Abstract

Buildings Automation Systems (BAS) are ubiquitous in contemporary buildings, both monitoring building conditions and managing the building system control points. At present, these controls are prescriptive and pre-determined by the design team, rather than responsive to actual building performance. These are further limited by prescribed logic, possess only rudimentary visualizations, and lack broader system integration capabilities. Advances in machine learning, edge analytics, data management systems, and Facility Management-enabled Building Information Models (FM-BIMs) permit a novel approach: cloud-hosted building management. This paper presents an integration technique for mapping the data from a building Internet of Things (IoT) sensor network to an FM-BIM. The sensor data naming convention and timeseries analysis strategies integrated into the data structure are discussed and presented, including the use of a 3D nested list to permit timeseries data to be mapped to the FM-BIM and readily visualized. The developed approach is presented through a case study of an office living lab consisting of a local sensor network mimicking a BAS, which streams to a cloud server via a virtual private network connection. The resultant data structure and key visualizations are presented to demonstrate the value of this approach, which permits the end-user to select the desired timeframe for visualization and readily step through the spatio-temporal building performance data.

1 Introduction

Parametric design tools, Building Information Models (BIMs), digital fabrication, and virtual construction scheduling generate a wealth of digital data on the built environment through the design and construction phases. As a building is put into operation, the volume of this information increases exponentially and Facility Management-enabled BIMs (FM-BIMs) are...
of specific value in this digital context, having demonstrated time- and cost-savings benefits
for a breadth of facility management activities [1, 2, 3, 4]. When Computer Aided Facility
Management (CAFM) data is integrated into a BIM, it supports operational uses such as
utility cost reductions, comfort management, space optimization, improved inventory
management, and energy management [4]. Over time, however, the volume of this
information becomes extremely large and cumbersome, as the operational data requires a
high level of effort for BIM maintenance and integration [3]. While seen as highly promising
in facility management [3, 2] BIMs are still used as standalone information systems by
building stakeholders. By integrating systems (ex: IoT sensor network and FM-BIM), and
working toward aggregating data in a single model, negative effects of standalone,
information systems can be minimized. A central FM-BIM facilitates the integration of all
building data sources, to be used through the building project and operational lifecycle.
This paper presents a database architecture integrating IoT sensor data to an FM-BIM, with a
specific focus on the pre-processing, effective storage, and mapping of timeseries data. A
case study of the proposed integration on a sensor data stream from a test-bed office is
presented, along with appropriate batch analytics and queries for the sensor data stream. In
this case study, each of the sensor data streams are mapped to fields within the FM-BIM
using Dynamo, a Visual Programming Language (VPL). Sensor data values for desired time
frames can be selected by the user, permitting a variety of methods to navigate and visualize
this data. The research offers a database architecture which could act as the data source for
cloud based Smart and Continuous Commissioning (SCCx), an accessible portal to the BAS
sensor data typically hidden within a proprietary system, and data analytics and visualization
strategies. Together, these facilitate FM-BIM Digital Twins that could be used by Facility
Managers (FMs) to test and plan maintenance projects, monitor, infer, and predict building
conditions as a function of outdoor weather conditions and system settings. These insights
can then be used within a SCCx approach to optimize building performance in near-real time.

2 Literature Review

Three challenges must be overcome to link an FM-BIM with live IoT data. First, a suitable
architecture to support the operational IoT data – both static and dynamic - must be defined
[5]. Second, the integration method [6] must be determined. Finally, the IoT data to integrate
must be identified and clearly defined [7].
2.1 Architecture for IoT – BIM Integration

A challenge in integrating IoT data to an FM-BIM is their heterogeneity. In general, FM-BIMs contain primarily semantic, geometric, and topographical (static) data, while IoT sensor data streams are timeseries (dynamic) in nature [5, 8]. The most common integration technique for static and dynamic data is referred to as linked data [9, 10, 11]. This approach stores each building data source separately, effectively creating a data lake that is accessible through a common data management system [12]. In the case of this research, static spatial data is hosted in the BIM and dynamics in the IoT datastore. Frequently this approach is used with links to decoupled ontology (static semantic data) and IoT timeseries (dynamic) database sets; a query processor then makes this data accessible to applications [11, 13]. In other instances, standardized naming formats can be used to create a link directly between the IoT and BIM data points [14].

