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Review

# A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends

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ABSTRACT

The integration of Building Information Modeling (BIM) with real-time data from the Internet of Things (IoT) devices presents a powerful paradigm for applications to improve construction and operational efficiencies. Connecting real-time data streams from the rapidly expanding set of IoT sensor networks to the high-fidelity BIM models provides numerous applications. However, BIM and IoT integration research are still in nascent stages, there is a need to understand the current situation of BIM and IoT device integration. This paper conducts a comprehensive review with the intent to identify common emerging areas of application and common design patterns in the approach to tackling BIM-IoT device integration along with an examination of current limitations and predictions of future research directions. Altogether, 97 papers from 14 AEC related journals and databases in other industry over the last decade were reviewed. Several prevalent domains of application namely Construction Operation and Monitoring, Health & Safety Management, Construction Logistic & Management, and Facility Management were identified. The authors summarized 5 integration methods with description, examples, and discussion. These integration methods are utilizing BIM tools' APIs and relational database, transform BIM data into a relational database using new data schema, create new query language, using semantic web technologies and hybrid approach. Based on the observed limitations, prominent future research directions are suggested, focusing on service-oriented architecture (SOA) patterns and web services-based strategies for BIM and IoT integration, establishing information integration & management standards, solving interoperability issue, and cloud computing.

## 1. Introduction

Building Information Modeling (BIM) has become an established paradigm for the development of enhanced project delivery practices. Properly developed and managed, BIM-centric project delivery makes available high fidelity, geometrically and positionally accurate, uniquely identifiable building component data sets together with a wealth of descriptive and operable metadata.

According to [1], IoT can be defined as “interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications”. IoT enabling technologies include sensing technologies, identification and recognition technologies, hardware, software and cloud platforms, communication technologies and networks, software and algorithms, position technologies, data processing solutions, power and energy storage, security mechanisms, etc. [2]. IoT primarily exploits standard protocols and technologies, of which IoT device constitute a major subset. Typical IoT devices include intelligent devices, smart mobile devices, single board computers, different types of sensors and actuators [3].

The potential of connecting BIM and IoT based data sources is a relatively new development. As a generalization, BIM and IoT data offer complementary views of the project that together supplement the limitations of each. BIM models offer high fidelity representations of the project at the component level. By incorporating geometry, spatial location and a scalable set of metadata properties, BIM models provide a high-fidelity operable dataset capturing the as-designed building objects, properties and spatial organization as a set of virtual assets. IoT data enhances this information set by providing real-time and recordable status from the actual operations in construction and operations. The potential information sampled from sensors is highly variable but includes both positioning information, physical measurements, weather, etc. This data is generally organized as time series data streams of individual sensor point samples over time, frequently with

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some higher-level organization into equipment, etc. Both BIM and IoT data may be accessed through several mechanisms, including manual interfaces of proprietary systems, programming APIs associated with these applications, potential database connections to the systems, and export via open standards. A number of open standards are emerging in both BIM and IoT fields.

Existing studies have adopted BIM and IoT devices in many aspects such as energy management, construction monitoring, health and safety management, and building management. However, BIM and IoT integration research is still in nascent stages where most studies are theoretically and conceptually proposed [4]. The concept of IoT is not just related to IoT devices like sensor and actuators, the key concern is the interconnection of sensing and actuating devices providing information sharing through the internet. Most of the current studies can only be considered as the integration of BIM and IoT devices that lack information sharing across the Internet through a unified framework. The applications of BIM and IoT device integration are scattered, it is sufficiently matured that patterns, issues, and opportunities can be identified.

While the BIM and IoT device integration is still nascent, there is a need to understand the current situation of BIM and IoT device integration including:

- What are the prevalent application domains for BIM and IoT device integration? How to categorize these application domains?
- What are the integration methods for BIM and IoT device?
- What are the limitations for both application domains and integration methods?
- What are the research gaps and fruitful future research directions?

This study attempts to address these research questions by conducting a comprehensive review on BIM and IoT device integration with the summarization of the application areas, integration methods of existing studies, examination of current limitations, and prediction of future research directions. Altogether, 97 papers from 14 AEC related journals and databases in other industry over the last decade were reviewed. The rest of the paper is structured as follows: Section 2 explains the research methodology; Section 3 categorizes the reviewed papers into 4 application domains and analyzes limitations; Section 4 concludes different methods for integrating BIM and IoT devices and demonstrates examples from reviewed articles and discusses limitations; Section 5 identifies future trends and Section 6 presents the conclusion.

## 2. Methodology

To ensure a comprehensive review of BIM and IoT device integration, both BIM related articles from AEC journals and IoT related publications from electrical & electronic engineering and computer science domains were included in the review. To acquire up-to-date and high-quality papers, the following steps were taken: (i) Journal search from Web of Science; (ii) Set journal selection criteria and select high impact journals; (iii) Paper search in individual databases and libraries; (iv) elimination of duplication and irrelevance; (v) Categorization based on the results of content analysis and discussion on reviewed articles; (vi) Explore potential research directions for the future.

In the first step, high impact journals in the AEC industry were identified through the Web of Science database, Journal Citation Report and past review articles' methodology [5–7]. Then, as shown in Tables 1, 14 journals with an impact factor above 1.5 or highly endorsed by professionals were selected. Afterward, advanced searching was operated in individual journal database including Science Direct, American Society of Civil Engineers (ASCE) Library, Taylor and Francis Online, Wiley Online Library and ITcon. To consider publication in other industry, Electrical and Electronics Engineers (IEEE) Xplore and Association of Computing Machinery (AMC) library database were searched. Searching keywords were combinations of “Building information modeling”, “BIM”, “Internet of Things”, “IoT”, “Smart Building”, “Smart City”, “Sensor” and “Building Management System (BMS)”. As summarized in [5], publications related to BIM has drastically increased since 2012. Publications related to IoT device integration with BIM were rare before 2012 in all searched database. In this review, articles were limited to those published in the last decade. There were 333 searching results in the selected journals and databases. This review focused on IoT devices integration with BIM for the smart built environment, duplicated and irrelevant papers were eliminated. By reading through articles' abstract, highlights and key scope, this screening process reduced the article number to 97. Table 1 summarized the article selection details. The final step was categorization and analysis of the reviewed articles. The categories in this paper were created based on articles' content and frequency of keywords. The authors analyzed these articles based on various domains of use (Section 3) and integration methods (Section 4).

**Table 1**
Searching result and reviewed articles.

| Journals/database | Total searching | Reviewed paper |
|---|---|---|
| Automation in Construction | 85 | 48 |
| Advanced Engineering Informatics | 25 | 8 |
| Journal of Computing in Civil Engineering | 53 | 6 |
| Journal of Management in Engineering | 12 | 3 |
| Journal of Construction Engineering and Management | 13 | 2 |
| Energy and Buildings | 25 | 3 |
| Journal of Information Technology in Construction | 29 | 3 |
| Building and Environment | 7 | 3 |
| Journal of Civil Engineering and Management | 5 | 2 |
| Building Research and Information | 11 | 1 |
| International Journal of Project Management | 2 | 1 |
| Expert Systems and Application | 1 | 0 |
| Project Management Journal | 0 | 0 |
| Computer-Aided Design | 0 | 0 |
| IEEE Xplore Digital Library | 22 | 9 |
| ACM Digital Library | 43 | 8 |
| Total | 333 | 97 |

## 3. BIM and IoT integration for different domains

To identify and provide more in-depth analysis of the reviewed papers, the author proposed several domains based on reviewed papers' research content and keywords. The overall categorization of the reviewed paper based on domains is shown in Table 2. For each of the domains, representative research works are described and discussed in this section.

