Lee Y., Yang F., Eastman C. M., and Roper K. O. (2017). "Modularized Validation of a Building Information Model According to the Specifications of the Facility Management Handover and COBie." In: *LC3 2017: Volume I – Proceedings of the Joint Conference on Computing in Construction (JC3)*, July 4-7, 2017, Heraklion, Greece, pp. 279-288. DOI: https://doi.org/10.24928/JC3-2017/0080.

MODULARIZED VALIDATION OF A BUILDING INFORMATION MODEL ACCORDING TO THE SPECIFICATIONS OF THE FACILITY MANAGEMENT HANDOVER AND COBIE

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Abstract: With increasing requirements and complexity in building projects, diverse domain experts employ a neutral file format, which is exchangeable and interoperable among heterogeneous BIM authoring tools and applications in diverse disciplines. The Construction-Operations Building Information Exchange (COBie) is a set of the specifications of building data exchange pertaining to building asset information. For interoperability, COBie is defined as a model view, which is the subset of the Industry Foundation Classes (IFC) schema. For ensured interoperability of BIM data, using COBie model view, domain professionals and software developers need to identify 1) whether their IFC instance files include required information on building asset management and 2) whether their IFC interfaces accurately import/export IFC files according to the COBie specifications. However, since no approach currently supports this validation testing, professionals manually evaluate an IFC instance file and their IFC binding processes in order to identify semantic errors, technical problems, and translation mapping issues. To enhance the efficiency of this time-consuming and labor-intensive evaluation process, this study proposes a validation framework for evaluating IFC instance files pertaining to the conformity to the COBie specifications. In addition, this study formalizes the requirements of the COBie model view using identified rule logic. For validation, rules are implemented on a modularized validation platform developed on top of the IfcDoc tool, which is a model view documentation and validation tool.

Keywords: BIM, IFC, Facility Management, COBie, Interoperability Checking

1 INTRODUCTION

The inadequate interoperability among model-based applications costs 15.8 billion dollars by losing its efficiency in the U.S. facilities, of which 10.6 billion dollar loss occurs during operation and maintenance (O&M) (Gallaher, O'Connor, Dettbarn, & Gilday, 2004). Data transition among different stakeholders from design to construction and to operation often leads to lack of integration and data loss (Autodesk Inc, 2008). The lack of data integrity and interoperability typically comes from different sources as follows: (1) a lack of

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coordination among stakeholders, (2) stakeholders' different internal readiness and adoption of technology, and (3) a lack of standardization (Gallaher et al., 2004).

To ensure interoperability of the data exchange of building information models, diverse disciplines have defined model view definition (MVD) that can reflect their distinct data exchange specifications. MVD consists of concepts that are modularized data sets subject to be reused by several building information modeling (BIM) data exchanges (Hietanen, 2006). In other words, data exchange requirements are specified by aggregating specifications defined in several concept descriptions (Solihin, Eastman, & Lee, 2015). Thus, one concept can be used several times with different settings of constraints and parameters to fulfill the required specifications of several model views (Lee, Eastman, & Lee, 2015). One MVD is the Construction-Operations Building Information Exchange (COBie), which is consolidated specifications for exchanging BIM data with regard to building asset information and facility management data (William East, Nisbet, & Liebich, 2012). As a big stream of current practices in the facility management, it is a key to integrate Computer-Aided Facility Management (CAFM) and BIM technology by using COBie in order to increase the efficiency and effectiveness of commissioning and handover of facility information for O&M. This can eventually improve day-to-day operation and management of facilities with data accuracy and integrity. However, it is uncertain whether the COBie delivers all information required for facility management (Gnanarednam & Jayasena, 2013).

2 Previous Efforts for MVD Validation

Diverse BIM authoring tools such as the Autodesk Revit support exporting facility O&M data of a BIM model in the Excel sheet according to the COBie specifications. However, in order to share BIM data across various domains, the Industry Foundation Classes (IFC) file should be used and evaluated according to COBie specifications so that end-users (i.e., facility managers, owners) and software developers can easily identify whether received IFC files conform to the COBie requirements and whether IFC exporters of BIM authoring tools accurately translate their native objects to IFC objects.

