compare observed energy consumption patterns under similar environmental and operational conditions. Therefore, the first sub-task of the proposed fault detection is to find energy usage data observed in past environments similar to the current environment.

- Given a current environment and operation data modeled in STM format, we first retrieve *k* STMs from the environmental data collection which are most similar with the current environment and operation data. Here, the similarity between two STMs are measured by using DTW (Dynamic Time Warping) [11,12,13]. DTW is a method of measuring the similarity between two time series data patterns through nonlinear pattern matching. Since DTW has the advantage that the similarity value measured is similar to human intuition more than the cosine method, it is utilized in various applications (for example, speech recognition). Thus, in this paper, we also compute the similarity between two STMs by using DTW, instead of the cosine measure.
- We, then, extract *k* energy usage data, STM_1, STM_2,…, STM_k, from the energy usage data collection which are associated to the *k* similar environmental data identified in the previous step.

The last step of the fault detection is to measure the similarity between the current energy usage data and the past energy usage data, STM_1, STM_2,…, STM_k, identified in the previous step. If the measured degree of similarity is greater than the threshold set by the BEMS system, it is assumed that the current energy usage pattern is abnormal. For this, it is necessary to effectively calculate the similarity between the energy usage data modeled in STM, and thus, in the same way as before, we use DTW measure. Given the current energy usage data, $STM_{current}$, and the *k* past energy usage data, STM_1, STM_2,…, STM_k, identified in the previous step, this can be formally written as follows:

$$\sum_{t=1}^{k} sim_{DTW}(STM_{current}, STM_t) > \theta .$$

Here, θ is the threshold set by the BEMS system, which can be learned from training data. In other words, we compute all pairwise similarity scores between $STM_{current}$ and STM_t (where $1\leq t\leq k$) by using DTW, average them and conclude that there is abnormality in current building energy usage pattern, if the averaged similarity score is greater than the predefined threshold

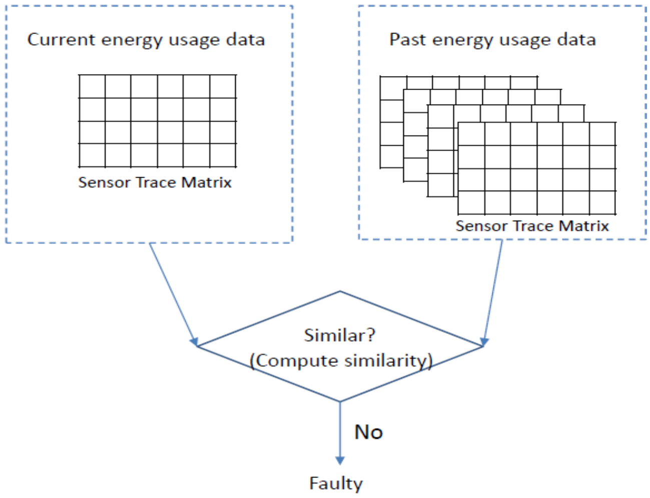

Figure 4. An overview of the fault detection phase

PRELIMINARY EXPERIMENT RESULTS

In this section, we describe the experiments we carried out to evaluate the effectiveness of the proposed approach. The data sets used in this section are generated by EnergyPlus [14] which is the most popular energy simulation tool.

For evaluation purpose, we create two different data sets: the past energy usage data set and the current energy usage data set. To collect the past energy usage data set, a single office building was simulated for one year on EnergyPlus. As explained earlier, the collected past energy usage data is modeled and stored in MongoDB. For the evaluation of the proposed method, we also generated the current energy usage data set (which corresponds to the testing data set) by simulating the same office building for 100 days on EnergyPlus. Furthermore, 50 out of 100 energy usage data were randomly extracted and added noise. Note that the reason we added noise to the energy usage data generated by the EnergyPlus is to create a set of test data that works as anomalous energy usage patterns.

Table 1 shows the false-positive and false-negative error rate in detecting anomalous patterns in building energy consumption. Here, the false positive error means that energy usage data that is not a fault is misclassified as an abnormal energy consumption. On the other hands, the false positive error means that energy usage data that is a fault is misclassified as a normal energy consumption. As can be seen in Table 1, with the proposed approach, we can achieve very low error rate. This verifies that the proposed approach is very effective in detecting anomalous patterns in building energy consumption.

Table 1. Error rate of the proposed approach

	False-Positive	False-Negative	Total
Error rate	0.08	0.06	0.07

CONCLUSION AND FUTURE WORK

With the growing concern about the energy crisis, the need for improving energy efficiency has become very important topic all over the world. Considering that the building sectors consume more primary energy than other sectors in both developed and developing countries, it is important to save energy consumption at these regions by detecting wasted energy. Thus, in this paper, we presented a middleware platform, FADECT, for automatically detecting abnormal energy consumption by leveraging BEMS big data analytics. Future work includes (1) testing the effectiveness of the proposed approach in diverse building environments, and (2) developing effective mechanisms that are able to diagnose the root cause of faults by exploiting big data analytics, when abnormal energy usage is detected.

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