### 3.1. Domain: construction operation and monitoring

The construction industry has experienced continuous digital transformation. The emergence of BIM and IoT devices brings the integration of real-time data like environmental data and localization data to assist construction operations and management. As sensors and BIM integration can accomplish real-time information sharing and communication, construction monitoring gets benefits in various aspects. These aspects include:

#### 3.1.1. On-site environment monitoring

On-site environment monitoring has adopted sensors and BIM. One noticeable usage was real-time site visualization through Virtual Reality (VR) [8,9]. Another aspect was automatic equipment operation. Real-time sensory inputs which captured realistic environmental conditions were combined with BIM models to calculate the equipment operator's instruction, compactor's path [14] and automatic crane operations

**Table 2**
Categorization of reviewed papers by domains.

| Domains | Subdomains | Related Research |
|---|---|---|
| Construction Operation and Monitoring | On-site environment monitoring<br>Resource monitoring<br>Communication and collaboration<br>Construction performance and progress monitoring | [8–21] |
| Health and Safety (H&S) Management | H&S training<br>On-site monitoring for H&S | [18–20,22–28] |
| Construction Logistic and Management | Automation in prefabrication<br>Lean construction | [29–40] |
| Facility Management (FM) | Building Operation and Maintenance (O&M) | [41–50] |
| | Building Performance Management | [6,44,51–58] |
| | Energy Management | [4,59–68] |
| | Disaster and Emergency Response | [50,65,69–73] |

[15,16].

#### 3.1.2. Resource monitoring

Sensors like Bluetooth Low Energy sensors and motion sensors were used to track the movement of labors, materials, equipment in complex construction sites [17–20]. These tracking systems incorporated BIM models to visualize moving paths, hence resource status and labor behaviors could be monitored.

#### 3.1.3. Communication and collaboration

The study from Ibem and Laryea implied that construction operation could be enhanced using real-time communication and collaboration with BIM and IoT devices [21]. Ref. [10] also supported this opinion by suggesting that the BIM model could be correlated with real-time construction data captured from IoT tags, sensors, and mobile devices to enable in-time communication and collaboration among various parties.

#### 3.1.4. Construction performance and progress monitoring

Construction performance and progress monitoring can profit from IoT devices and BIM in many aspects. Firstly, reality data including actual performance, project status (e.g. laser scanned point-cloud data), construction activity and physical context and other real-time project information could be captured with sensors. Integrated with models and BIM tools, these data could be leveraged to monitor the construction process and update construction schedules [10–12]. In addition, sensors have been used to detect progress data for quality control. For example, Radio-Frequency Identification (RFID) and GPS sensors were used to collect position data of construction components for comparison against BIM models [13].

Current research showed some limitations in construction operation and monitoring. Firstly, some of the reviewed articles proposed framework or workflow with only the prototype tests, single use case for a company or limit testing scenarios [9,11,12,19,20]. Whether these solutions can be generalized or not remains to be investigated. In addition, some prototype tests [9] were based on heavy and expensive equipment in the laboratory which failed to consider the applicability in the real construction site. Furthermore, issues like the cumbersome design of the process, manual data conversion [12], the reliability of sensor collected data for calculating mechanisms [13,17,20] still remains to be streamlined and addressed. Research studies have been successful on a specific use case, like visualization, crane operation, location tracking, and risk warning, however, these solutions are fragmented and there is lack of a more cohesive framework that integrates various sensor's collected data to manifest smart construction site in the future.

### 3.2. Domain: health and safety management

Health and safety are specialized high impact concerns, due to the legislative and risk exposure associated with both worker and occupant health conditions. IoT data sources are providing widely useful for detailed monitoring of environmental and human activities associated with health and safety risks, as well as programs for continuous improvement, insurance optimization, and compliance, etc. BIM datasets contain rich information on building equipment and organizational conditions (proximity, connectedness, etc.) that can be leveraged to provide context for these sensor-based data streams. Some of the prevalent applications integrating BIM and IoT data for health and safety management include:

#### 3.2.1. H&S training

Both in [23,24]' s research, H&S training systems that used BIM and sensors like Ultra-Wideband (UWB) technology were proposed. The location of trainers, trainees, materials, and equipment was tracked during the training course. Sensor collected location data and BIM models were used to analyze safety and productivity, meanwhile providing real-time and post-event visualization through a VR environment.

#### 3.2.2. On-site monitoring for H&S

Sensors and BIM integration for H&S have been widely implemented for safety matters. IoT devices were integrated with BIM tools to achieve real-time data query, risk identification, visualization and notification over BIM models. Sensor networks and BIM model were used to avoid risk in complex and confine-spaced construction sites [19,20,28]. Structure monitoring sensors, RFID tags, and BIM models enabled visualization of the malfunctioned component for structure health monitoring [25–27]. Together with the surrounding environment monitoring system, further improvement could be realized by adding a portable warning device for works to achieve early hazard warning [18].

Several limitations were identified in these studies: i) The majority of H&S applications leveraged RIDF tags and BIM for monitoring location data and sending out warnings [19,22]. However, safety issues were not only related to location data, how to identify works behaviors [24] and other potential safety hazards [25] required deployment of various types of sensors; ii) For most of the structural health monitoring research, proposed solutions were only tested with limited scenarios, further research is needed to investigate their scalability and reliability [25–27]; iii) Another issue would be the ease of implementation of the proposed solutions, considering workers' privacy in most of location-tracking required solutions; iv) Several researchers mentioned the limitation in sensor reliability and energy efficiency of battery [19,20]. A solution to this limitation would be necessary for long-term and sustainable implementation.

### 3.3. Domain: construction logistic and management

In terms of Construction Logistic and Management, BIM and IoT device integration can largely facilitate automation in prefabrication and lean construction management.

#### 3.3.1. Automation in prefabrication

Advanced sensor technologies and BIM facilitate automation in prefabrication. BIM and IoT devices like RFID tags are effective tools for prefabricated component manufacturing, logistic, tracking, visualization with BIM model and automatic assembly. Various research works have proposed solutions to demonstrate applications in prefabrication [29,30,33–38].

#### 3.3.2. Lean construction

Digital technologies like IoT and BIM can assess work progress, constraints and productivity using constant and reliable information flow. This character expedites the development of Lean Construction. Studies like [31,32,39,40] stated that the use of IoT devices such as sensors, actuators, auto-ID system networks enable real-time information exchange. Together with BIM models, communication between systems, human and devices across the supply chain and construction project lifecycle could be automated.

Limitations for reviewed articles in construction logistic and management: i) Because of sensors like RFID tags deployment, a large amount of data could cause information overload. It was necessary to consider how to standardize construction process data, prefabrication data from vendors and tracking data from sensors to conform to local code and regulations [30]; ii) Solutions' generalizability: majority of the solutions were conceptually proposed and tested in lab environments and not in real projects [30,31,40]; iii) as current studies were based on conceptual frameworks and prototype test, the challenge to overcome conservatism in construction industry was critical. The issues like return on investment, human capital, training, technical problem in implementation might hinder implementing innovations [33,40]; iv) for prefabrication construction using RFID tracking, full BIM models were needed during the design phase. Information exchange with BIM models throughout various project stages involved serval parties. Hence, the feasibility and effectiveness of information exchange and collaboration needed further consideration [34].