The use of an ontology acting as a proxy to link IoT and Building Monitoring System (BMS) data and BIM has previously been explored, this includes the use of the Semantic Sensor Network (SSN) ontology [15] and a custom Building Automation and Control Systems (BACS) ontology [16]. The SSN ontology is a “generic language to describe sensor assets” [17] and has been used to describe BMS data with semantic tags such as “building”, “room”, and “device” and relate them using the “hasPhysicalProperty”, and “sensingMethodUsed” attributes so that it can be linked to the BIM [15]. Some of the SSN tags are custom extensions, needed to create the link between the SSN ontology and BIM, additionally a large amount of semantic data needs to be specified manually for each point in the BMS. Further, because SSN is a broad approach rather than one developed specifically for the building domain, there is no functionality to map SSN ontology data to the BIM as represented in open format (Industry Foundation Class, IFC). As such, an initial mapping schema must also be created to support the linked data approach. The BACS ontology is a new ontology developed by reusing existing ontologies such as SSN, Building Topology Ontology (BOT), Sensor Observation Sample and Actuator (SOSA), a fragment of the ifcOWL ontology (ifcmr), and others. Within BACS, BOT is used to describe spatial building data such as “floor”, “space” and “element”, SOSA is used to describe “Sensors” and other “FeatureofInterest” within the IoT network, and ifcmr is used to represent sensors readings as Values” [16]. The resulting ontology is robust and covers semantic data required to link BMS, IoT, and BIM data. The reuse of existing ontologies resolves issues of using the SSN
ontology alone, the SSN ontology does not need to be extended, and the inclusion of ifcimr indicates that linking the BIM IFC would be possible. However, the need to manually map ontology tags to data points remains unresolved at this time.

Ontologies that have not been directly used to link BMS/IoT data to BIM but could conceivably be used for the application include Brick [18] and the Haystack Tagging Ontology (HT0) [19]. The Brick ontology is specifically designed to describe building HVAC system data. It has a hierarchical design, where tags of each subsequent layer of the ontology provide more detail, for example a “Fan” is part of an “AHU” which is part of “HVAC”, etc. [18], which is similar in structure to a traditional BMS. The availability of some locational data in the Brick ontology further makes it a good candidate to link BMS and BIM data. HOT expands the Haystack ontology [20], which has an embedded, but incomplete, tagging approach. HOT uses Semantic Web technologies (RDF, OWL, SPARQL) to address gaps in Haystack from an IoT perspective; notably the requirement for computational power at the IoT device, the incompatibility of the API with standard web approaches such as REST and JSON, and the lack of a formal representation that can limit scalability [19].

The use of an ontology acting as a link proxy between BMS/IoT and BIM presents the issue of data redundancy. The ontology tags facilitating the link are related to spatial or contextual building information, however FM-BIMs already store this data inherently. This renders the new ontology tags and associated supplementary data redundant. Directly linking BMS/IoT to BIM using standardized naming formats is a much simpler approach. Within the construction sector, the Constuction-Operations Building information exchange protocol (COBie) [21] was developed to develop such a standard naming format to facilitate the integration of Computerized Maintenance Management System data to BIM. Research aiming to leverage this format to automatically create these links and circumvent manual work had limited success due to interoperability issues with real world application [7]. Despite this limitation, there have been industry examples where systems conforming to a parsable and interpretable naming convention enable direct linking of data For example, the taxonomy present in a data point tag can indicate the space, system, and equipment a data point is related to within the BIM [14]. This directly linked data architecture requires no manual tagging; instead, the integration and connection between BMS/IoT data stores and other datasets define the resultant input data structure.
2.2 Integrating to FM-BIM

Central to both architectures approaches – either directly linked, or linked though an ontology – the use of a query processor is required to retrieve the appropriate subset of summarized timeseries data to be imported to the FM-BIM. This is because a link exists between IoT and BIM data point in either architecture, however this research highlights the value of presenting summarized IoT rather than raw timeseries. Two query processors have been developed to address this integration using an ontology linked approach: HodDB [22] and ForTÉ [23]. HodDB contains a query processor, which accepts SPARQL queries and processes, first accessing Brick ontology data is stored in a LevelDB, and then the timeseries BTrDB database [22]. Query time is very fast using HodDB due to the use of specific database and ontology types used. ForTÉ, is a more flexible query processor, while it also uses SPARQL, it can be used for any database types and ontology [23]. Selecting the appropriate query processor when integrating IoT timeseries data to an FM-BIM if using and ontology linked approach has large implications on the overall integration time when a user is requesting multiple visualizations within the FM-BIM during a single session, as can be expected in the use of an FM-BIM [22].

