

ENHANCING CONSTRUCTION SAFETY MANAGEMENT THROUGH EDGE COMPUTING: FRAMEWORK AND SCENARIOS

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Ke Chen, Dr.,
Huazhong University of Science and Technology;
chenkecm@hust.edu.cn

SUMMARY: *With the increasing complexity of construction activities, timely data collection and analysis become the prerequisites for supporting safety management decisions. However, conventional methods generally use centralized computing platforms, which might encounter challenges such as high latency and resource consumption. The recent development in edge computing brings new opportunities to address these challenges by offloading parts of the computing tasks from the center to the edge. This study thus attempts to develop a comprehensive edge computing framework to enable real-time construction safety management (CSM). Existing architectural frameworks of edge computing are reviewed, based on which an edge computing framework suitable for CSM is proposed. Then, the deployment of the proposed framework is elaborated through three safety management scenarios derived from actual construction projects. This study suggests that edge computing can improve the efficiency and quality of CSM. This study will also inform future studies on exploring the applications of edge computing in other construction management areas.*

KEYWORDS: *Edge computing, cloud computing, construction safety management, framework.*

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1. INTRODUCTION

Safety has long been a perplexing issue in construction. On the one hand, safety in construction is the result of complex and dynamic interactions between a large number of entities (e.g., workers, machines) and procedures, all of which make up a volatile site environment (Park and Kim, 2013; Li et al. 2015). Maintaining safety is more than just ensuring the proper and safe function of each of these elements in a construction project. The complicated and manifold interactivities between them also greatly influence, or even determine, construction safety. Thus, it is imperative to perform construction safety management (CSM) in a top-down manner that involves the systematic control of workers, machines, the environment, etc. (Lingard and Rowlinson, 1997; Zou and Sunindijo, 2015).

On the other hand, parallel to top-down control, it is equally important to undertake a bottom-up route in CSM to make immediate safety management decisions. The reason here is rather obvious. Since construction projects have unique characteristics such as decentralization, fragmentation, and temporality, workers have to work in separate spots and might not have standardized behaviors. As a result, hazards on construction sites are scattered, novel, variable, and real-time (Li et al., 2015). When they run into danger, workers are on their own in making decisions about how to react. From this perspective, the key to successful CSM is to identify hazards and provide this information to workers so that they can create as long a time buffer as possible before an accident actually occurs (Abdelhamid and Everett, 2000; Ding et al., 2018). Without sufficient and quality information, all workers can do to deal with danger is to react based on their knowledge and experience, which will very likely lead to loss of control or jeopardize the systematic control in CSM. Thus, the other important side of CSM is to deliver the right information at the right time to the right person so that safety management decisions can be made locally and immediately without any delay (Zhang et al., 2017).

In agreement with the above reasoning, many researchers have dedicated themselves to deploying approaches to providing real-time information for CSM (Li et al., 2015; Ding et al., 2018; Niu et al., 2019). Many CSM systems have been developed by exploring combined applications of different information technologies (ITs), including Auto-ID, sensors, and augmented reality (VR), just to name a few (Zhou et al., 2015). Various degrees of usefulness of these IT-based CSM systems have also been proved through lab experiments or case projects.

An important problem follows, however: existing IT-based CSM systems intrinsically presume the achievability of both real-time control and decentralized decisions based on centralized platforms for data storage, processing, and analysis. A centralized platform is useful when the data size is rather small, but its effectiveness and efficiency drop dramatically when data from many different types of sensors need to be processed and when immediate decision making plays a key role, which, unfortunately, is the situation when performing CSM in real life. A proper CSM approach, as discussed above, must be able to provide sufficient and quality information for all workers, machines, the environment, etc., in a timely manner to enable both overall control and localized decisions. Hence, the data collected on a dynamic construction site for CSM would not only be of significant size and of various formats but also need to be processed and analyzed dispersedly and locally. As such, the use of centralized platforms will face three specific challenges. First, the computing capacity of a centralized platform is heavily burdened. Second, the data transmission very likely stagnates, not to mention that the network on site usually has limited bandwidth and speed. Third, the time needed for a centralized platform to analyze data and make responses is greatly increased. All these issues will make timely and accurate safety management decisions extremely difficult to achieve.

This study proposes the use of a new computing paradigm — edge computing — to facilitate the actualization of both top-down safety control and localized decision making in a real-time manner by avoiding the issues of a centralized platform mentioned above. Rather than transmitting all data directly to the centralized platform, edge computing is a distributed computing paradigm that transfers data processing and analysis close to the edge of the network or to data sources (Shi et al., 2016; Sittón-Candanedo et al., 2019). The advantages of edge computing include shifting the storage and computation load from the center to the edge, reducing ingress bandwidth into the cloud, enabling a real-time response, reducing latency, and enhancing scalability (Satyanarayanan, 2017). With these advantages, edge computing has been gradually adopted in industries that require intensive data collection and analysis for real-time decision support. Recently, a few enlightening studies on applying edge computing to construction projects have emerged, including Kochovski and Stankovski (2018), George et al. (2019), and Rossi et al. (2019). Nevertheless, thus far, there is still a lack of research pertaining to utilizing edge computing for comprehensive CSM.