### 3.4. Domain: facility management

Researchers have studied BIM application in supporting FM for years. The integration of BIM and IoT device can provide facility managers with automated ways for building O&M, building performance management, energy management and developing disaster & emergency response strategies [74].

#### 3.4.1. Building operation and maintenance

BIM integrated with IoT devices can create beneficial platforms for assisting O&M practices such as real-time data access, checking maintainability, creating and updating digital assets and space management [41]. Studies related to building O&M can be summarized into: i) Identify physical building components and link with BIM models through RFID tags [42,43] for asset tracking; ii) link physical objects with digital objects by linking BMS and BIM [44,45] using BIM tool APIs for O&M; iii) Extract real-time data, visualize problems either from Augmented Reality (AR) devices [46] or BIM tools on mobile device on facility managers' perspective to conduct maintenance or control of assets [47–49].

#### 3.4.2. Building performance management

Publications in BIM related building performance simulation, assessment, optimization, and management have experienced an exponential increase over recent years [51]. BIM enables interoperability, visualization, automation and integration with other systems. Consequently, BIM integration with IoT devices can bring ultimate potential in: i) Linking BIM with BMS data for visualization and management of real-time building performance data [44,45,51]; ii) monitoring Indoor Environment Quality (IEQ) by reading temperature and humidity information from BIM tools in a timely manner [52] and improving user comfort [53]; iii) using semantic web technologies for real-time building performance monitoring and assessment [6,54–57]. Building context data in either BIM models or Industry Foundation Class (IFC) file is adapted to web standard. These studies can adapt cross-domain information and real-time sensor reading to web standard, so that cloud-based applications and services like energy management, building performance monitoring and building operation management can be fulfilled [58].

#### 3.4.3. Energy management

Existing research on IoT devices integration with BIM for Energy Management was focused on real-time energy usage visualization and monitoring at building and city scale, energy performance analysis and energy benchmarking. Researchers tried to propose energy management solutions and study on Wireless Sensor Networks (WSN) integration to achieve above-mentioned goals. These research were related to: i) web-based energy management solution which allowed facility manager to view BIM models, query sensor data and get actuation suggestions at a "near real-time" basis [59,61,62]; ii) Geographic Information System (GIS) integrated energy management solutions that are capable of visualizing 3D models and monitoring geospatially referenced energy usage [63]; iii) software/system architecture as energy management solution to monitor real-time energy consumption and building condition with BIM [4,64,65]; iv) energy performance analysis based on real-time energy consumption using co-simulation tools like Building Controls Virtual Test Bed (BCVTB) and Cyber-Physical Building Energy Management System (CBEMS) [75,76] which extracted building data from BIM models; v) integration of WSN and BIM for energy monitoring, real-time feedback & control and energy benchmarking [66–68]. It has come to an agreement that WSN integration with BIM could improve the AEC industry, however, issues like interoperability, return on investment, the limitations with sensor device still need future studies [60].

#### 3.4.4. Disaster and emergency response

BIM and various types of sensors can be effective tools in disaster and emergency response both at the building and urban scale. Researchers have utilized BIM and IoT devices for: i) detecting indoor location of trapped victims and display location in BIM models [69]; ii) calculating shortest evacuation path with building information from BIM models in real-time and location data from sensors or victims' mobile devices [70–72]; iii) creation of mobile guidance for evacuation with BIM tool API and mobile devices [73]; iv) large scaled emergency response using BIM, IoT devices and GIS [50,65].

There were 4 limitations identified for FM studies: i) Most of the reviewed articles were theoretical, for example, several studies proposed conceptual frameworks without implementable platforms or systems [42,43,46]; ii) Some researchers only tested their prototypes under laboratory condition or limited and small-scale test scenario [48,50]; iii) Most of the research did not achieve real-time information queries, the research results were either manual information update on static information or near-real-time queries that requires user-defined time interval for information renew; iv) Although many works have achieved information acquisition from BIM and IoT devices, none of the reviewed articles provided solutions on controlling actuators through BIM. As a result, future studies focusing on tackling these limitations are necessary.

## 4. BIM and IoT devices integration methods

In this section, five methods were concluded from reviewed articles' methodologies and implementation. The authors described the basic steps for each integration methods, demonstrated how a method was implemented in various examples from reviewed articles and analyzed the pros, cons, and applicability of each method.

When discussing BIM and IoT device integration, there are three components:

> Firstly, BIM serves as a data repository for contextual information including building geometry, IoT devices' description, static information and other soft building information collected from occupancy patterns and schedule data like social media, building feedback, occupant interactions, room allocation, weather forecast and financial pricing [6]. Contextual information can be stored in BIM tools (e.g. Revit Model) or IFC formats.

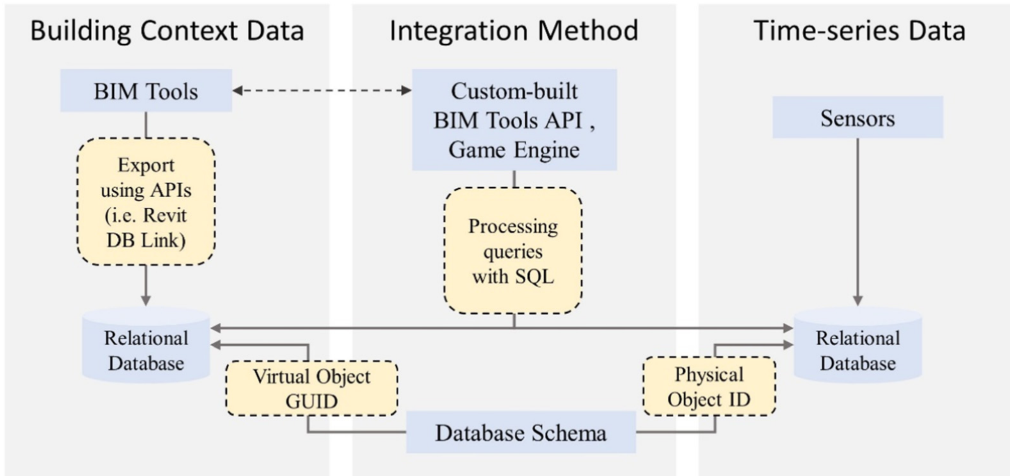


**Fig. 1.** BIM tools' APIs + relational database.

The second component is the time-series data which records continuous sensor readings [68]. Traditional time-series data is stored in a well-structured relational database and can be effectively queried using Structured Query Language (SQL).

The third component is the integration method between contextual information and time-series data. This section explains different integration methods of contextual information (BIM data) and time-series (sensor collected) data.

### 4.1. BIM tools' APIs + relational database

#### 4.1.1. Description of this approach

A widely adopted approach is to use existing BIM tools' APIs and relational database. The basic steps as shown in Fig. 1 can be concluded as the following points: i) Sensor collected time-series data is stored and updated in relational database (e.g. SQL server database, Microsoft Access); ii) BIM models which are constructed in BIM tools (e.g. Revit), can be exported into relational database formats using APIs (e.g. Revit DB Link, Dynamo, Grasshopper); iii) Define a database schema which clarifies the relationship between virtual objects and physical sensors. For example, virtual objects can relate to physical sensors using unique identification (Global Unique Identifier (GUID or UUID)); iv) A two-way importing and exporting of a relational database and BIM model can be achieved using APIs; v). Processing queries of sensor data through custom-built API (e.g. graphic user interface (GUI) based on Revit), third party processing engine (e.g. Unity engine) and direct query over SQL database (as the object properties).

