Data-Driven Edge Computing

A Fabric for Intelligent Building Energy Management Systems

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Building energy management systems (BEMSs) have been successfully adopted as key control units for modern structures to maintain energy efficiency and provide a comfortable thermal environment for occupants. Recent advances in information and communication technology toward "Industry 4.0" are enhancing the utility of BEMSs. However, challenges, such as how to process the exponentially growing amount of heterogeneous data generated in buildings, need to be addressed to realize "Building 4.0," which encompasses next-generation smart systems that provide user-centric services. In this article, we propose BEMS–Edge, a framework that integrates seamless, real-time information acquisition, transmission, interpretation, and action in intelligent BEMSs. The primary components, including the Internet of Things (IoT), cloud/edge computing, big data analytics, and artificial intelligence (AI), converge to create a data-driven edge computing fabric offering a range of benefits, such as real-time data analytics and cost savings.

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The effectiveness of BEMS–Edge is verified by an established, real-world BEMS testbed.

The Role and Challenges of BEMSs

According to the International Energy Agency, buildings were responsible for 28% of global energy-related carbon dioxide emissions in 2018 [1]. Buildings' energy consumption will increase due to the necessity to construct more homes and offices to accommodate the rapid growth of the world population. BEMSs are needed in regions with harsh climates. Currently, buildings in such regions are generally equipped with fewer BEMSs, while it is forecast that these areas will experience the greatest population expansion. Hence, the expected growth rates for BEMSs are much higher than those of the global population. As a result, an efficient BEMS is in high demand to monitor and control a variety of building services, including heating, ventilation, and air conditioning (HVAC) and lighting, occupant activity detection, energy measurement, intrusion/fire alarms, and water supplies.

As an essential element of smart buildings, BEMSs are designed to reduce energy use while meeting requirements such as indoor comfort for occupants. Current BEMSs are computer-based, automated systems designed to support building management through services. Although BEMSs play an important role in managing those services, their operation and maintenance are costly and inefficient [2]. Moreover, they are mainly based on centralized and static control via central computers located at management stations. For example, various classical control techniques, such as on/off control, are used, in which the process is regulated based on a given upper/lower threshold [3]. Accordingly, tuning parameters is rather cumbersome for on/off control, especially for services, such as HVAC, that are designed to cope with time-varying environmental conditions. Due to a lack of detailed data for building states, current BEMSs fail to offer real-time data processing [4].

Challenges, such as how to process the exponentially growing amount of heterogeneous data generated in buildings, need to be addressed to realize "Building 4.0."

Realizing Intelligent BEMSs Toward Building 4.0

Advanced information and communication technologies have been deployed in various industrial fields [5]. They can also be exploited toward Building 4.0. By improving hardware and operations, along with user interaction, Building 4.0 will create an innovative ecosystem and transform the entire industry. This innovation will ultimately enhance all aspects of essential building phases, including system operation and maintenance, as well as user experiences.

Efforts toward realizing Building 4.0 support the development of emerging technologies, including the IoT and cloud computing. To enhance data analytics for BEMSs, the literature discusses the advantage of introducing a cloud-based computing paradigm. This arrangement transfers collected sensor data to the cloud, where machine learning is harnessed to generalize overall system behavior [2], [6]. In terms of implementation, an IoT-enabled smart building system is developed, and its stability and robustness are confirmed [7]. A real-time digital model of an office building is created by analyzing building information modeling (BIM) and data collected from an IoT-enabled sensor network [8]. It is verified that the cloud-based computing paradigm can achieve energy savings up to 20% on HVAC installed in an experimental building [9]. Despite the fact that cloud computing offers exceptional big data processing capability, with increasing quantities of heterogeneous building data, it is challenging for the paradigm to achieve real-time results, especially considering issues such as communication overhead and network congestion [10].

Motivation

As a distributed computing paradigm that brings data computing, storage, and network functions closer to end users, edge computing has been a feasible solution in various fields, including 5G networks and smart manufacturing [11]. Its development is motivated by the following two essential goals:

- a framework empowered by edge-based computing that is realized on top of existing BEMSs
- a data processing scheme that utilizes collaborative edges located near user sites for information sharing to reduce the amount of data transmitted to the cloud while improving data analytics.