This study attempts to provide the first research on applying edge computing to enhance CSM. An edge computing framework for CSM is developed, and an intelligible description of the key components of the developed framework is provided. A three-step research design is followed. Namely, the existing architectural frameworks of edge computing are reviewed. Next, suitable functional modules of the existing architectural frameworks are adapted to meet the specific requirements for CSM. Finally, the application of the developed framework is elaborated through three illustrative scenarios.

2. LITERATURE REVIEW

2.1 Real-time Construction Safety Management

Safety records of the construction industry are unenviable in many countries and regions around the world. In mainland China, 3,843 construction workers died from occupational deaths in 2018. In Hong Kong, the number of construction fatalities was 73 in 2017, hitting its highest level in the last couple of decades (Labour Department, 2018). The conditions of construction safety in developed countries are also not very optimistic (Guo et al., 2017). In the U.S., for example, construction accounted for less than 7% of total employment but 20.93% of the overall occupational deaths in 2017 (Bureau of Labor Statistics, 2017). The startling fatal accident rate in the construction industry has stimulated persistent endeavors to promote construction safety (Zhou et al., 2015). In the CSM research arena, researchers have realized that, in addition to regular safety inspections, the dynamic interactions among entities on a construction site make it necessary to enable real-time CSM that allows immediate reactions to potential hazards (Xu et al., 2019; Asadzadeh et al., 2020). Research efforts on real-time CSM could be divided into three categories according to the technologies (e.g., sensors) used and functions (e.g., risk identification, behavior-monitoring) targeted.

The first category of studies focuses on tracking and monitoring the location data of workers and machines, with a common aim of collision reduction. Abderrahim et al. (2005) developed a safety helmet that can periodically report workers' location data to monitoring stations through radio. Riaz et al. (2006) developed a proactive CSM system by integrating global positioning systems (GPSs), sensors and wireless networks to calculate distances between vehicles and between vehicles and workers. Teizer et al. (2007a) proposed a method of using video laser range scanning technology to detect and track the positions of static and moving obstacles on a construction site. Teizer et al. (2007b), Giretti et al. (2009), and Cho et al. (2010) adopted Ultra-wideband (UWB) technology to track mobile assets at dynamic construction sites. Carbonari et al. (2011) developed a CSM system using UWB-based tracking technologies to track the real-time location of workers and alert workers when approaching danger zones. Lee et al. (2012) developed a real-time locating system using radio frequency identification (RFID) technologies. In their system, the Chirp spread spectrum and Assistant Tag were used to overcome signal attenuation in the changing environment on site.

The second category of studies is on the identification of workers' unsafe operations and behaviors. Yang et al. (2012) deployed an integrated ZigBee RFID sensor network to avoid accidents caused by unauthorized operations and access to machines. Li et al. (2015) developed a proactive behavior-based safety system to collect the real-time location-based behavior data of workers to provide automatic and immediate information on safety supervision. Jebelli et al. (2016) and Lim et al. (2016) attached an inertial measurement unit (IMU) or accelerometer to workers to detect potential slips, trips, and falls. Niu et al. (2019) developed a smart chip to capture the data on operations of a tower crane. The captured data, after being processed and analyzed in a cloud-based platform, can provide real-time information aiding in safety instructions. In addition to sensors, artificial intelligence (AI) has been used in the second category of research. Ding et al. (2018) proposed a hybrid deep learning model to analyze site images to detect workers' unsafe climbing actions. Fang et al. (2018a) and Fang et al. (2018b) also adopted deep learning models for detecting non-helmet-use and non-harness-use based on image data. Fang et al. (2018c) recognized workers' faces in site images to ensure that each worker is working within his/her certified areas.

The third category of CSM studies concerns the collection of condition data, namely, the structural condition of construction objects, the environmental condition of sites, and the physiological condition of workers. In these studies, the condition data are generally made available by embedding sensors into objects, localities and workers' clothes or hamlets. The sensors used are of various types, including temperature sensors, strain sensors, vibration sensors, and phonometers (Ding et al., 2013; Lee et al., 2014; Yi et al., 2016). For example, Ding and Zhou (2013)

developed a CSM system using pressure and displacement sensors to measure the ground surface displacement, diaphragm wall inclination and other types of data for risk identification. Regarding workers' physiological condition, Hwang et al. (2016) used a wristband-type photoplethysmography sensor to measure the heart rate of workers to prevent worker fatigue. Aryal et al. (2017) and Lee et al. (2017) used different types of wearable sensors, such as infrared temperature sensors and electroencephalograms, to measure the physiological status of workers. Apart from these on-body sensors, Yu et al. (2019) used site images to assess the fatigue level of workers.