As noted previously, building information from IoT output can be integrated to FM-BIMs using the directly linked data architecture, where queries are written using the know naming convention to extract summary timeseries data from the IoT database. Preidel et al. [6] explored the use of VPLs for the purpose of querying a directly linked data architecture and developed two task-specific VPL query engines: (1) QL4BIM for querying BIM semantic data represented in IFC; and (2) VCCL for code compliance checking. Neither of these are optimized for querying IoT summarized data however VPLs are easily learned and implemented by users and are well-integrated into some BIM software, for example Dynamo for Revit.

Once summary timeseries data is available, VPLs such as Dynamo for Revit can be used to integrate timeseries IoT data and CAFM data to BIM, for example [24, 25]. Central to these approaches are the parsing and cross-referencing of unique identifiers for individual elements that can be matched between datasets. This is critical when using a directly linked data architecture; in such approaches, the integration method is uniquely responsible for mapping uniquely identified data points. Conversely, in the ontology linked approach the semantic tags
associated with the timeseries data also aid in mapping IoT data points to the BIM. An alternative approach to VPLs is the Extract Transform Load (ETL) tool, which was developed to handle multiple data sources to populate an FM-BIM, however this tool did not consider timeseries FM data sources [26].

2.3 Summary Data for Integration

The need for appropriate “data resolutions” refers to the need for summarized timeseries data with larger time granularity within an FM-BIM as opposed to the raw, fine granularity collected by sensors, actuators and meters [27]. Independent of the architecture used – whether ontology linked or directly linked – summarized data is required based on the desired visualizations and stored in the timeseries database along with the raw IoT data. For cases where a directly-linked architecture is used, the summary data point tag would also need to be available to the query engine, whereas if using an ontology-linked architecture, the summary nodes would have to be available in the ontology to permit summary data discovery during timeseries data queries. An example of the former is the work of Gerrish [27], who proposed a directly-linked data architecture approach to integrating IoT data to BIM using a built in IFC node “PerformanceMetric”, noting that its connection to IFC sensor nodes would facilitate direct import to the BIM, though this is not yet possible in the IFC schema. An example of the latter is the Brick ontology, which was designed to permit the inclusion of summarized data tags [18].

Looking beyond sensor data streaming, there has been a significant body of work undertaken to identify information required by FM to support building operations [2, 3, 28]. In one example [29], IoT data from the Building Management System (BMS) was used to support building operations and maintenance. The integration and visualization of complex timeseries data, for example timeseries visualization within 4D BIM, has been shown to allow FM users to synthesize more complex data than was previously possible [30]. Motamedi et al [30] demonstrated the value of visualizations using icons and symbols, the inclusion of 3D building components, and color coding zones/spaces to support root cause failure detection.

2.4 Summary of Literature Review Findings

The use of standardized naming conventions with the linked data approach offer significant benefits for IoT-BIM integration, as evidenced by the literature, reducing data redundancy and facilitating implementation by avoiding the ontology mapping step. The use of consistent data tags between the building and BIM further support direct transfer, reducing the work
required for implementation of IoT to FM-BIM. Previous research [5, 24, 25], demonstrates the value of Dynamo to integrate such tagged timeseries data stores when using a linked database structure. This approach suffers from a lack of optimization for querying and visualization and an alternative approach to circumvent this issue is presented herein. Further, timeseries data summarization to the appropriate granularity and their navigation over a time window are required to create visualizations supporting higher-level analytical decision making for FM.

Despite the significant research to date on the topic of IoT-BIM integration, there remains a paucity of literature regarding data streaming from sensor networks, particularly with regard to the mapping of timeseries summary information to an FM-BIM [28]. This research paper aims to fill this gap by presenting a complete IoT data acquisition, management, and BIM mapping integration method in the form of a linked data architecture.