The primary aim of this article is to explore new research opportunities in utilizing edge computing in BEMSs. BEMS–Edge is proposed to provide a data-driven edge computing fabric: in-network computing edges that provide an intermediate function, including the network proxy and data processing, between the cloud and massive sensors. The main contributions of this article include the following:

- A framework that performs comprehensive data processing, from information acquisition to decision making, is proposed. Edge intelligence that utilizes AI is introduced to enhance the data-driven analytics.
- Hybrid edge–cloud analytics paradigms for BEMS–Edge are studied. These paradigms assign distinct roles to the edges and cloud to achieve data-driven processing that meets BEMS service requirements.
- Verification based on a real-world BEMS testbed demonstrates that BEMS–Edge can achieve satisfactory data analytics in real time.

Overview of BEMS–Edge

As a fundamental framework for realizing Building 4.0, BEMS-Edge provides

An efficient BEMS is in high demand to monitor and control a variety of building services, including heating, ventilation, and air conditioning and lighting.

an edge computing fabric for intelligent BEMSs to perform comprehensive information processing, which is realized on top of a combination of software and data communication/processing hardware.

Vision

Figure 1 illustrates the vision for BEMS-Edge. The system improves traditional BEMSs to achieve seamless, real-time information acquisition, transmission, interpretation, and action. The basic data flow is as follows:

1) Sensors in every room collect data reflecting building conditions, such as temperatures and luminous intensities.
2) The edge aggregates sensor data and forwards processed information to the cloud for further analytics and storage. It acts as a gateway that supports communication among sensing devices through various protocols and that can also be used for data filtering and analytics. By harnessing edge intelligence [11], building tasks can be partially or entirely processed in the form of in-network computing via collaborative edges that manage local, real-time data. Meanwhile, employing other available edges and communication gateways can resolve issues when designated edges are temporarily unavailable due to unexpected incidents.
3) The cloud receives information from the edges and analyzes the collected data, if necessary. Based on the results, it relays actionable information to BEMS administrators, which consist of integrated machines, programs, and human operators. Accurate data analytics can support BEMSs to achieve automatic control over building equipment, while human operators carry out regular reviews of system settings to gradually reduce room set points, operating times, and energy consumption [12].

Key Components

Ubiquitous Energy-Efficient Sensing

Ubiquitous sensors that support wireless communication have attracted increasing attention because of their ability to solve issues related to traditional hard-wired meters, which fail to provide sufficient building data to BEMSs. However, simultaneously operating a large number of sensors placed throughout buildings increases BEMS energy consumption, especially when transmitting data [13]. To resolve this, BEMS–Edge conducts sensing in an energy-efficient manner by applying lightweight messaging protocols, such as constrained application protocol or message queuing telemetry transport.

Meanwhile, using sleep mode for certain sensors is a direct approach to reduce the energy consumed during