The above-mentioned literature shows that advanced information technologies contribute to real-time CSM by enabling real-time monitoring and early warning throughout the construction progress. However, one cannot ignore that the large amount of data collected often contains much noise, and most existing studies adopted centralized platforms for data processing and analysis. Both common points together, however, have resulted in an open problem important for achieving real-time CSM. Due to the volume and velocity of data accumulation, uploading all collected data to a centralized platform imposes massive burdens on the communication channel and computing resources that are often very limited on sites. In addition, not all collected data need to be transferred to a centralized platform for further analysis. For example, not all video frames can support CSM, but a set of key frames containing the targeted entities (i.e., worker or machine) should be used. Therefore, one promising approach is to make use of the edge computing method to offload the data processing and analysis tasks from the centralized platforms to the edge devices.

2.2 Requirements and Applications of Edge Computing in Construction

The concept of edge computing is not new. It has been widely used in the manufacturing industry for tasks when a large amount of data needs to be transmitted in a timely manner, processed, and analyzed. However, there are few studies on the use of edge computing in construction projects. A summary of these studies is presented in Table 1.

TABLE 1 Summary of studies on edge computing in construction

| Application | Functions of the edge nodes | Functions of the cloud server | References |
|---|--|--|---------------------------------|
| Video communication and construction process documentation | Conduct time-critical data process tasks | Conduct non-time-critical data process tasks | Kochovski and Stankovski (2018) |
| Underground structure health monitoring | Access control; real-time response to inquires | Smart contract-based data analysis; participant-to-machine and machine-to-machine communications | Jo et al. (2018) |
| Live video analytics | Process the video frames captured by a drone | Not mentioned | George et al. (2019) |
| Vibration characteristic analysis of underwater shield tunnel | Identify structural insecurity based on data from vibration sensors | Receive records of vital events and conduct in-depth data analysis | Li et al. (2019) |
| Monitoring of activities and power consumption of machinery | Identify the states of machines based on the power consumption signal | Provide historical sensor data to supervisors; control the edge nodes | Rossi et al. (2019) |
| Health monitoring of workers | Process raw sensor signals; display environmental and physiological data; trigger alerts | Data storage and web monitoring | Wu et al. (2019a) |
| Condition assessment of infrastructures | Deploy DCNNs to identify surface defects | Train the DCNN model, which involves heavy computations | Wu et al. (2019b) |

Among them, the very first group of studies focused on the design of physical edge devices for computation and storage or contain dockers offering virtualization supports at the edge. Kochovski and Stankovski (2018) developed an edge computing platform for video communication and construction process documentation. George et al. (2019) developed an edge computing platform to enable real-time registration of the video taken by a drone. Although few studies pay special attention to the application of edge computing to CSM, some existing studies are insightful for this research, as they have, for example, introduced the use of edge computing to process operation and condition data on construction sites. Rossi et al. (2019) equipped a sawing machine, hoist and concrete mixer with a microcontroller, i.e., an edge device, with feedback on the sensor signal that identified the typical patterns of the machine state. Wu et al. (2019a) devised a standalone local gateway as an edge device that can process raw sensor signals, display environmental and physiological data, and trigger an alert if any emergency circumstance is detected. The gateway can also be connected to a cloud server to provide more functions. Jo et al. (2018) used edge computing technologies for raw data storage, data processing and arrangement in underground structure health monitoring. Li et al. (2019) implemented a vibration test of an underwater shield tunnel using a wired accelerometer network enhanced by edge computing. In the method proposed by Li et al. (2019), the raw data can be temporarily stored and simultaneously analyzed in edge devices.

Most of these reviewed studies suggested that edge computing would not replace cloud computing but would complement cloud computing by sharing computing tasks so that the quality of service can be enhanced. They also reported many benefits of edge computing, of which the most important are perhaps low latency, scalability, and high data privacy. However, the edge computing solutions presented above often focus on a single facet of applications and do not consider data such as the worker’s location and operation, which are necessary for CSM. In addition, some key features of edge computing, such as the coordination among edge devices, were discussed with insufficient details. Thus, existing edge computing solutions in construction cannot fully satisfy the inherent complexity of CSM. A comprehensive framework is urgently needed to promote the application of edge computing for CSM.

3. RESEARCH METHODS

As shown in Figure 1, this study adopts a three-step research design by following a “bottom-up” strategy. The first step is to review existing edge computing frameworks in construction and other industries based on a screening of academic literature and industrial reports. This step is carried out to analyze the structures and key functional components of existing edge computing frameworks that can facilitate CSM.