There have been several efforts to utilize MVD as validation criteria even though the COBie has been not touched. These efforts have been targeted on validating IFC instance files according to particular MVD, not to public MVD such as IFC Coordination View 2.0 or COBie. One study (Lee, Eastman, & Lee, 2015) surveyed the following two approaches for model view validation: IFC server-based checking and the IfcDoc tool. This paper explains strengths and weaknesses of both semantic validation methods and points out that their rule checking features must be more extended and developed to address diverse checking types. Another available checking method is Global Testing and Documentation Server (GTDS) provided by buildingSMART International (buildingSMART, 2010). GTDS is a server-based application supporting the validation of IFC instance files according to Coordination View 2.0 (CV 2.0). Users, however, cannot look at and modify the specifications of concepts and their corresponding rules. In addition, new model view checker using mvdXML and BIM Collaboration Format (BCF) was proposed for providing a stable IFC validation approach (Zhang, Beetz, & Weisen, 2015). This paper presents four types of use-cases captured from the Rdg BIM Norm and Statsbygg BIM Manual. The authors of this paper acknowledge that implementable agreements of model views are still insufficient and thus the validation process cannot be strictly applied. The mvdXML specifications and associated rule sets are described in the mvdXML document (Chipman, 2012). For establishing a robust validation process, the rule types and evaluation scenarios should be accurately identified and executed by a formal checking process (Lee, Eastman, & Solihin, 2016). As one of effort, the semantic validation process using the precast concrete industry (PCI) MVD was proposed to improve interoperability of BIM data exchange (Lee, Eastman, Solihin, & See, 2016). The concrete MVD validation process using modularized checking frameworks has assessment features for diverse types of MVD rule sets that can cover PCI MVD specifications. The limitation of this application resides in extending rule definition and execution processes that are only available by hard coding.

To improve the current MVD validation process and enhance this cumbersome procedure regarding facility management and BIM data, this study proposes to develop accurate requirements and associated rule sets of the COBie on top of the IfcDoc tool and to provide a robust MVD validation process. The IfcDoc tool, the model view document generator, has been updated by the ConstructabityTM and the Digital Building Laboratory (DBL) at Georgia Tech so that it can embed diverse validation features that can execute several rule types in terms of model views.

3 Research Method and Process

A number of BIM authoring tools and facility management software have IFC import and export interfaces developed based on the specifications of diverse model views such as CV 2.0. Since the development of these interfaces can have unexpected errors and omissions, software vendors need to ensure whether their IFC interfaces accurately import/export IFC files according to the COBie specifications. In addition, domain professionals who use such IFC instance files as end-users or owners should confirm whether IFC instance files exported from their software solutions include required information on building asset management. These instance files provide designers or constructors with such customized format for the software of facility managers or owners so that they can demand necessary handover information.

To achieve such goals, this study defines specifications and associated rule-sets of COBie and proposes a validation process of IFC instance files according to the updated COBie requirements. Figure 1 illustrates the data flow of this research using the IfcDoc tool, which is a model view documentation and validation tool.

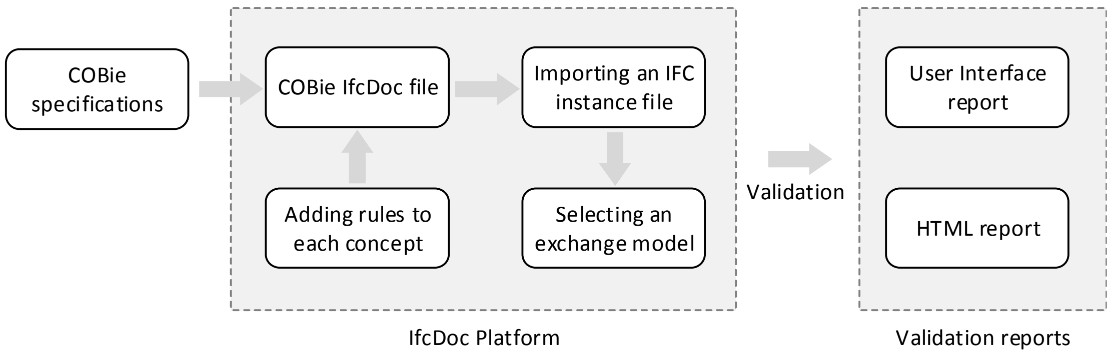


Figure 1: Research processes- Validation of IFC instance files according to COBie