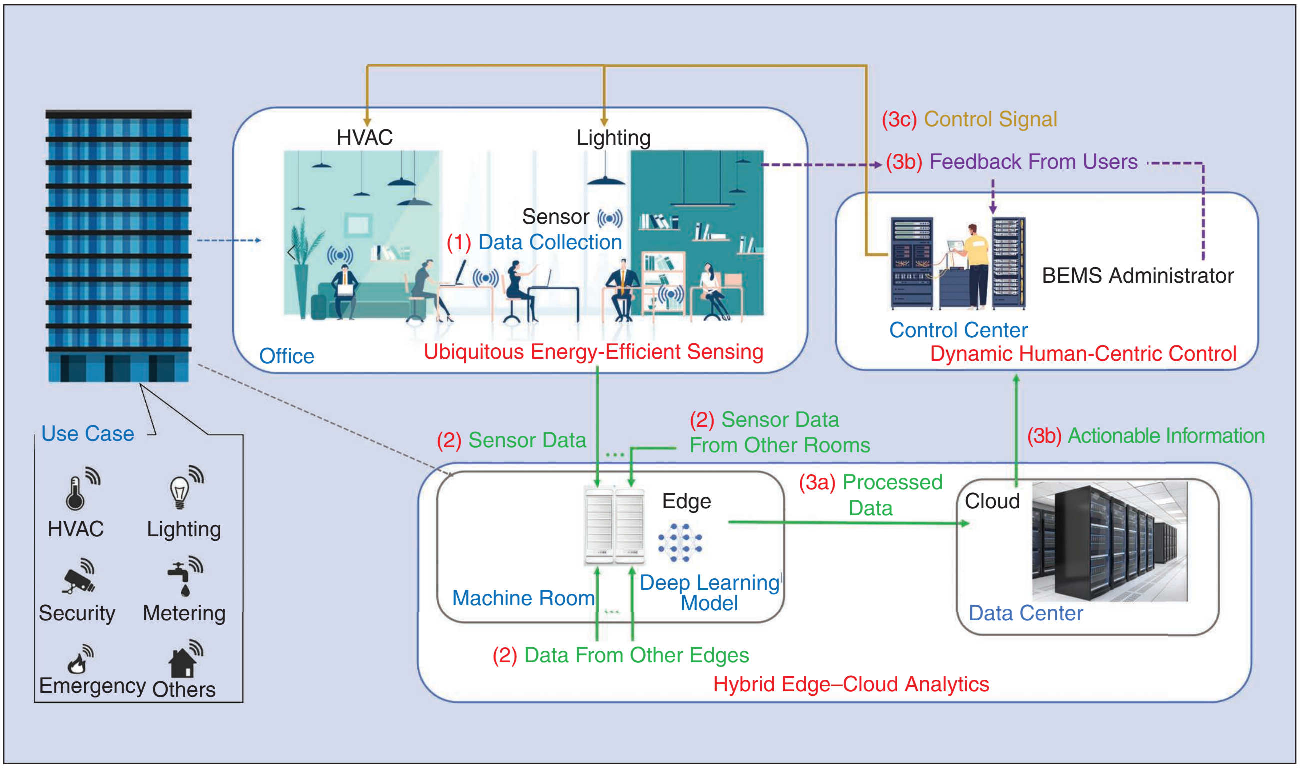

FIGURE 1 – The BEMS–Edge architecture to enable real-time IoT data analytics.

long-term monitoring. However, with this approach, data analytics might degrade due to a lack of valid sensor information. Our solution is to utilize an edge fabric to learn time series correlations within available data and extrapolate missing information from the sensors in sleep mode [14]. In this scheme, a deep autoencoder built on a long short-term memory (LSTM)-based, sequence-to-sequence structure is applied as the core of the data analytics at the edge fabric. LSTM is empowered by different cell states and gates capable of capturing underlying correlations among time series sensor data. The obtained complementary information can be processed at the same edge for a given BEMS application, e.g., hotspot detection. The output of each edge is aggregated to the cloud to infer an overall building status.

Hybrid Edge–Cloud Analytics

The proliferation of the IoT has created concerns about how to process big data, especially for BEMSs that generate massive amounts of redundant sensor information. As indicated previously, delays caused by transferring these data to the cloud and waiting for control feedback are a critical concern for establishing intelligent BEMSs. It is important to integrate the advantages of cloud and edge computing to provide satisfactory data analytics with minimum response times. Emerging edge intelligence leveraging AI can enhance analytics by executing deep learning training and inference phases at edges in the vicinity of end users. As an analytical tool, deep learning involves the generation of a model by learning correlations and dependences among data. The model is used to forecast intended knowledge by analyzing sensor data. To cope with changes in sensing environments, it is necessary to update the model by analyzing the most recent information stored at an edge through a given period.

Dynamic User-Centric Control

Meeting requirements for user-centric control is crucial for BEMSs. In this article, the term *control* refers to decision-based actions. For instance, based on the results of real-time data analytics, electric loads can be dynamically controlled according to system usage patterns and building environment statuses. In addition to models based on BIM and information from sensors, BEMS control can be supplemented with a human-in-the-loop (HITL) approach, which integrates human factors into the data interpretation and action process [15]. The HITL method captures the knowledge of the users themselves to support an intelligent dynamic control scheme. Users can be BEMS experts, local administrators, and even occupants, who are vital participants in BEMSs. A typical HITL application is user trajectory prediction. This can control building equipment based on an area's status. In cooperation with hotspot detection, BEMSs adjust the air conditioning in crowded areas where low-thermal-comfort statuses are registered.

By improving hardware and operations, along with user interaction, Building 4.0 will create an innovative ecosystem and transform the entire industry.

Capabilities of BEMS–Edge

BEMS–Edge is expected to provide various enhanced capabilities to tackle potential challenges of implementing Building 4.0. Figure 2 summarizes the key benefits of BEMS–Edge compared with the capabilities of two similar BEMS schemes.

- *Current BEMSs*: These are connected to a central computer terminal, where the status of building systems is statically controlled based on rules defined in advance.
- *BEMS–Cloud*: Sensors are deployed for building status monitoring, while collected sensor data are forwarded to the cloud for analytics. Based on the results, administrators control services [2], [6].