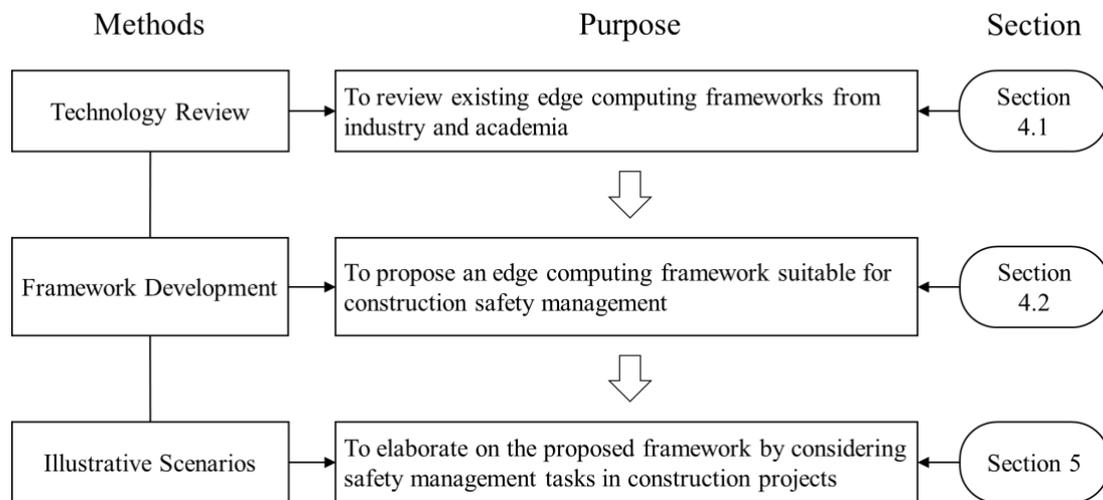


FIG. 1: Overall research flow

Based on the first step of this work, the edge computing framework for CSM in this study is developed by adapting the functional components of existing architectural frameworks of edge computing to satisfy the requirements of data collection and processing for real-time CSM. Once individual components of the proposed framework are determined, they are organized into different layers. The interrelationship and coordination mechanisms between these components are also designed.

The third step is to elaborate on the proposed framework through three illustrative scenarios. A scenario is descriptions of events that represent specific parts of a setting. Using scenarios for elaboration is suitable for studies introducing new technologies that have not been adopted in the current market and involve high levels of complexity (Akanmu and Anumba, 2015). To ensure the representativeness of the selected scenarios, all of them will consider common safety accidents and risks in construction projects.

4. EDGE COMPUTING FOR CONSTRUCTION SAFETY MANAGEMENT

4.1 Existing Edge Computing Frameworks

In recent years, some companies and industrial organizations have designed different architectural frameworks of edge computing, which are flexible and allow end users to develop their customized edge computing systems. Examples can be found in the GS MEC 003, Multi-access Edge Computing (MEC); Framework and Reference Architecture published by the ETSI, the Edge Computing Reference Architecture 3.0 proposed by the joint work of the Edge Computing Consortium (ECC) and the Alliance of Industrial Internet (AII), a loosely-coupled edge computing framework developed by the Edge Foundry, and a tiered framework proposed by the Edge Computing Group of OpenStack. In addition to these frameworks, some studies attempted to develop edge computing frameworks for specific application scenarios. For example, Ferrández-Pastor et al. (2018) proposed an edge computing framework that can enable smart building applications. Other examples can be found in Liu et al. (2019), Hu et al. (2019), and so on.

Despite that existing edging computing frameworks have different structures and functional modules; they share many similarities. First, all frameworks have a structure of hierarchy, which provides scalable communication, computation, storage, and application services. Second, most of these frameworks emphasize that the data generated by the edge devices at bewildering rates can be stored and processed by the local edge serves and only a small volume of processed data is required to be sent back to center. Third, virtualization technologies, such as network function visualization (NFV) and software defined networks (SDN), are included in these frameworks to flexibly coordinate the resources. NFV enables edge devices to provide computing services and operate network functions (Ai et al., 2018). SDN enables rapid deployment of services and dynamic adaptation of the network to changing traffic patterns and users' requirements. These three aspects will be fully considered in this study to develop the edge computing framework for CSM.

4.2 Proposed Framework

This study proposes the framework for applying edge computing to CSM (see Figure 2). In Figure 2, individual layers in the proposed framework contain different sets of functional modules, the coordination of which will enable real-time data collection, efficient data processing and analysis, and safety management decision support.

The shop floor layer—the sensing and actuating layer—of the proposed framework is related to the physical entities (e.g., workers and machines) and contains a number of sensing and safety alert devices. The sensing devices collect the location, operation, and status data of workers and machines, as well as the condition of the site environment. Some of the sensing devices are attached to the workers and machines, and others can be placed at fixed locations within the construction site. The collected data is transmitted to the edge computing layer, according to a predefined frequency, through corresponding protocols. The safety alert devices are on stand-by during the construction process, waiting for a request from the upper layer to inform different entities about various safety risks.

The middle layer of the proposed framework is the edge computing layer, which provides all edge computing services through a group of smart edge nodes (SENs). All SENs are managed by the edge management system and play a central role in supporting CSM through temporary data storage, real-time data processing, efficient data analysis, and seamless data sharing.

- Temporary data storage: CSM requires data to be analyzed in a timely manner to prevent accidents and minimize safety risks. Therefore, the SEN should store the incoming data in local storage for instant processing and analysis. The data can be stored in a compressed way to conserve storage resources. In addition, local storage is important when data transfer from an SEN to the upper layer is limited by the network bandwidth, and computations are limited by the computational power of the SEN. Local storage acts as a cache to avoid data loss.