#### 4.1.2. Examples of this approach

The BIM and WSN system proposed by Marzouk et al. [52] allows the user to read temperature and humidity information from the Revit model in a timely manner. Temperature and humidity data were collected by WSN, stored and updated in Microsoft Access relational database. Revit project data (contextual information) were then exported into Microsoft Access format. Data visualization, importing and exporting was achieved using Revit DB link between Microsoft Access and Revit. Sensor readings were then displayed in Revit as object properties. Zhang and Bai's [27] method can also be categorized into this approach. Revit models were exported to MySQL or MS Access and linked with physical objects using identification. However, this study was only tested with a few structural objects under laboratory condition. The same problem happens to [26]'s work. If the number of sensors and objects is enormous, a data mapping schema will be necessary to clarify the virtual object and physical objects linking process.

More advanced query processing was done by Arslan et al. [19] and Riaz et al. [20]. The real-time H&S monitoring systems also used a relational database and Revit DB link to achieve sensor-BIM integration. They differed from [52]'s work by creating a GUI as a Revit API using C# language. The GUI once invoked can display latest sensor values. Another example is Woo et al. [66] developed a virtual campus model which integrated BIM, WSN data in a game engine environment for energy benchmarking. WSN was first installed to collect energy data. The Revit DB link plug-in was used to export Revit model into the MySQL database. Sensor data was stored in MS Excel then exported to MS Access relational database before stored in the Revit model. The connection between query and MySQL database was processed by Unity game engine [8,77] so that real-time energy performance data could be queried.

There were other research works implemented with Grasshopper and Dynamo. Habibi [53] developed a prototype smart system using Grasshopper to obtain and monitor real-time sensor data. A genetic algorithm was then implemented in Grasshopper to identify the optimized solution. An intelligent user interface allows the user to understand real-time sensor data and take actions based on the optimal solutions. [51] created a prototype method linking BIM with BMS data. Revit was firstly used to hold model and building design performance data that had been extracted into JSON using Dynamo. Continuous sensor data was stored in a SQL server. A Python script was used to extract sensor data stored in the SQL database and link it to JSON file.

#### 4.1.3. Discussion of this approach

This approach is found in most of the related research, as there are a few obvious advantages. The integration process can be done using the existing APIs. Model data can be exported to open database connectivity (ODBC) format which is compatible with external database software (e.g. MS Access, MySQL). The second advantage is the ease in linking model data and sensor data because of they both store in the relational database. The third, time-series data can be automatically updated in BIM tools with these APIs. However, there are some drawbacks. Since only shared parameters between projects and families can be exported, there will be limitations on what to update. In addition, although sensor data can be automatically updated in the relational database, manual export of model files incurs repetitively if model change happens.

This approach is suitable for less complex BIM models with a limit number of sensors, as this approach requires the construction of virtual objects to represent physical sensors manually. It is particularly useful to integrate existing BMS with BIM. Since there are available API to export BIM data into the relational data model, it requires less expertise in IFC and programming and provides ease of use for a wider adoption.

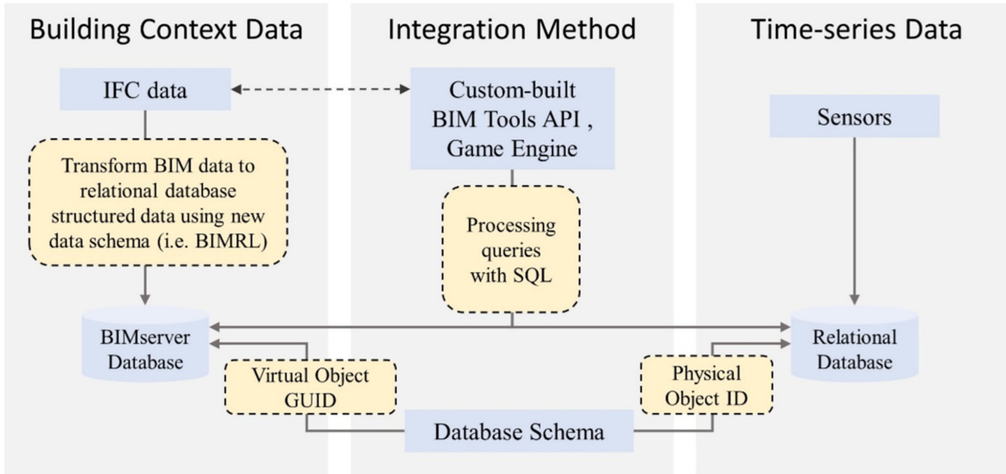


**Fig. 2.** Transform BIM data into relational database using new data schema.

### *4.2. Transform BIM data into relational database using new data schema*

#### *4.2.1. Description of this approach*

One effective way to integrate sensor data with BIM is to transform BIM data into a queryable database which allow information extraction from different users' perspective (see Fig. 2.). Traditional building management system store data (e.g. facility data and sensor readings.) in a relational database which is well structured and effective for SQL query. Transforming BIM data into relational database structured data is the foundation step for binding time-series data with BIM. Once BIM data is SQL queryable, sensor data can be linked to BIM, for example connecting virtual sensor objects with physical sensors via GUID, and map sensor collected data as virtual sensor objects' properties.

#### *4.2.2. Examples of this approach*

Solihin et al. [78] created a new relational database schema named BIMRL to transform BIM data into a queryable database. BIMRL allowed efficient SQL queries on BIM data without storing entire IFC-STEP data in a database, BIMRL schema was generated using the relational database structure following the star schema definition in the Data Warehouse (DW) domain. BIMRL extended BIM data query capability by integrating spatial set operations into standardized SQL. BIMRL showed potential applications in rule checking, facility management, sensor data integration and real-time optimization of building operations.

The prototype system in [48] also converted BIM data into a relational database through manipulation on IFC. Various sources of facilities' data (e.g. sensor readings stored in the relational database) were integrated with BIM. Logical and spatial relationships between entities were manually added to IFC file and mapped to Microsoft Access relational database. GUIDs were used to link entities, related attributes, data sources throughout the whole system. User applications can be instantiated using SQL queries based on the manually coded relationships.

Kang and Choi [47] tried to transform BIM data into a database based on a proposed BIM perspective definition (BPD) metadata structure. The BPD metadata structure was used to bind BIM and facility management, and achieve data extraction based on users' queries. Multi-sources data including BIM objects, facility management data and sensor data was extracted, transformed and loaded (ETL) into a DW database based on BPD metadata structure. Data were linked with BIM objects via OBJECT_GUID and expressed as BIM object properties. Users were able to view requested metadata in XML format based on their purposes.

Another example was the IFC-based graph data model for topological queries created by [79]. The research proposed a new schema named graph data model extract analysis and represent topological relationships among 3D objects. Although this new data model did not transform the BIM model into a relational database, it enabled topological queries on building elements (e.g. virtual sensor objects).