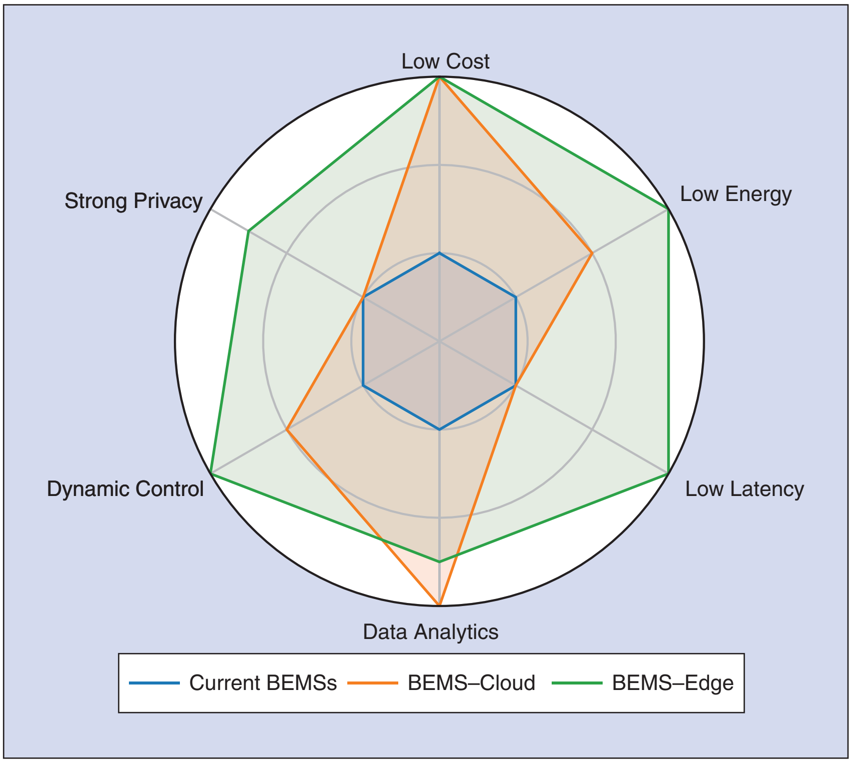

FIGURE 2 – A comparison of different BEMS capabilities.

By harnessing edge intelligence, building tasks can be partially or entirely processed in the form of in-network computing via collaborative edges that manage local, real-time data.

Cost

For BEMS–Cloud and BEMS–Edge, integrating IoT technologies reduces system installation and operation costs. Moreover, from the perspective of system diagnostics, by analyzing regularly collected sensor data, maintenance costs are lower than those of current BEMSs, which require periodic inspections due to sensing and control limitations [6].

Latency

Current BEMSs and BEMS–Cloud need to send collected sensor data to a central computer terminal or the cloud and wait for control information from administrators. On the other hand, for BEMS–Edge, since data analytics can be performed at edges near buildings, the latency can be significantly reduced.

Data Analytics

Although BIM models are constantly being developed and upgraded, current BEMSs fail to provide satisfactory data analytics due to a lack of real-time building information [4]. BEMS–Cloud guarantees satisfactory analytics with the help of the cloud. The aggregation of data from different edge participants in the cloud enables the adoption of more complex deep learning models, leading to superior analytics. In contrast, BEMS–Edge encounters so-called data isolation if analytics are independently performed at each edge participant. Nevertheless, it has been shown that a collaborative edge can produce analytics comparable to those achieved by centralized cloud servers, while local data privacy is preserved to some extent [16].