- **Data processing:** Considering the heterogeneity of data required for CSM, an SEN will use a local processing unit to carry out hierarchical processing. Methods including filtering, compression, and fusion are necessary to conserve resources and minimize latency. The SEN will use filtering algorithms to reduce noise in the raw data captured by sensing devices. The SEN will also compress and fuse the data according to the predefined rules and algorithms. For example, a body sensor attached to a worker can collect his/her physiological data, and images taken by a camera can be used to identify the PPE equipped by that worker. The SEN will fuse these two types of data to check whether that worker will experience potential safety risks.
- **Data analysis:** Many safety risks in construction projects require minimum delay for alerts and intervention. An SEN can analyze the processed data and make safety management decisions without sending data to the centralized platform. Depending on the type of data and the safety management tasks, the SEN will apply different rules and models for data analysis. Lightweight models and simplified rules should be adopted to conserve computing resources and increase the speed of data analysis. However, when complex data analysis models need to be applied, the SEN might not have sufficient resources to completely process the data and will transmit the processed data to the cloud layer for further analysis.
- **Data sharing:** A group of SENs can share data with each other to ensure data comprehensiveness for local processing. Since workers and machines continuously move within a construction site, their attached sensing devices might not always communicate with a single SEN. When workers move to another location and their attached body sensors need to communicate with another SEN, the physiological data stored in the previous SEN can be transmitted to the current one so that the full picture of the physiological status of workers is always available for safety management.

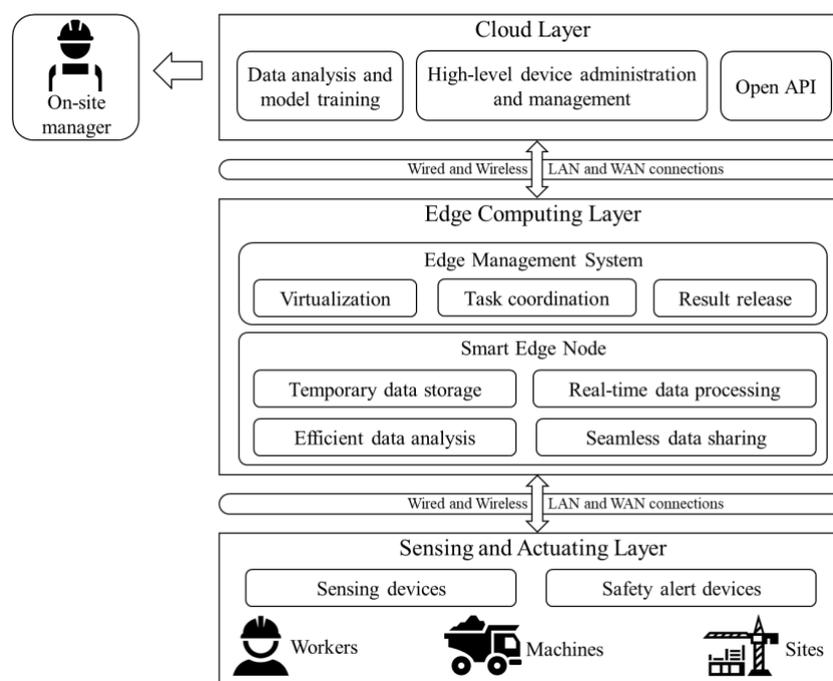


FIG. 2: Edge computing framework for construction safety management

It is worth noting that the management of different construction safety issues requires different types and amounts of data with various levels of accuracy and response times. Therefore, the edge management system will dynamically coordinate the data processing and analysis tasks among SENs based on the task priority, resource availability, and network conditions throughout the construction phase. For example, if tracking the real-time location of workers working at a certain height has been given higher priority than monitoring the temperature of the construction site, the SENs should spend more resources on conducting the former task than on the latter one. This process will benefit from virtualization technologies. The distributed orchestration allows monitoring and configuring the hardware and software resources. In recent years, both commercial and open-sourced tools (e.g.,

KubeEdge and Amazon ECS) have become available to help implement distributed orchestration for edge computing.

The top layer of the proposed framework, i.e., the cloud layer, consists of a cloud platform that has a stronger capacity for data processing and analysis than does the SEN. The cloud platform provides three major services to facilitate CSM. First, since a large portion of the data processing tasks are offloaded to SENs, the cloud platform can focus more on complex and high-precision computing tasks. For example, the deep learning models for detecting workers' unsafe behaviors from images can be trained in the cloud platform, and the trained models can be distributed to those SENs that use models for local data analysis. Second, the cloud platform is responsible for the life cycle management of SENs and sensing and actuating devices. This service is necessary to ensure the scalability and adaptiveness of the proposed framework. For instance, when some CSM tasks are completed or new CSM tasks need to be accomplished, the cloud platform will provide instructions about devices leaving or entering the network. Third, the cloud platform provides an open API to ensure its expandability for more value-adding functions. For example, statistical analysis of the overall safety risks and hazardous issues throughout the construction process can be conducted, which will help on-site managers develop effective safety management strategies.