#### *4.2.3. Discussion of this approach*

As a new schema or data structure is defined based on the user's perspective, this approach shows its flexibility in expanding users' perspectives while effectively extracting external system data. Time-series data retains in its original database. This approach has the capability to use existing SQL in normal database management system platforms, avoiding rewriting query interface from scratch. However, creating a new data schema requires significant efforts in mapping data which is time-consuming. In addition, manipulation on SQL is necessary if special queries or operations are needed.

Although this approach requires constructing virtual objects to present physical sensors manually, it is more flexible for complex projects with complicated spatial context and a large number of sensors. The reason is that a new schema or data structure is designed based on the user's perspective. Exporting entire complex IFC data into a queryable structure is unnecessary. Compared to using existing BIM tool APIs, this method requires more expertise in language design, IFC, database and programming knowledge.

### *4.3. Create a new query language*

#### *4.3.1. Description of this approach*

Another approach identified from reviewed papers is to create a new query language to query sensor data over BIM models or IFC models instead of using SQL. As shown in Fig. 3**.** the newly developed query language is used to developing queries that process time-series data.

#### *4.3.2. Examples of this approach*

One example could be found in Mazairac and Beetz's [80] study. They proposed a domain-specific query language named BIMQL to select and partially modify IFC-based BIM models. BIMQL allowed selection of objects and attributes based on schema names or arbitrary properties for example IfcSensor. However, this method had a limitation in query real-time sensor data. The language was developed to query IFC based BIM model, only static sensor information that stored in IFC-based BIM model can be queried. Since it is almost impossible to transform real-time sensor data into IFC format and store in the BIM model, this solution had a limitation in the integration of real-time

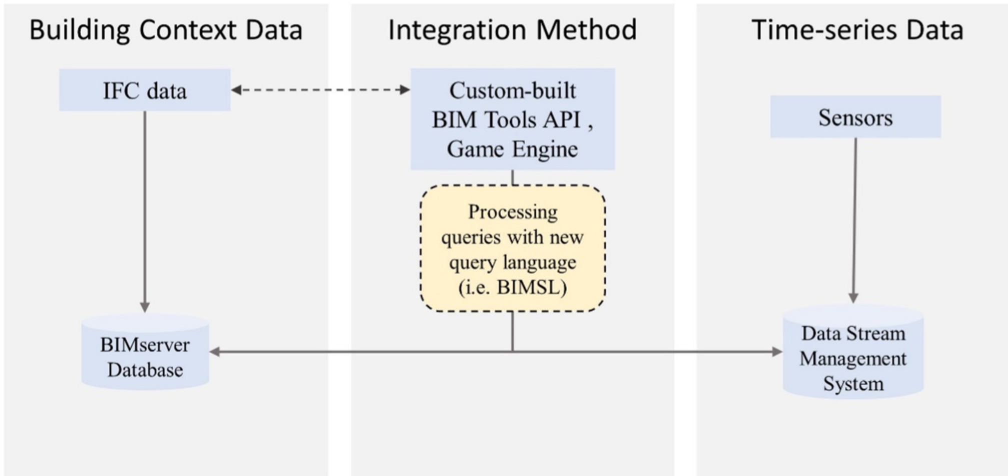


**Fig. 3.** Create a new query language.

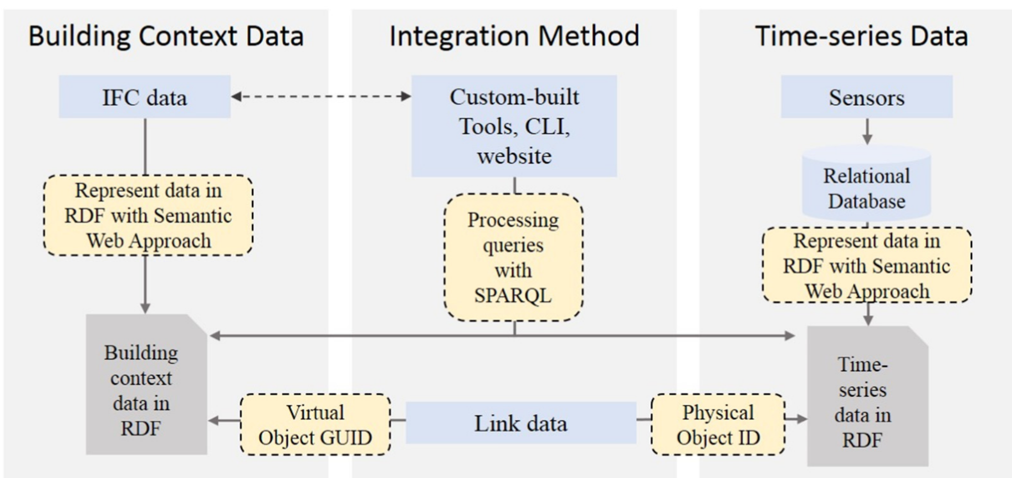


**Fig. 4.** Using semantic web technologies.

sensor data with BIM.

This problem was noticed by Alves et al. [81], so that they created another domain-specific query language named BIMSL. The implementation of the BIMSL language was through a custom-developed API named BIMSL API. BIMSL queries contained both contextual information query and dynamic component related to time-series data. While the contextual information query could be directly fed to the BIMserver database, the real-time data query utilized the open-source Java-based Esper engine for event stream processing. Esper software has its own query language named event processing language (EPL) which is a SQL-standard language, the dynamic component of BIMSL invoked EPL queries to return real-time sensor readings.

#### 4.3.3. Discussion of this approach

The purpose of developing a new query language over time-series sensor data is steadfast, so the advantage in expressiveness and ease of use is obvious when compared to general purpose language. However, the newly developed query languages either lack real-time sensor data query capability or used external ELP. Moreover, to implement a newly developed query language about real-time sensor data and BIM, a corresponding platform need to be developed at the same time [81]. Furthermore, new query languages that are not standardized may not be widely adopted. There are standardized query languages (e.g. SQL, SPARQL) which have already been maturely implemented to satisfy the query needs. The standardized query languages function more effectively among various tools and users in different domains than new query languages.

This approach is seldom discussed in reviewed articles. This approach retains both contextual data and time-series data in their original form and does not require heavy modeling or data mapping, it can be applied to various kinds of projects. However, it requires knowledge of language design and API programming to realize functions.

### 4.4. Semantic web approach

#### 4.4.1. Description of this approach

In modern AEC processes, data sets such as building geometry and topology data, sensor data, behavior data, geospatial information data, are generated and consumed across building's lifecycle. The integration of BIM and Semantic Web Technologies has the potential to meet the requirements for storing, sharing and using heterogeneous data sets. The key concept is to have those data sets to be represented as or tagged using Resource Description Format (RDF). Linking BIM ontologies e.g. IfcOWL and ontologies in other domain e.g. Smart Appliances Reference ontology (SAREF), Semantic Sensor Network (SSN) for sensor devices domain is an effective approach for BIM and IoT device integration.

This approach requires both building context data and time-series sensor data to be represented into a homogenous format (see Fig. 4.). The basic steps are listed as follows: i) represent contextual information including building context data, sensor information and other soft building information into a web interchanging standard named RDF using semantic web approach; ii). Sensor collected time-series data is extracted from the relational database and represented to RDF format using semantic web approach; iii). Linking data silos across different domains via unique identification; iv). Conduct contextual building information queries or real-time sensor data queries using an RDF query language named SPARQL; v). Query results can be shown on applications in different forms such as Command Line interface (CLI), dashboards, GUI, API, and other tools.