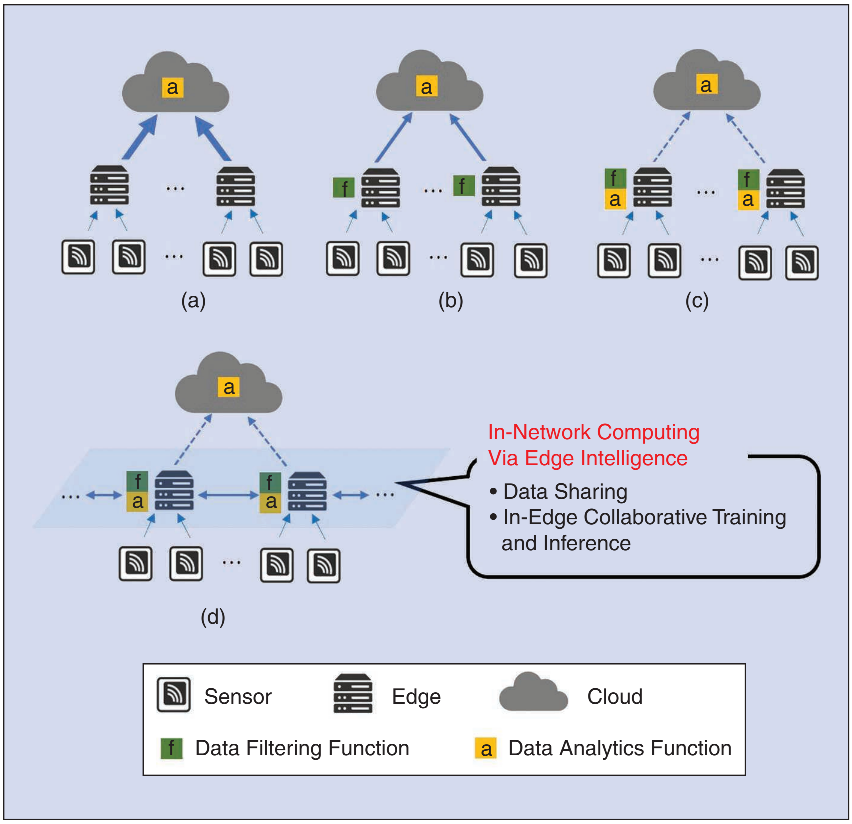

FIGURE 3 – Hybrid edge–cloud analytics paradigms for BEMS–Edge. (a) Analytics in the cloud. (b) Filtering at the edge. (c) Analytics at the edge. (d) Analytics at collaborative edges.

Dynamic Control

Current BEMSs are not designed specifically for dynamic and diverse building management. BEMS–Cloud changes this by utilizing real-time sensor data; however, latency is a critical issue for services requiring prompt control. By conducting real-time analytics at edges, BEMS–Edge offers user-centric control with adaptability to occupant behavior and changes to building layouts.

Energy Consumption

BEMS–Edge, powered by AI, can achieve accurate and dynamic control over building equipment to reduce energy use. It can further lower networking equipment energy consumption by transmitting aggregated data to the cloud.

Privacy

Although BEMS–Cloud uses the cloud to analyze sensor data to achieve acceptable analytics, it also increases risks associated with data leaks. BEMS–Edge eases this concern by processing private information via edges located in or near buildings as much as possible.

Paradigms of Hybrid Edge–Cloud Analytics for BEMS–Edge

Figure 3 illustrates four hybrid edge–cloud analytics paradigms expected to be used in Building 4.0. Here, event-driven BEMSs are designed to detect incidents from collected sensor data and react to them based on user requirements.

Paradigm 1: Analytics in the Cloud

For BEMS services designed for security and safety, providing accurate information about emergencies is the priority. Taking fires and evacuations as an example, BEMSs are required to produce valid information about where the flames are, the status of egress routes, additional hazards, and so on [17]. Analytics in the cloud are a solution for obtaining reliable information by conducting aggregated analytics. To support this, sensor data are forwarded to the cloud via edges for communication among devices with different protocols.

The proliferation of the IoT has created concerns about how to process big data, especially for BEMSs that generate massive amounts of redundant sensor information.

Paradigm 2: Filtering at the Edges, Followed by Analytics in the Cloud

If all BEMS services are implemented through analytics in the cloud, IoT network energy costs and delays will be critical due to the data volume that must be transferred. Filtering at the edges moderates this issue because it does not directly upload all the information to the cloud. The filtering can be a simple removal of erroneous sensor data or an advanced process that creates clusters based on collected information that are sent to the cloud for outlier detection [18]. Since the edges fuse sensor data to some extent, the data volume transmitted to the cloud can be reduced. This paradigm is designed for BEMS services that require cloud services, such as smart metering, in which the cloud is used to coordinate distribution grid operations [19].

Paradigm 3: Analytics at the Edges

To reduce the information volume sent to the cloud, in this paradigm, all relevant sensor data are analyzed at the edges, with a data analytics function. Contrary to filtering at the edge, in which preprocessed results must be sent to the cloud for further analysis, analytics at the edge send only actionable information, such as the ID of a sensor that detects an anomaly, to the cloud as a notification to the administrators. Thus, latency can be significantly reduced. Analytics at the edge can be applied for services that require prompt responses. Taking HVAC control as an example, an air conditioner may take 10 min to cool a room that is too warm. Hence, it is vital to rapidly and accurately identify hotspots to maintain a comfortable environment [20]. Compared with emergency BEMS cases, raw building data do not have to be sent to the administrators via the cloud in real time. Instead, it is reasonable to execute data processing at the edges to reduce transmission congestion while achieving acceptable analytics.