In the proposed framework, the data transmission among different layers relies on various communication networks, such as Bluetooth, WiFi, 3G, and LET. In the near future, 5G will become a promising candidate for the data transmission network (Andrews et al., 2014). Since the services provided by SENs and the cloud platform require different amounts of resources, network slices can be adopted to virtualize the physical infrastructure resources of the communication network into multiple independent and parallel virtual network slices in accordance with the demands of individual services.

5. ILLUSTRATIVE SCENARIOS

Three scenarios are presented to show how the proposed edge computing framework can enable safety management in construction. These scenarios are derived from actual construction projects and focus on common safety accidents and risks.

5.1 Control of Unauthorized Jobsite Access

Unauthorized jobsite access is one of the major unsafe behaviors leading to many safety risks (Chi et al., 2005). Some technologies have been used to collect data for unauthorized access detection. RFID (radio-frequency identification) or other Auto-ID technologies can also help check the authorization of workers based on their identification numbers. However, unauthorized access cannot be detected if some workers use others' tags. The video frames captured by a video camera can be used to detect whether a worker entering a controlled area is an authorized person based on face recognition algorithms. For each working day, the volume of video data from even one video camera with a 2-million pixel resolution can be over 30 GB, but only frames containing workers are useful for detection. Transferring volumes of video frames to a centralized computing platform and processing all of them requires a large amount of network, storage, and computing resources. Based on the framework proposed in this study, an edge computing solution can be developed to integrate the video camera and Auto-ID technologies to improve the effectiveness and efficiency of unauthorized access control.

In this scenario, as illustrated in Figure 3, video cameras and UHF RFID readers placed at the entry of each restricted area and UHF RFID tags attached to individual workers are the main devices in the sensing and actuating layer of the proposed framework. Each video camera transmits real-time video frames to an SEN through a wired network, and the RFID reader communicates with the SEN through wireless networks. The SEN has the capacity for data communication and temporary storage and contains the data (a processing module that is equipped with a computer vision model trained on the cloud platform). The major function of the model is to find workers in each video frame and to obtain each worker's face images in that frame.

When the SEN does not receive any tag information from the RFID reader, none of the video frames transmitted to the SEN are stored in the cache. The moment that the SEN receives the tag information from the RFID reader, the SEN applies the model to process and analyze the captured video frames to obtain the face images of workers who enter the restricted area. Then, each worker's face image is transmitted to the cloud platform through wireless networks. Once the images are received, the cloud platform applies a face recognition algorithm to match the

workers' faces with those registered in the database. The recognition result is presented as a value between 0 and 1, where the closer the value is to 1, the higher the matching level. Then, the cloud platform checks whether the recognized workers have been authorized to access the restricted areas. If any workers are guilty of unauthorized access, the final result is shown in the user interface of the cloud platform for the site manager to review. In the meantime, the result is transmitted to the SEN, and the SEN sends a request to the safety alert devices to broadcast the safety issues. With the help of edge computing, the total response time can be significantly reduced. Therefore, more timely control of unauthorized jobsite access can be achieved to avoid potential safety risks.

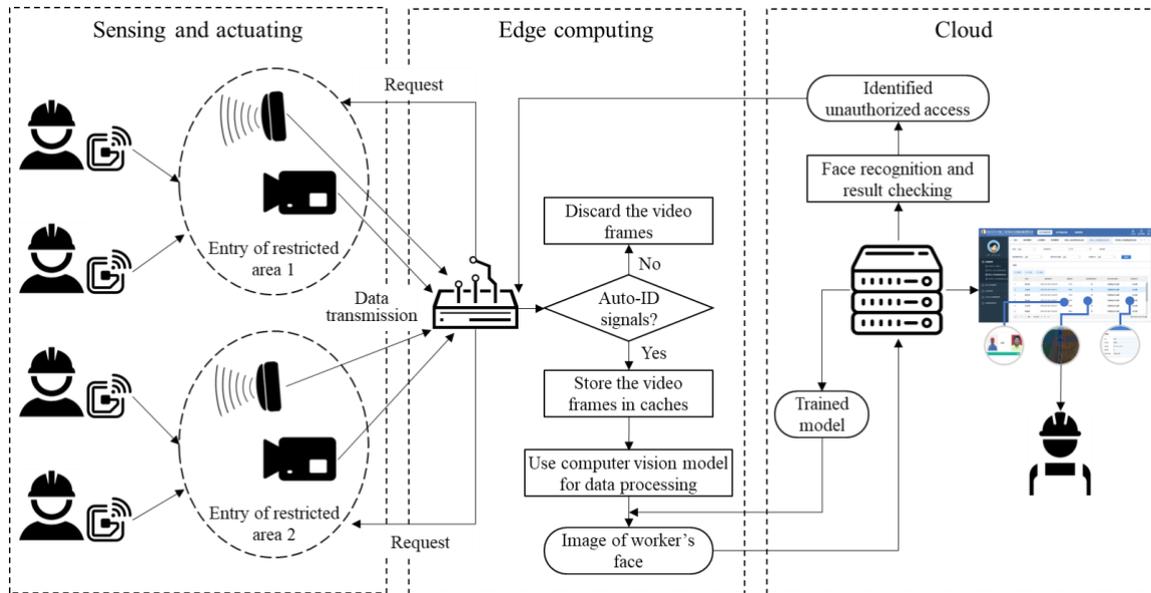


FIG. 3: Illustration of using edge computing to control unauthorized jobsite access