The COBie rule-sets required for evaluating the IFC instance file were developed in concepts of the IfcDoc tool. Each concept entails particular rules associated with an entity, an attribute, a relationship, and a property-set. The rules of concepts are composed as one Exchange Model according to predefined COBie data exchanges. Thus, if a user wants to evaluate an IFC instance file according to the Facility Criteria exchange model included in COBie, the concepts of IfcDoc that are contained in the Facility Criteria exchange model are referred and implemented to assess whether the IFC instance file satisfies their rules. The authors utilized the COBie IfcDoc file as a baseline provided from the buildingSMART International website. This COBie IfcDoc file was modified according to new COBie specifications and rule set features of the IfcDoc tool. The updated IfcDoc file was imported to IfcDoc to evaluate an IFC instance file that embeds facility and asset management information. The validation process of this IfcDoc application generates two types of checking reports: a user interface (UI) report and an HTML report. Such reports will be helpful for software vendors to identify errors in inaccurate COBie binding with native objects and to keep track of locations of errors of their IFC exporter of BIM authoring tools. In addition, end-users would be able to ensure their IFC models with regard to conformance to the COBie specifications.

4 COBie Rule Definitions and Types

As shown in Figure 2, COBie V2.4 consists of 28 exchange models (EMs) that embed exchange requirements defined for each specific data exchange. Such exchange requirements are formulated by combining several concept descriptions. A concept is a modularized specification for an entity, an attribute, a relationship, and other necessary data (Hietanen, 2006). A concept can be defined by a set of pre-generated concept templates defined based on the structure of the IFC schema. Thus, end-users can manipulate entities, attributes, relationships, and properties of the predefined concept templates in order to facilitate concept definition processes that have duplicated data exchange requirements. Figure 3 represents 16 concept templates that are supposed to define general exchange requirements. Such concept templates are assigned to corresponding entities so that they can use predefined requirements multiple times. Thus, based on the COBie specifications, the authors modified the COBie IfcDoc file and applied rule-sets to each concept template to generate concept definitions required for the COBie model view. The usages of assigned concept definitions for each exchange are defined by the mandatory/optional/none setting underneath each entity on IfcDoc. In other words, if the Metadata concept template in Figure 3 is assigned to the IfcActor entity and is defined as mandatory for the Facility Criteria EM, this EM then includes the specifications that the IfcActor entity must follow requirements correspondingly defined in the Metadata concept template.

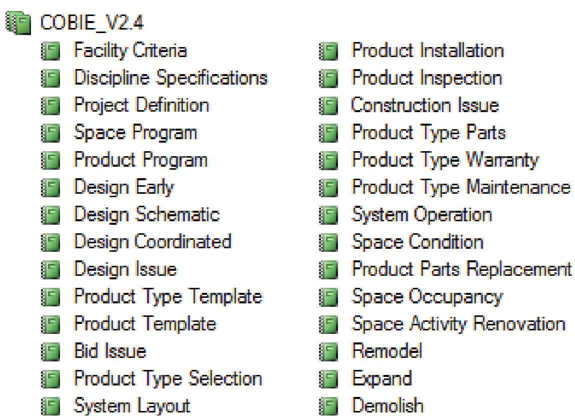


Figure 2: Exchange models of COBie V2.4

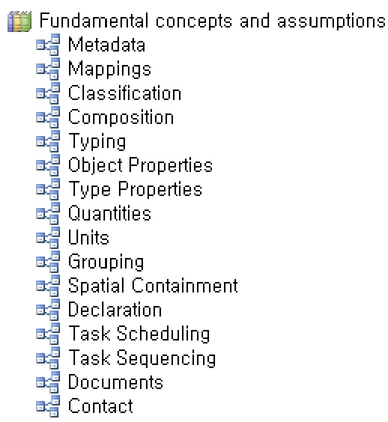


Figure 3: Concepts of COBie V2.4

The types of the COBie requirements can involve diverse facility O&M specifications such as space usage, contact information, operations, cost, and maintenance. The following list shows the detailed requirements:

- Authoring information (a person or an application)
- A mapping reference (connection between IFC instances and external data)
- A classification (an OmniClass table)
- A decompose relationship (levels of details)
- An object type (characteristics)
- A property (a property type and value)
- A quantity set (count, length, area, volume, weight, and time)
- A unit (a measurement and data exchange unit)
- A group (member assignment)
- A spatial containment (physical elements in a space)
- A context reference (availability within a project)
- A task scheduling and sequencing (a task and associated date and time)
- An external association (a referenced document)
- A contact information (postal and telecom addresses of an actor and an organization)

These specifications are defined in concept templates and reused by several entities according to their distinct purposes. These concept templates must entail rule sets for each definition in order to be used as validation criteria. The authors identified that COBie V2.4 includes four types of rules: (1) Uniqueness, (2) Semantic accuracy, (3) Relational references, and (4) General syntax checking.