Paradigm 4: Analytics at Collaborative Edges

As a complement to cloud computing, analytics at collaborative edges obtain data from neighboring edges to mitigate data isolation. Edge collaboration can incorporate in-network computing to achieve superb analytics while reducing the amount of private information that is exchanged. In summary, in-network computing breaks down into the following key elements:

- *Data sharing*: Collaboration enables authorized data sharing from edges located in different building areas and even from management systems that control various equipment. Shared data can be used for processing by deep learning models installed at the edges.
- *In-edge collaborative training and inference*: To enhance data analytics, collaboration calls for edge participants to optimize the training parameters of a machine/deep learning model. Additionally, this enables dynamic selection of the parameter/coordinator server to facilitate the training process, in which cloud involvement is no longer mandatory.

Real-World Testbed for Evaluation

Setup

A testing environment is established inside an office building in Osaka, Japan. Sensor placement information is provided in Figure 4, where 34 instruments (T&D RTR-500 series) are deployed to collect temperature data within an area of 1,800 m^2. Data for two months are collected at an interval

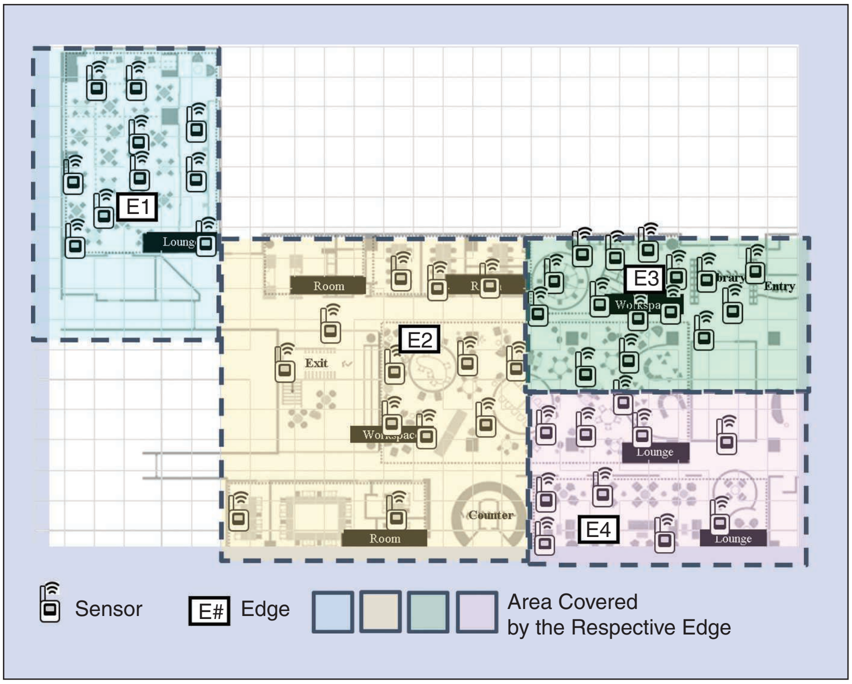

FIGURE 4 – The sensor deployment environment.

A collaborative edge can produce analytics comparable to those achieved by centralized cloud servers, while local data privacy is preserved to some extent.

of 30 min. Note that selection of the interval depends on how a building is used. Four edges are employed to process information obtained from an equal number of areas. In particular, the testbed focuses on 1) hotspot detection and 2) user trajectory prediction, as illustrated in Figure 5. Hotspot detection, which is a key component for HVAC control, determines whether the sensors detect the hotspot areas by analyzing data from nearby devices. For each time stamp, the status of all the sensors is assessed to score the hotspot detection accuracy. Based on the result, a BEMS administrator can specify an abnormal area and control the air conditioners there.

For user trajectory prediction, Bluetooth Low Energy (BLE) beacon sensors (Sanwa MM-BLEBC1) act as reference devices that send wireless signals to points (see Figure 5) users might walk through every 0.5 s. Due to the inapplicability of GPS in indoor environments, we use BLE as the source of the wireless signals to analyze the received signal strength indicator (RSSI) for trajectory prediction: when a user walks between two points, his or her mobile phone receives RSSI signals from the beacon sensors, and it sends collected RSSI data to surrounding edge nodes to predict his or her trajectory.

Hotspot Detection

Figure 6 graphs the performance of different hybrid edge–cloud analytics paradigms. Regarding the transmitted data volume, analytics in the cloud need to send all information to the cloud for aggregated processing, while filtering at the edge reduces the amount by sorting information in advance. The accuracy of detecting anomalies in sensor data depends on the use of the edge and cloud for processing, and hence, analytics in the cloud achieve the best performance because they are centralized. Two hybrid edge–cloud paradigms, deep reinforcement learning (Edge-DRL) [10] and plug-and-play learning (PPL) [21], are introduced for comparison. For Edge-DRL, model training and data analytics decision making are executed at the edges. Due to the limited local data pool at each edge for model training, the prediction accuracy obtained by Edge-DRL is limited. To resolve this, PPL and analytics at the edge offload model training to the cloud. Analytics at the edge excel at prediction accuracy due to the adoption of deep learning techniques, from which correlations among the massive amounts of data collected from multiple sensors in different areas are learned, while PPL uses other traditional algorithms suitable for training small data sets.