5.2 Monitoring of Poor Site Environment

A poor site environment is dusty, noisy, too cold or too hot, which can lead to many safety risks (Sawacha et al., 1999). To improve the condition of a site environment, data about the air pollution level, noise level, temperature, and many other environmental indicators should be continuously monitored. A number of sensors can be used in this monitoring process, but the analysis of all their captured raw data brings a heavy burden to the conventional centralized computing platform. An edge computing solution, based on the proposed framework, can help execute the monitoring of the site environment.

In this scenario, as illustrated in Figure 4, the sensing and actuating layer consists of various types of sensors allocated within the construction site. These sensors are responsible for capturing each category of the environmental data. Owing to the separated distribution of sensors, a group of SENs are placed within the construction site to guarantee that each sensor can communicate with at least one SEN for data transmission. When one sensor can communicate with more than two SENs, the edge management system will administrate the detailed status, e.g., resource utilization, of these SENs and dynamically allocate the data processing tasks.

The SEN first stores raw data, with more or less noise, in the cache. Then, the SEN applies filtering and compression algorithms to decrease the noise and reduce the data volume. The processed data are organized into a time series with predefined structures. After this processing, each SEN transfers data, indicating the environmental condition of the surrounding area, to the cloud platform. Through the analysis of integrated data from all SENs, the cloud platform visualizes the environmental conditions of the construction site in the form of heat maps, noise maps, air pollution maps, etc., and identifies the site areas with poor environments according to the predetermined threshold with a buffer range. In addition, the cloud platform displays results in the user interface, based on which the site manager can easily monitor the poor site environment and take corresponding measures to address any problem.

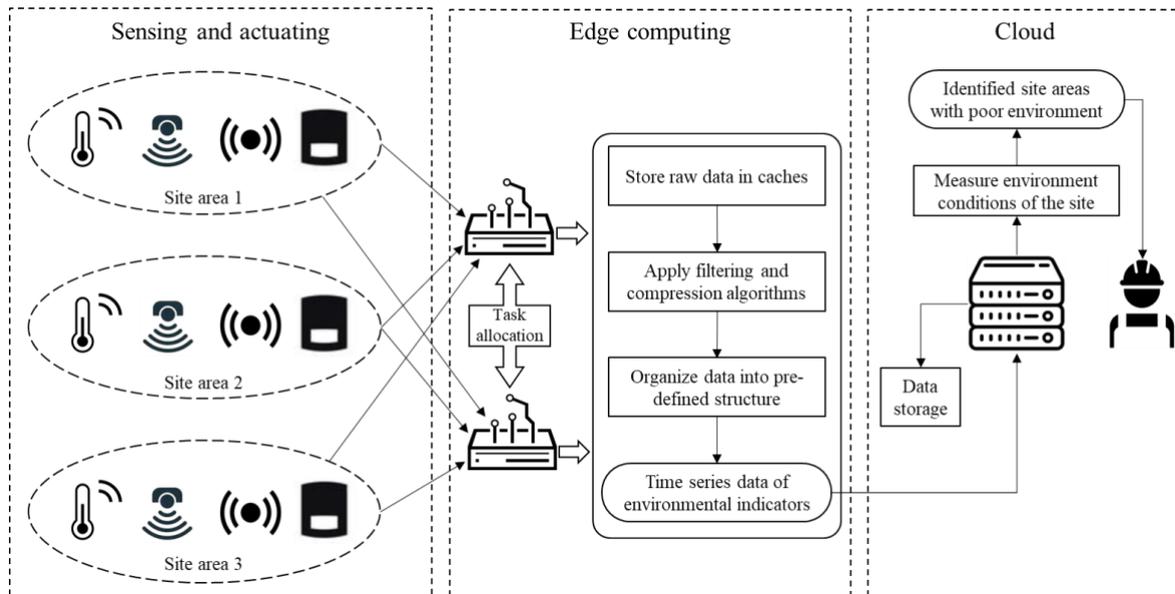


FIG. 4: Illustration of using edge computing to monitor poor site environment

5.3 Prevention of On-site Unsafe Movement

Unsafe movement at a construction site mainly includes workers or machines moving within dangerous areas (e.g., edges at height) or workers getting too close to parts of machines (Mitropoulos et al., 2005). Unsafe movement might lead to safety accidents such as falls and electrocution and should be avoided as much as possible. Therefore, the real-time locations of workers and machines within a construction site should be accurately collected.

In this scenario, as illustrated in Figure 5, the sensing and actuating layer mainly consists of tracking and safety alert devices attached to workers and machines. Each tracking device contains a unique identification number and can transmit signals to the SEN for location estimation. The safety alert device can alert the workers or machine drivers once it receives a request from the SEN. In the edge computing layer, a number of SENs are separately distributed within the construction site for full coverage because both workers and machines will move among various locations on a daily basis.