3 Methodology

An IoT sensor data integration to FM-BIM requires three data processing components: (1) a data acquisition and ingestion system; (2) batch analytics, and (3) an integration engine. The data acquisition and ingestion system collects the raw sensor data and transfers it to a cloud database. The batch analytics summarize the data using a set of defined business rules to permit faster data querying, and the queried data is then mapped to the FM-BIM using the integration engine. Figure 1 shows how these processes act on the various system elements (sensor points, database of historical records, and the FM-BIM). This approach follows from the findings cited in the literature review.

*Figure 1: System architecture for IoT data streaming to FM-BIM*
3.1 Data Acquisition and Ingestion

In order to provide an efficient and flexible architecture, minimal processing should occur during acquisition and ingestion. Cloud based environments offer the best environment for data processing given their computational power. Data point values are given tags, unique identifiers stored as string of characters in the database system, organized in a hierarchical schema where the building is broken into successively more granular components. The hierarchy for a building is shown in Figure 2. For controls system mapping, relevant elements are assigned a Building Automation System Identifier (BASID), which may be either the equipment name or room number depending on the element type. Each sensor point type is then assigned a PointID. The resultant nomenclature concatenates the building, system, element, and point names to create both a machine-parsable and human interpretable ID, allowing FM users to interpret the relevance of each IoT point to the building.

Controllers accept sensor data and periodically push it to a local buffer that synchronizes the timeseries data. This is a more efficient approach than synchronizing each data point stream directly in the buffer, accommodating different measurement timescales while avoiding the need for multiple network connections. A streamer then pulls a larger set of synchronized data from the buffer and inserts in the cloud datastore representing a longer timeframe. The controller will allow data to be streamed more quickly from IoT data point to the FM-BIM, giving FM users a near live view of building operations [5]. Recommendations for software and hardware to be used at each step of the IoT data acquisition and ingestion as well as a schematic of the process can be seen in Figure 3.

Figure 2 Database Hierarchical Schema – general (left) and controls-specific implementation in this paper (right)

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Because a hierarchical schema is used for tagging data points in both the timeseries data stores and FM-BIM, a variety of timestep granularities can be supported for visualization. This is achieved by aggregating run time queries using SPARK, a process further described in section 3.2. Because the timeseries database point data is partitioned by element, point, and month, individual points (POINTIDs) can be decoupled from their element groups (BASIDs), i.e. a data row can be created for individual BUILD.SYS.BASID.POINTID series to permit batch analytics to be run in parallel, increasing computational efficiency. It should be noted that in this approach row size restrictions of a NonSQL database such as Cassandra forced the point data be partitioned by month. Figure 4 visualizes IoT data storage within a Cassandra a nonSQL database. Time-date stamps are not used in Cassandra database, a count value is used instead and gives relatively to each timestep from the beginning to the end of the month. Because time is represented on this scale, it increases the importance of the buffer to synchronize timeseries data before pushing to the streamer.
Once raw data has been acquired and streamed to the cloud-based database, timeseries analytics can run in batch jobs to summarize data to single human readable metrics, which is desirable to simplify interpretation by FM users. The cloud-hosted environment is the appropriate place to run these analytics due to its stability, high capacity, and computational power, all of which are required to achieve the high complexity summary calculations. Figure 5 shows the general process using Spark for batch analytics. In this process, the batch analytics are run on a Spark processor and apply business logic. The returned results are then returned to the database for insertion to summary tables on the database.

### 3.2.1 Summarization Strategies

![Batch Analytics Diagram](image)

*Figure 5: Batch analytics process*
Appropriate timeseries analysis methods depend greatly on the desired FM-BIM visualizations. Summarization functions, including but not limited to counts, averages, and min/max values can be integrated to an FM-BIM. In addition to selecting the most appropriate summarization function, the appropriate time granularity for reporting must also be selected. Time granularity refers to the amount of time be considered in a summary value, ex: one-hours’ worth of data, four-hours, one-days, one-months, etc. Figure 6 gives an example of temperature data being summarized from the sensor data – read in five-second intervals – to daily maximum values.

Average values, desired for generalized result reporting rather than event counts, can be applied to any point data that are normally distributed. If sensor data is not normally distributed an average will not provide an accurate representation of conditions. Batch analytics will calculate the average value for each sensor at each hour, as well as identify the minimum and maximum value for the sensor within the hour.