However, analytics at the edge fail to detect some hotspots due to the limited information resources available at an independent edge, at which data are collected from sensors in specific areas. Analytics at collaborative edges obtain data from neighboring edges to resolve this limitation. It is worth noting that the analytics time for these two paradigms, which are tested on a Raspberry Pi 2 Model B, is shorter than 1×10^{-3} s, which is acceptable for real-time BEMS hotspot

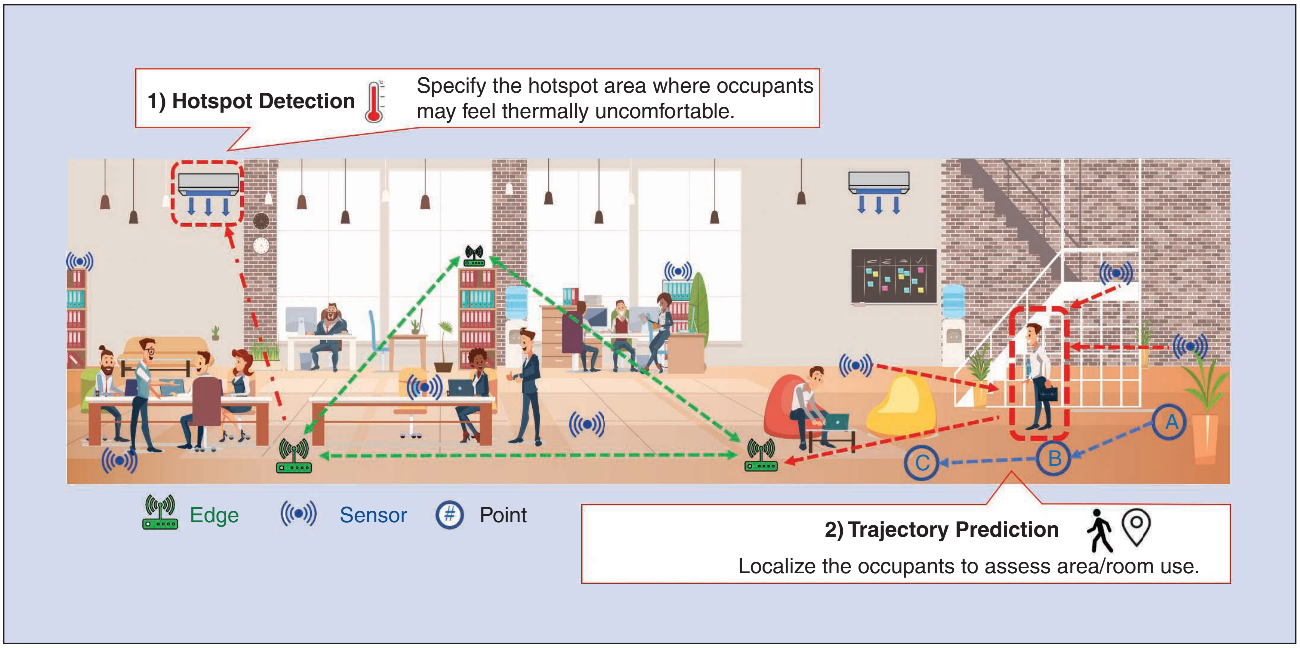

FIGURE 5 – The example BEMS use cases.