With the progression of a construction project, the danger zones within a construction site dynamically change, and the site manager identifies the danger zones for each day of construction in the cloud platform. This information is stored in the caches of the SENs. Each SEN receives signals from the tracking devices when any workers or machines enter its reading range. Then, the SEN filters the noisy data and estimates the locations of the corresponding workers and machines by using different positioning algorithms. If more than one SEN receives signals from the same tracking device, this information is shared to improve the accuracy of location estimation.

After estimating the real-time locations of workers and machines on the construction site, the SENs integrate this information and the predefined danger zones to determine whether there are on-site unsafe movements. A set of thresholds is determined for the identification of hazardous situations. If the duration that a worker stays in a danger zone is less than the threshold, i.e., five seconds, no alert is released. In contrast, if the duration exceeds the threshold, the SEN requests the tracking device to warn that worker about his/her unsafe movement. Additionally, each SEN constantly calculates the distances between workers and machines. If an SEN identifies that a worker is getting too close to a machine, it sends requests to the safety alert devices to inform the workers and machine drivers about the potential safety risks. Since individual SENs need to track only a limited number of workers and machines within a suitable communication range and can share the processed data with each other, minimum latency for tracking unsafe movements can be achieved. All the identified on-site unsafe movements are transmitted to the cloud platform for the site manager to establish improvement strategies.

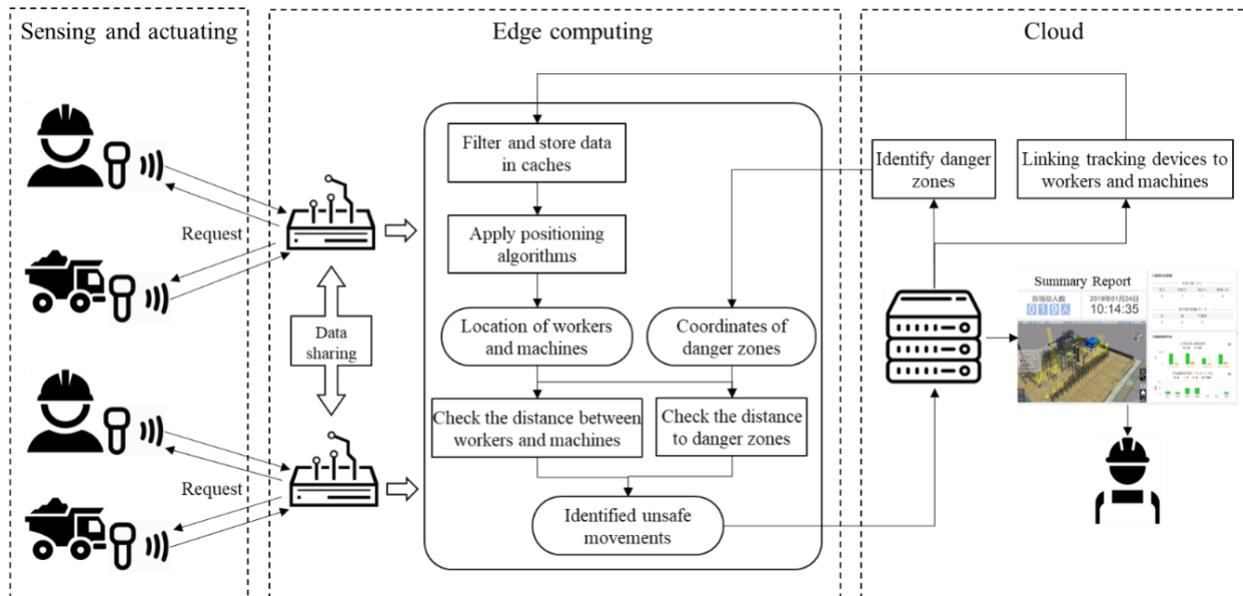


FIG. 5: Illustration of using edge computing to prevent on-site unsafe movement

6. CONCLUSIONS

In this study, the authors attempted to introduce the use of edge computing to support time-critical CSM. An edge computing framework was proposed to facilitate the deployment of edge computing for CSM and illustrate their interrelationship. The proposed framework contains three layers, including a sensing and actuating layer for collecting CSM-related data and delivering immediate safety alerts, an edge computing layer for providing edge computing services, and a cloud layer for performing high-level device administration and complex data analysis. Edge computing offloads parts of the resource-intensive data processing and analytical tasks from the center to the edge and thus enables fast response times and decreased latency. Three scenarios, considering the most commonly occurring safety risks, were presented to show how the proposed framework can be used to collect and analyze the required data in a timely and accurate manner to support different safety management tasks.

This study provided knowledge regarding how to use advanced edge computing technologies to improve the effectiveness and efficiency of safety management in construction. Future studies can implement an edge computing prototype of the proposed framework in actual construction projects to collect more empirical data for further evaluation.

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