Counts can be used as an effective means to visualize building deficiencies and therefore deficiency percent changes over time. Counts are an appropriate method of timeseries analysis when point threshold values and time delays before a point value can be considered...
deficient are known. If counts are employed without time delays or specific threshold values are not known, they will transform data rather than effectively summarizing it. In the context of IoT sensor data, hierarchical alarms defined by a BAS system offer time delay and threshold values to be used as count conditions for system and building deficiencies. ASHRAE Guideline 36 mandates hierarchical alarms, where high-level alarms indicate only minor deficiencies, and low-level alarms indicate major system deficiencies. This approach can also be applied to timeseries IoT data analysis so that building stakeholders can visualize system and room deficiencies in the FM-BIM.

### 3.3 Integration

The integration of the IoT data to the FM-BIM consists of three key steps, summarized in Figure 7.

![Integration Diagram](image)

**Figure 7: IoT Sensor Database to FM-BIM integration process**

Within the VPL, there are three intermediate steps required to support FM-BIM mapping. First, a .csv file (format in Table 1) is passed to the VPL using a script. This file must be maintained from the summary tables, a separate file is required for each desired visualization summary type. This file is updated regularly as batch analytics are run with new incoming sensor data and saved with a fixed filename. This .csv file is a 2D list, columns headed with BASID and rows with timestamp inferred on querying the Cassandra datastore and reading the time value. Cells contain ordered comma delimited point values for the intersecting ID and timestamp. Second, the Dynamo script imports the .csv file, sorts it to match the FM-BIM element ordering, and creates a 3D list by converting the ordered point values for each BASID from a string to a list. Each index of the list contains a Revit element ID ordered list of point values. The user selects the desired time for display in the FM-BIM using a slider, which inputs to a function that filters the transposed 3D list using a python script and outputs
a 2D further transposed list of sensor data for each BASID at the specified timestep. Finally, this list is mapped to the FM-BIM using the Dynamo `Element.SetParameterByName` node, updating the parameter in Revit of the element.

Table 1: Sample CSV format for BAS mapping to BIM (truncated)

| BASID1  | BASID2  |
|---------|---------|
| 2019-04-24 17:00:00 | 0.23, 22.3, 5 |
| 2019-04-24 16:00:00 | 0.22, 22.3, 0 |

The .csv files can be used to map times series data such as averages or counts, a sample .csv can be seen in Table 1. A time slider can be used to select data for mapping and navigate over a desired time frame, for example a 72-hour window with hourly average values, or a monthly window with daily averages values, for a given type of data point. These sliders control the FM-BIM visualization, providing FM users a visual and interactive platform to interpret sensor data. Figure 8 shows the Dynamo implementation for hourly navigation.
The codes for creating the 3D list of inputs for mapping, as seen in Figure 8 as Code Block 1 are as follows:

```python
# Transpose and Select Required Elements
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *
importList = IN[0]  # the main list imported from excel
elementList = IN[1]  # the list of elements in revit
newList = []
for i in range(1, (importList[0])):
    for j in range(0, len(elementList)):
        if elementList[j] == importList[0][i]:
            element_to_add = []
            element_to_add.append(importList[0][i])
```

Figure 8: Dynamo script for time-specific data mapping; high-level summary showing node relationships and enlarged views of individual code blocks
for k in range(1, len(importList)):
    tuple_to_add = []
    tuple_to_add.append(importList[k][0])
    temp = importList[k][i].split (",")
    for z in range(0, len(temp)):
        tuple_to_add.append(temp[z])
    element_to_add = newElementList.insert(i-1, tuple_to_add)
    break;
else:
    continue

OUT = newList

# Reorganize Room Objects to Revit Order
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *

importList = IN[0]
ImportList = IN[1]
newElementList = []
for i in range(0, len(ImportList)):
    for j in range(0, len(elementList)):
        if (ImportList[i][0] == elementList[j].GetParameterValueByName("Number")):
            newElementList.insert(i, elementList[j])
        else:
            continue

#Assign your output to the OUT variable.
OUT = newElementList

The code for selecting the appropriate list in the 3D list, as seen In Figure 8 as Code Block 2 is as follows:

# Selected Time Vals
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *

allData = IN[0]
selectedTime = IN[1]
valsToMap = [[], for _ in range(len(allData[0][1])-1)]
for j in range(0, len(allData)):
    for k in range(1, len(allData[0][int(selectedTime)])):
        valsToMap[k-1].insert(j, allData[j][int(selectedTime)][k])
OUT = valsToMap

Figure 9 shows the five steps of the data transformation process during integration. In step 1, the BIM elements are retrieved from the BIM, this is a table of the element ID’s as defined by the BIM and their corresponding BASID which relates to a BASID in the timeseries data store. In step 2 the import .csv file with summarized timeseries data is imported into the VPL, this data is formatted as previously described in Section 3.3. Step 3 creates a temporary 3D list, where a list is created for each data point (POINTID) in the .csv file, i.e. a list for every point relating to the BASID. For example in the .csv file ARC.AIR.AHU contains a string of sensor point values related this this BASID (an Air Handling Unit (AHU), one of these points is Supply Air Humidity (SAH) and is found in the second place in the value string for any given timestep. The desired time for visualization is selected in Step 4 using time slider; this is shown in a Dynamo node with a sample value of 2. Once the time is selected the values for each POINTID at the selected time are extracted from the temporary list. In this example the second value, i.e. the average value for each POINT 2 days ago is selected from the temporary 3-D list and stored in a 1-D list. Finally, in step 5, the 1D list is shown as it will be mapped to the BIM fields, where there is a value for each POINTID.

### BIM element query

| BIM Element ID | BASID         |
|----------------|---------------|
| 35526          | ARC.AIR.AHU1  |
| 34729          | ARC.AIR.AHU2  |
| 4562           | ARC.AIR.AHU3  |

### Import .csv

|          | ARC.AIR.AHU1 | ARC.AIR.AHU2 | ...   |
|----------|--------------|--------------|-------|
| 2019-05-24 17:00:00 | 0.23,22,3,... | 0.72,22,0,0... | ...   |
| 2019-05-24 16:00:00 | 0.5,23,3,...  | 0.8,25,5,1,... | ...   |
| 2019-05-24 15:00:00 | 0.22,23,8,... | 1.1,22,0,1,... | ...   |
Figure 9: Data transformation during integration.

Note that the scripts presently do not support null point values as this causes data type errors within the Dynamo and therefore a large dummy value (555555) was inserted for missing data points. Future work is necessary to overcome this issue and permit null value mapping so that sparse matrices of point value data can be handled, as these are computationally the most efficient for data storage.
4 Case Study from an Office Living Lab

A living lab test cell has been established within a single faculty office, which incorporates a local sensor network. Sensors measuring occupancy, lighting state, door position, and HVAC are integrated with an Arduino Mega 2560 and streamed via an Ethernet connection to a private cloud. Other systems in this office but not discussed in this paper measure ambient temperatures in the office and adjacent spaces (direct cloud streaming) and thermocouples for surface temperature measurement. Figure 10 shows setup of the IoT sensor network in the office living lab and a sample of .csv data to be mapped to BIM.

This sensor data has been mapped to an FM-BIM for the host building created in Revit 2019. This model uses the room number as the BASID as in this simplified case all sensors are room-mounted. ARC-309 is the sensor test room showing actual data; dummy data has been mapped to the other rooms for visualization purposes. The Dynamo script presented in
Section 2 has been integrated with this FM-BIM and a sample visualization of the daily average temperature data is shown in Figure 11. Because all current data is mapped to the BIM, the other sensor data averages are also available by viewing the room properties, as shown in Figure 12.

*Figure 11: Top: Inputting desired time in Dynamo “5 days ago”. Bottom: FM-BIM visualizing average temperature for “5 days ago”*
5 Discussion

BAS data is highly valuable within an FM-BIM, however due to the high measurement frequency, the supporting database architecture and data visualization must be carefully considered in order to facilitate BAS to FM-BIM integration. This paper presents a linked database architecture that allows for high-frequency low-latency data transmission by using sensor point controllers, dedicated database buffers and streamers, a cloud-based database, and batch analytics. This architecture permits efficient summarization of heterogeneous BAS data on the cloud where scalable computational resources are available. The data summarization techniques proposed include averages and counts on an hourly, daily, and monthly basis. Consistent with building energy modeling norms, data regarding occupancy or lighting state are indicated in real time as integers, however these must be stored as floats for hourly, daily, and monthly averages to better reflect the percentage time that a space is occupied or illuminated. The summarization of sensor data using this method allows the FM-BIM to be the single building data model for FM users to consult during the operational life of a building, while maintaining a data structure that can also be used by building applications for energy management and other building controls.