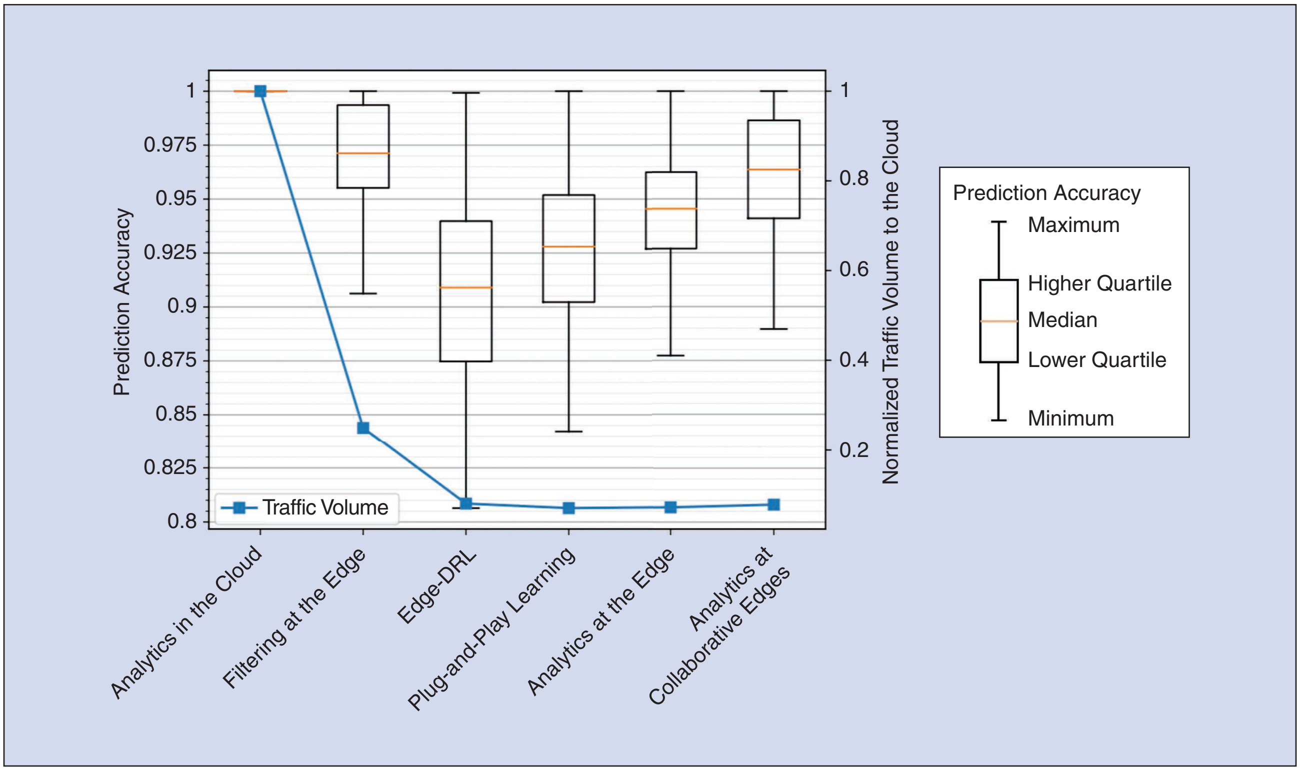

FIGURE 6 – The performance of hybrid edge–cloud analytics paradigms for BEMS–Edge.

detection. The communication expense is also simulated for each paradigm in terms of the Amazon Web Services IoT Core data publishing cost, based on the May 2021 rate in the Tokyo region. For our established testbed, the monthly cost of analytics at collaborative edges is US$1.40, compared to US$18.40 for analytics in the cloud. For the Tokyo Station locale (with a total floor area of 700 ha), a large business district with multiple commercial buildings with BEMSs, the estimated monthly cost of analytics at collaborative edges is US$420, while analytics in the cloud cost US$5,460.

Trajectory Prediction

This evaluation focuses on the use of analytics in the cloud and analytics at collaborative edges since these paradigms are expected to achieve satisfactory data analysis for life-saving services, such as emergency evacuations. To explore the underlying correlation among RSSI signals, analytics in the cloud data processing is based on a cloud-based computation, while analytics at collaborative edges utilize in-network computing edges to train a deep learning model with sensor data. Our results demonstrate that analytics at collaborative edges attain competitive performance against analytics in the cloud in terms of user trajectory accuracy; i.e., in general, they achieve real-time (the calculation time is shorter than 1×10^{-3} s), four-point trajectory prediction with an accuracy of more than 80%. It is worth noting that they provide data analytics in the proximity of BEMS users without sharing private information to the cloud. Furthermore, by introducing data obfuscation based on ε-differential privacy [22], users' locations can remain private.

Conclusion

In this article, BEMS–Edge, with a data-driven edge fabric facilitating intelligent BEMSs, was proposed for Building 4.0. By incorporating the IoT, cloud/edge computing, and AI, the system enhances BEMSs in terms of costs, latency, and data analytics. Four hybrid edge–cloud analytics paradigms were studied to meet the requirements of event-driven BEMS services. A BEMS testbed was established in a commercial building to evaluate the effectiveness of BEMS–Edge in two use cases. The results demonstrate that BEMS–Edge can achieve satisfactory data analytics for hotspot detection and trajectory prediction. A future research direction is to upgrade BEMS–Edge to support dynamic data processing, e.g., analyzing information provided by occupants' mobile devices.

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