#### 4.4.2. Examples of this approach

The ontology framework for intelligent sensor-based building monitoring fitted into this approach [55]. The framework named OntoFM contained a building ontology based on IFC, a sensors ontology generated from OntoSensor and a general-purpose ontology for domain-independent concepts capture. IFC was used to represent building geometry and converted to Web Ontology Language (OWL). SPARQL was used to conduct ontology queries. However, this study focused on the process of ontology development rather than how sensor real-time data was represented into RDF.

A more explicit example from Curry et al. [58] was using RDF and Linked Data in the cloud to integrate cross-domain building data. Building context data representing in IFC was first converted into RDF. All data related to building operations (sensor data) need to be expressed in RDF. Universal Resource Identifiers (URIs) were used to globally identify resources and associate isolated data silos. SPARQL was implemented to query RDF data and resulting data can be visualized via applications. The authors stated that SPARQL queries can be translated from other query languages such as SQL and XQuery, while Hu et al. [57] held an opposite point of view as discussed in Section 4.5.

#### 4.4.3. Discussion of this approach

This approach shows its advantage in linking cross-domain data in a homogeneous format and the ease of interlinking silos. Although there are some existing data silos which can be directly utilized for various purposes, this approach can be problematic. These issues are: i) most of time-series sensor data was stored in well-structured and relatively mature relational database, the way the relational database store sensor data is more effective for query than store sensor data in RDF format; ii) Duplication of data may incur when converting time-series data into RDF; iii) The performance of RDF representing fixed-structured data is inefficient and storage consuming [57].

Although this approach requires modeling virtual objects, knowledge of semantic web technologies and heavy data transformation, it is useful for projects with a broader scope that connects various kind of data sources. Since data silos can be represented in RDF format, this approach extends the possibility to achieve the real concept of IoT, which requires interlinking with the internet through a unified framework. However, heavy data transformation is cumbersome for complex building and BMS with continuous real-time readings.

### 4.5. Hybrid approach: semantic web + relational database

#### 4.5.1. Description of this approach

In this approach, both the Semantic Web and relational databases are used to store cross-domain data. The authors conclude the key steps to implement this approach (see Fig. 5.) as follows: i) represent contextual information including building context data, sensor information, and other soft building information into RDF format using semantic web approach; ii) Retain sensor collected time-series data in the relational database; iii) Map contextual information with time-series data, in particular, time-series data can be referenced using sensor ID described in RDF.

This approach brings two technologies together, hence results in integrated query methods. Contextual information represented in RDF is queried by SPARQL, while time-series data stored in the relational database is queried using SQL. Since contextual information and time-series data are mapped, SQL queries can be created using SPARQL queries on RDF data.

#### 4.5.2. Examples of this approach

Hu et.al [57] introduced a hybrid architecture which integrated building performance data with semantically-described building context data. In this hybrid architecture, contextual building data – typically represented as BIM model or IFC format – converted to RDF using the semantic web approach. Static sensor information such as sensor type, vender, identification was also converted to RDF format using Semantic Sensor Network (SSN) ontology. However, sensor collected time-series data was stored in a relational database and maintained its original form. Time series data (sensor collected data) was then cross-referenced with SSN ontology using sensor ID. In this way, building data and time-series data stayed in their appropriate platform and format. The same approach has also been implemented in another example. McGlinn et al. [59] presented a building energy management solution which used Semantic Web and Relational database technology to integrate BIM, sensor data, and actuator infrastructure. The solution contained a knowledge base as a central integration component of heterogeneous data sources. Building semantic model which represented RDF format was uploaded to a SPARQL server. Application in a proposed interface was used to conduct SPARQL queries about building elements. Instead of converting sensor data into RDF format, sensor data was stored in the relational database and ID-referenced with the semantic model. Sensor monitoring application could query sensors' time-series data via SQL queries.

#### 4.5.3. Discussion of this approach

The highlight of this approach is that different data sources retain their most suitable platforms and formats while achieving interlinking. This approach retains the effectiveness of storing time-series data in the relational model, flexibility to link building contextual data using semantic web approach and query using standardized language without heavy data conversion. The highlight of this approach contributes to several advantages: i) Time-saving: as time-series data still stored in the relational database, duplicating time-series data into RDF format is not necessary; ii) Storage saving: the way that RDF data is stored (triple stores) requires more storage than relational database; iii) Better performance: relational database performs better in data lookup than triple stores [57]; iv) Effective query language: the integrated query method use existing SPARQL and SQL to query RDF data and sensor data respectively.

This approach is one of the most promising methods to facilitate IoT deployment in the construction industry. It retains different data sources in their most suitable platforms and formats while achieving interlinking with the Internet to achieve the real concept of IoT. It is suitable for different kinds of projects without heavy data conversion. As this approach utilized standardized data formats and query language, it offers an opportunity to integrate other domain data sources to extend project scope.

## 5. Future research direction

As the discussion for each application domain and integration method is explained in Section 3 and Section 4, this section focuses on proposing future research directions based on existing issues detected. Apart from reviewed articles, relevant books, web pages, papers from Springer, AMC digital library and IEEE Xplore library were also adding into account for future research directions. Some potential research directions related to BIM and IoT devices integration are proposed as follows:

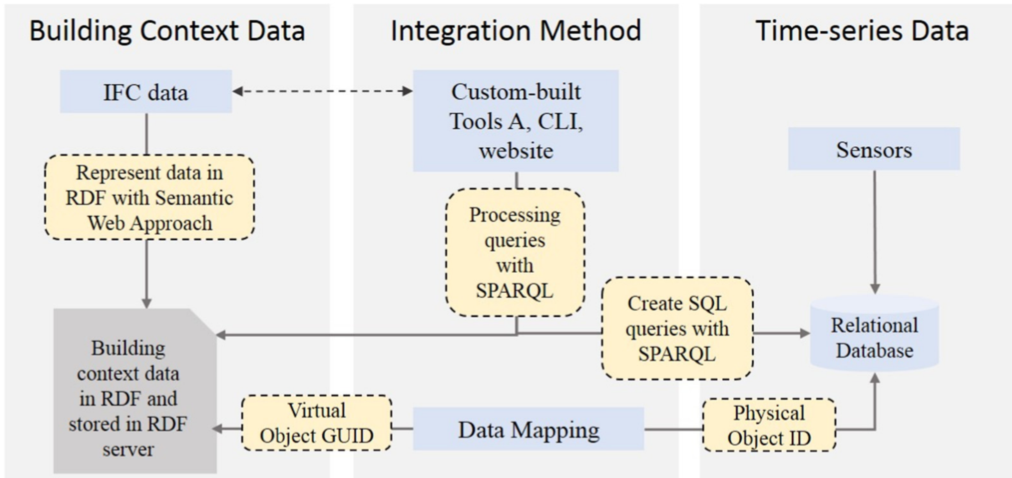


**Fig. 5.** Hybrid approach: semantic web + relational database.

### 5.1. Service-Oriented-Architecture (SOA) and web services for BIM and IoT integration

SOA acts as the premier integration and architecture framework for the complex and heterogeneous computing environment. It uses the concept of software design where various services can be combined to provide functionalities of a large application through a communication protocol over networks. The idea starts with combining various services such as visualizing BIM model, querying real-time sensor data, analyzing sensor readings and other IoT applications. The SOA unique features such as – service composition, service discovery, asset wrapping, model-driven implementation, loosely coupled and platform independent – enable information flow, organizational flexibility, and scalability while maintaining internal functionality for each service. The reusability of services can extend and combine other applications with existing services so that software development cost and management time can be decreased. These features can largely benefit the integration of BIM with IoT devices and further extend future applications. Although there are existing research on proposing system architectures for BIM and IoT devices integration [67,73,82], these system architectures are not supposed to be one-size-fits-all solution. There are still abundant applications of BIM and IoT integration that need new designs of SOA, web services, and integration methods. Web services are building blocks for SOA's service layer. Loosely coupled web services amalgamate semantic information in BIM and feed from sensor networks with various SOA design patterns. The Representational State Transfer (REST) architecture style is often used to utilize and interact with IoT nodes [83]. The design patterns of SOA and Web services offer opportunities for making BIM stateful (e.g. real-time, information update). The potential applications are:

#### 5.1.1. Real-time model update based on IoT device readings

BIMs provide rich semantic information about building elements but fail to display element states and indoor conditions. Static models become real-time information models if BIM entities' states can be updated by real-time IoT devices' readings. A new design of SOA patterns using RESTful Web Services named RESTful endpoint would be a potential solution to enable BIM entities' status update based on IoT devices' readings. A RESTful endpoint, on one hand, receives readings from IoT nodes, on the other hand, conducts create/read/update/delete (CRUD) operations in the BIM data layer [83]. How to utilize different SOA design patterns to enable BIM entities' status update based on sensor readings will be research to be investigated.

#### 5.1.2. Information acquisition and control - a two-way-interaction

Most of the existing research have already achieved reaching information residing in BIMs and visualize IoT devices readings from models. This multi-source information acquisition and fusion can be done with SOA pattern which utilizes a RESTful service façade (web services) [83]. However, current research only realized one-way interaction (e.g. energy monitoring, IEQ monitoring, building performance monitoring). Only a few studies have explored human-building interaction for cognitive buildings [32,84]. No two-way interaction that involves control of actuators through BIMs has been discovered in the reviewed articles. When combining with control on actuators through Web services, information acquired from BIM and IoT devices offers opportunities for smart cognitive buildings and human-building interaction like emergency response and disaster evacuation. Potential research problems regarding information acquisition and control will be: How to create SOA patterns for information acquisition and control interactions? How these SOA patterns can benefit advanced building technologies like cognitive building and human-building interaction?

#### 5.1.3. Ubiquitous monitoring and crowd sourcing monitoring

For future smart cities, information residing in BIMs are valuable. City modeling and management application like smart city platform and city portal can absorb BIMs and IoT. Thousands of APIs, BIMs, IoT devices will involve in SOA design patterns for smart cities. Potential solutions utilizing a RESTful service named Callback Responder can blend with traditional SOA patterns to realize ubiquitous monitoring and crowdsourcing monitoring. Ubiquitous monitoring continuously providing information about building elements and IoT devices regardless of the situation in a 24/7 manner. When an event happens, crowd-sourcing monitoring can produce information about this event and physical condition by IoT devices near the event site [83]. Rich spatial and temporal information gathered from the integrated BIM, GIS and IoT devices is efficacious for city modeling and management applications. How to blend potential solutions like RESTful service with traditional SOA patterns to realize ubiquitous monitoring and crowdsourcing monitoring that can be applied to application like smart city energy management [63], urban-scaled facility management and emergency response [50], flood analysis, transportation monitoring and indoor/outdoor positioning [22] is worth exploring.

#### 5.1.4. Integration with other cutting-edge technologies

New technologies such as VR, AR, mixed reality (MR) are leading to greater integration across BIM and IoT. Adding VR/AR/MR web-based application framework like the mobile agent to the SOA design patterns, digital models can be superimposed into the real world for web-based AR applications [85]. A large number of applications using the combination of VR and AR can support effective information flow and display [31]. For example, using AR, BIM and sensors can be beneficial to automatic schedule update [86], safety inspection [87], smart building design [88,89], facility management, construction lifecycle management, smart learning environment for educational institutions. Hence, the study on adding VR/AR/MR web-based application frameworks to SOA patterns to achieve integration between IoT devices and BIM for various applications will continue to be a future direction of interest.

### 5.2. Standards for information integration and management in the AEC industry

With the emergence of new technologies like the web of data and IoT, information diversity and overload will happen [40]. Heterogeneous data sources among different stakeholders, data across different domains, data throughout all phase of lifecycle need to be well handled for different purposes [90]. Furthermore, as data amount drastically increases over time, it is important to ensure information consistency, traceability, and long-term archiving [91]. A standardization way to integrate and manage data for BIM and IoT integration arise to be a problem [59]. Some effort has been made by the U.S. Department of Commerce's National Institute of Standards and Technology (NIST) by releasing IoT-Enabled Smart (IES) Cities Framework and Framework for Cyber-Physical System (CPS). The continuous developing frameworks aim to develop a shared understanding of CPS and smart cities including their foundational concepts and unique dimensions such as common language, taxonomy, architectural principles. These frameworks are useful for exchanging ideas, integrating research across domains and to develop new IoT applications with BIM. However, these framework does not fully tackle above mentioned issues [92–94]. Yet, hardly any approach is available for this industry that i) provides a comprehensive overview of data sets that need to be handled in AEC industry; ii) evaluates the effectiveness of different methods that query and represent cross-domain data sets. Semantic web technology is claimed to be a solution, which integrates concepts from knowledge representation and reasoning (KRR). KRR aims to represent data in a form that a computer system can utilize and solve problems through finding logic, rules, and relationships. However, the performance of the query, knowledge representation and reasoning in dealing with these data cannot be evaluated [95]; iii) globally manages collected data, processes information, and accumulates knowledge; iv) assures seamless information flow across different domains throughout lifecycle [91].

Without standards for information integration and management, it is costly and time consuming to sort large and heterogeneous data sets into usable order [51]. As a result, poorly designed and implemented information integration and management system can hinder the future development of IoT and BIM-enabled smart environment. As a fundamental step for future data integration related research, a potential question will be how information integration and management process can be standardized to facilitate effective data flow for various purposes, industry, time phase, IoT applications, and future technologies?

### 5.3. Interoperability: IoT devices-BIM-smart cities

Although there is plenty of on-going research on solving interoperability issues among IoT devices and BIM, the interoperability issues among IoT paradigm and AEC industry still remain [31].

Firstly, there are diverse data schemas for devices, buildings, and cities. On IoT device level, there are many data communication protocols such as BACnet, OPC, LonWorks, EIB/KNX and MODBUS that play key roles for information exchange between different sensors and subsystems in BAS. While IFC is the most commonly known data exchange schema for BIM, CityGML dominates the city-level data interoperability. Some effort has been made in data schemas mapping. BuildingSmart has partially mapped BACnet and OPC objects with IFC Entities in IFC 2 × 4 RC1. In terms of interoperability between CityGML and IFC, research work like [96,97] has mapped some CityGML objects with IFC entities. However, i) only part of the communication protocol's objects has been mapped to IFC entities; ii) neither object's attributes or services have been mapped; iii) communication protocols are updating, continuous data mapping is necessary; iv) no device level data has been mapped to city level; v) data mapping between all these schemas and protocols are heavy, various application requires distinguished data, standard data models views for different applications need to be generated to achieve efficient data exchange.; vi) Current CityGML and IFC integration is not sufficient to represent the entire built environment lifecycle [98], so that some IoT applications cannot be realized. Hence, a potential research question can be how different data model, schema, standards and protocols like IoT device protocols, open BIM standards, and city-scale data model can be integrated to solve interoperability issues for smart devices, smart buildings, and smart cities.