As an example of uniqueness checking shown in Figure 4, the Metadata concept defines that the Name of an object must be unique within the project so that it can support efficient data referencing with external data sets such as tabular data from spreadsheets. Figure 4 shows the IfcDoc interface that allows end users to define information for Metadata.

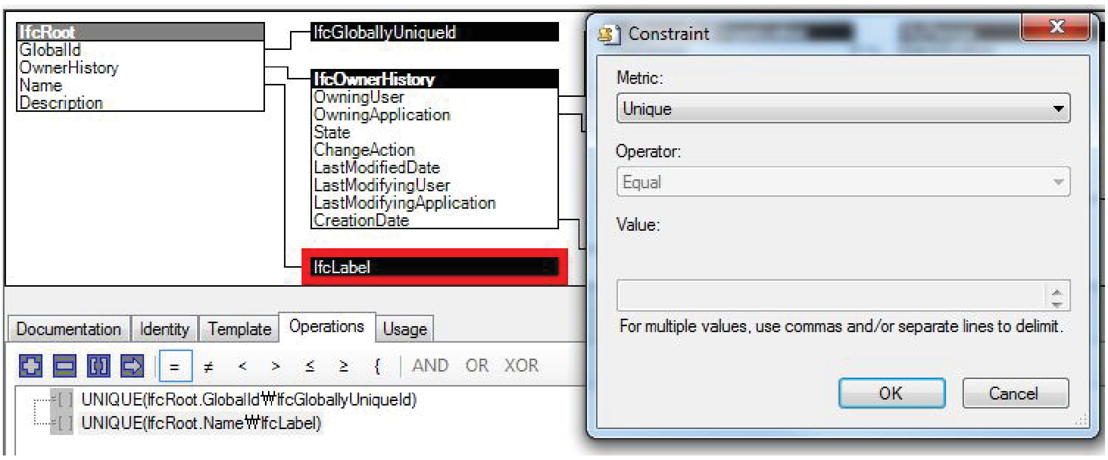


Figure 4: Uniqueness checking of an object name

The second rule type is the accuracy of attribute semantics. The FM Handover model view defines specifications for classification of assets, referring to CSI's OmniClass taxonomy. The Classification concept template defines three parameters that allow each entity to require particular semantics for each attribute. As shown in Figure 5, an IfcBuilding instance should satisfy values defined in Source, Name, and Tokens attributes.

If IfcBuilding does not meet any one of these values, the validation report shows FAIL for this entity validation.

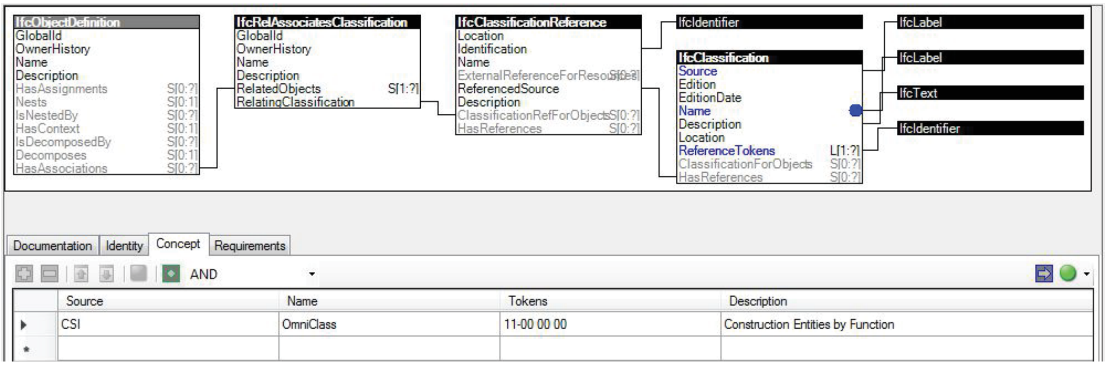


Figure 5: Semantic accuracy checking

Figure 6 shows the rule type of a referential relationship. The composition template defines the relationship between BIM objects: IfcSpace uses this template so as to define the relationship with IfcBuildingStorey. In other words, IfcSpace must have a reference to IfcBuildingStorey to declare the hierarchical composition. In addition, this object relationship defines a spatial containment so that users can identify the spatial clusters or zones of a facility and determine the locations of systems or equipment.