The use of Dynamo, a VPL, was found to be highly effective in mapping timeseries data integration from a .csv file to an FM-BIM, provided proper structure. The presented format
contains sensor data for each point as a string to form a tuple, which is then inserted into a 2D list with time in rows and BASIDs in columns to create a 3D list with indices of time, BASID, and point values. From this list, sub-arrays mapping BASID vs POINTID can be accessed for a given time using the slider and code presented. This study has been limited to room-hosted data points and a more complex mapping algorithm will be required to update both room-hosted and element-hosted timeseries data, as the existing script can only map to a single element type at once. An additional limitation of this work requiring further development is that null values cannot be processed by the script; as a temporary solution, a dummy value (555555) has been substituted for missing data, but code refinement is necessary in future work to overcome this limitation. This will reduce the computational cost by permitting the use of spare matrices for data storage.

Cyber physical systems are concerned with the feedback loop of sensing, evaluating, and acting on building conditions. Schmidta & Ählund [31] describe building automation as a three-layer architecture facilitating this feedback loop. This research focuses on making the bottom layer of this architecture- the field level comprised of sensors and actuators - available to the top layer - the management level comprised of building management system and visualizations tools while maintaining the ability to engage the middle layer where applications such as predictive control are applied. Most current research in cyber physical systems focuses on optimizing operational energy cost or consumption [31] through the development of the middle layer. However, sensor data visualization should be considered and further researched in cyber physical systems. The middle layer is not easily interpreted by FM users, and without a thoroughly developed top management layer there will be a loss of agency for FM users as cyber physical system development progresses. This is increasingly important for cyber physical systems with tightly coupled sensing and actuating embedded systems as described by Kleissl & Agarwal [32] where there is no discussion of visualization at the management level.

6 Conclusions

The move toward digitized building information has removed some access to building information from FM. An FM-BIM with integrated summarized IoT sensor, actuator, and meter data would reintroduce access to this information, enabling FM to complete more complex analysis than previously possible. Appropriate time granularity of sensor data will be available to FM through the use of time sliders, which map summarized data of common metrics: min/max, averages, and counts to corresponding BIM fields for each datapoint, and
are visualized using color coding. A linked data architecture is presented in this research. Where Dynamo is used to link IoT data and the BIM. Although functional, Dynamo is not optimized to query databases, a query processor which can directly receive time slider requests and return relevant data would be more efficient. Furthermore, an appropriate query processor would remove the need for a custom.csv file to be linked in Dynamo before using the time slider. While the linked data architecture with predetermined summary tables has been successful in this study, a centralized model with a sophisticated query processor would provide increased flexibility and permit new data summaries to be developed on an as-needed basis. This demonstrates the key limitation of the linked data approach, which is the fixed nature of the architecture.

This research lays the foundation for a long-term project to develop a cloud-hosted BIM-integrated FM platform, permitting data analytics with complex predictive modeling and classification algorithms to support applications such as Smart and Continuous Commissioning and Model Predictive Control. The visualization of the summarized sensor data provides an integrated view for facility managers and building operators to support integrated asset management and optimization. This work has yet to be scaled to the full-building or tested by facility-users and this scaling and testing will form the long-term future work in this field. In addition, incremental functionality will be developed to enhance the analytics to integrate deficiency alarms using the trended data as defined in accordance with ASHRAE Guideline 36-2018 High Performance Sequences of Operation for HVAC Systems [33]. A more refined graphical user interface should be developed, where users can interact with sliders outside of the VPL to initiate IoT sensor data integration with an FM-BIM. Further work on defining relevant BAS data summarization techniques should be done in collaboration with end-users such as Facility Engineers to ensure that the most useful data is presented. Topics for future consideration include additional measures to be mapped, for example data maxima and minima, different timeframes, and dashboard integration.

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