Furthermore, the AEC industry is part of the IoT-enabled smart city system. Information is more valuable when exchanged across systems in different domains inside the complete smart city ecosystem on the Internet [99]. The possibility to get access to the information from all these schemas and protocols through web-service (mentioned in Section 5.1) will arouse a great interest. The Open Geospatial Consortium (OCG) and the World Wide Web Consortium (W3C) developed some interoperability interfaces and metadata encodings to integrate heterogeneous sensor webs into the Internet. For example, the OGC's Sensor Web Enablement (SWE) including Sensor Model Language (SensorML), Observations and Measurements (O&M), Sensor Observation Service (SOS), Transducer Model Language (TML) and the W3C's Semantic Sensor Network ontology [32]. How to map between different data schemas and enable cloud-based smart environment is a key step for future integration of BIM and IoT. Potential research directions can focus on current limitations, including: i) differences in vocabulary, context, and semantic meaning in various domains; ii) differences in the data structure like data attributes and data formats among these schemas, IoT devices' communication protocols, and web-services' protocols.

### 5.4. Cloud computing

The concept of IoT is not just related to IoT devices like sensor and actuators, the key concern is the interconnection of sensing and actuating devices providing information sharing through the internet. Cloud computing involves hosting computing services over the Internet and enables connecting different IoT devices to existing Internet infrastructure [82]. Cloud computing has been widely adopted in the AEC industry as it supports some BIM tools applications and storage. Most of the current sensors and BIM integration research are not yet connected with the cloud, hence further exploration in cloud computing for IoT and BIM integration is essential. With IoT devices integration with BIM, some potential problems are worth exploring.

#### 5.4.1. Enable real-time big data analytics

Recently, people start focusing on big data techniques in the construction industry. These techniques such as statistics, data mining, and warehousing, machine learning infused into the context of the construction industry [100]. Based on BIM and IoT devices collected data, big data techniques can be applied to automated decision making that enables intelligent monitoring and actuation. Current research is focusing on how the massive AEC data can leverage artificial intelligence algorithms and big data techniques in potential areas such as generating the optimal solution based on sensor data [59,101,102], assisting real-time operation [14,86] and problem identification [26,103]. Future research should also focus on real-time big data analytics and cloud-based big data management solutions for extensive real-time data from

IoT devices and AEC data resides in BIM.

To enable real-time big data analytics, information acquired needs to be stored in an online storage which can be accessed from multiple IoT devices. Design patterns such as Message-Based Cloud Update and On-Demand Cloud Update for SOA can effectively solve BIM and multiple IoT device information cloud storage and information querying issue [83]. Web services and cloud services need to be combined to perform effective managing and processing of data.

In the IoT cloud paradigm, there is no perfect big data management solution for the cloud [93]. One important factor which hinders the quality of service, security and privacy is that data integrity is not guaranteed. Combining BIM data with sensor big data will exacerbate this issue. Some research work listed in [104] tried to propose solutions to collect and managing sensors data in the smart building in the IoT environment, but the solutions are still in infancy.

#### 5.4.2. Create standards for the BIM-IoT cloud

tHe lack of standards is considered to be an open issue for IoT and Cloud paradigm. Although some research tried to standardize IoT and Cloud paradigms, there is no clear standard protocols, architecture, and APIs that interconnect various IoT devices and services in the Cloud [93]. With BIM data infused into IoT and Cloud paradigm, the problem further extends to AEC industry. A general standard must be established to connect hardware, BIM data, communication protocols, ontologies, semantic rules, middleware and applications [94] as a future research direction.

#### 5.4.3. BIM and IoT data storage

Cloud-based storage solutions became increasingly popular since 2012 [1]. The massive data amount coming from IoT deceives and BIMs will arouse problems in cloud-based data storage. Future research should be to conducted to tackle existing issues, as follows: i) current commercial BIM clouds like A360 and proposed cloud-based BIM systems [92] are focused on data sharing, collaboration, analyzation, and visualization of BIMs. However, these solutions do not involve sensor data storage, future research is needed to explore how to link sensor data with BIMs in the cloud; ii) what are the optimal solutions to store both sensor data and BIM data in an appropriate format (without heavy data conversion) with current cloud-based data storage like NoSQL database? The open storage solution should preserve integrated information which can be shared with other industries [90]; iii) research is needed to investigate how to transfer data from IoT devices to the server side with the timestamp to enable reconstruction and processing that does not arouse the problem of transferring timing [93]; iv) how to update continuous scene of IoT enabled BIM models stored in the cloud? Game industry solves scenes updating through patches and downloadable content (DLC). A similar patching procedure is necessary to continue updating BIM-IoT models when new buildings or devices are connecting [105].

#### 5.4.4. Using cloud-based IoT integration portal for BIM

There were a few studies that used IoT clouds/platform/services like Eclipse IoT, Xively, ThingSpeak and other technology listed in [83] to integrate BIMs. These integration portals enable the machine-to-machine integration, visualization of sensor data, user interaction with actuators, service development and web resource update based on sensor data. These cloud-based integration portals together with cloud storage will facilitate BIM applications integration in more convenient ways. Future studies can explore how to utilize these cloud-based IoT integration portal with BIM for different applications.

#### 5.4.5. Create general integration methodology

even though several applications were built around IoT, BIM, and Cloud [12,46,58,103], little effort has been made to produce a universal methodology which integrates IoT, BIM and Cloud systems [93]. A common workflow, generic architecture or platform will be beneficial for building applications which share common requirements and characteristics for the future.

#### 5.4.6. Other issues

Some other issues, which have been mentioned in the computing domain, can be extended to BIM and IoT integration in the cloud and can be the subject of future studies: i). security and privacy [10]; ii) pricing and billing; iii) network and communication; iv) scalability and flexibility; v) IoT devices performance management [93].

## 6. Conclusion

This paper contributes to the body of knowledge by presenting an in-depth review of BIM and IoT devices integration in the AEC industry from domain application perspective and integration methodologies, and by shedding lights on current limitations and prominent areas for future research and development. Altogether, 97 papers from 14 AEC related journals and databases in other industry over the last decade were reviewed. The authors analyzed these articles based on various domains of use namely Construction Operation and Monitoring, H&S Management, Construction Logistic & Management, and FM. The authors summarized 5 integration methods with description, examples, and discussion. These integration methods are utilizing BIM tools' APIs and relational database, transform BIM data into a relational database using new data schema, create new query language, using semantic web technologies and hybrid approach. Based on the observed limitations, the authors concluded some prominent future research directions for BIM and IoT devices integration. Potential research directions include creating SOA patterns and web services for BIM and IoT integration, establishing information integration & management standards, solving interoperability issue and cloud computing. The AEC industry cannot escape from the pervasive digital revolution. The great potential of BIM, IoT and other emerging technologies can be foreseen.

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