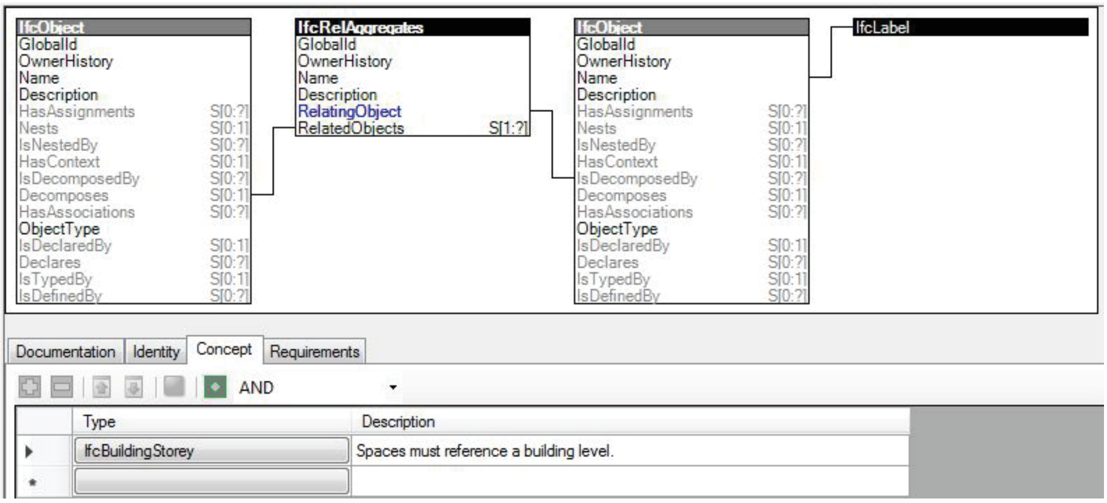


Figure 6: Referential relationship checking

Syntax checking is automatically embedded in a concept template when users define relational reference. For example as shown in Figure 7, an IfcPostalAddress instance must have one IfcLabel for the AddressLines attribute because IfcPostalAddress has AddressLines, which have an arity One-To-Many relationship.

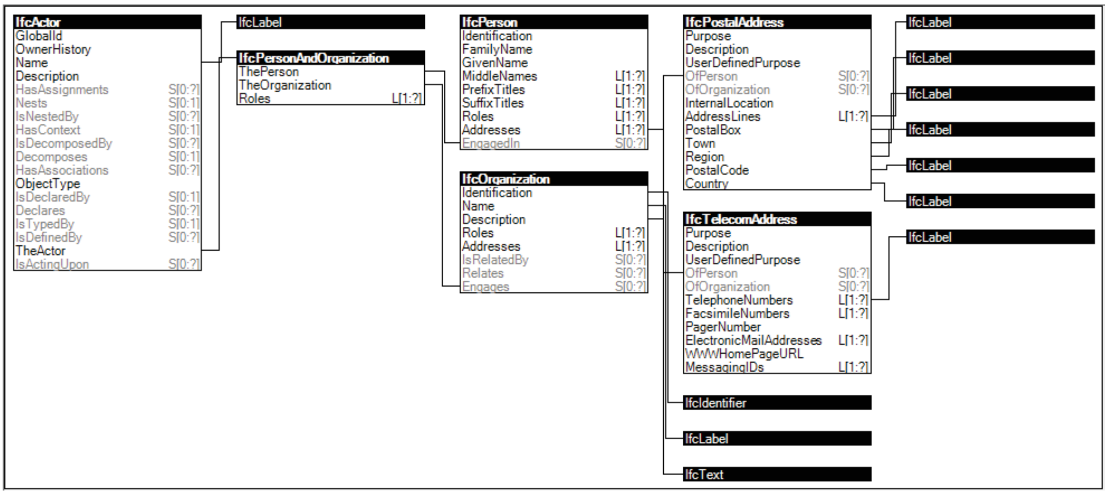


Figure 7: Cardinality checking

5 Validation of Instance Files

To execute the validation process according to the updated COBie model view, the authors created a sample IFC model for a clinic building shown in Figure 8. This sample model includes spaces and spatial requirements for a doctor, a nurse, a patient, operating, special clinic, X-ray, an exam, a customer service, an information desk, an HVAC, a restroom, and a storage. This model also has several equipment and devices such as nurse calls. In addition, actors and given tasks, element quantities, properties, and schedules were embedded in this model. These facility O&M data should be thoroughly managed throughout the design and construction phases for availability and passed over to the facility management phase.

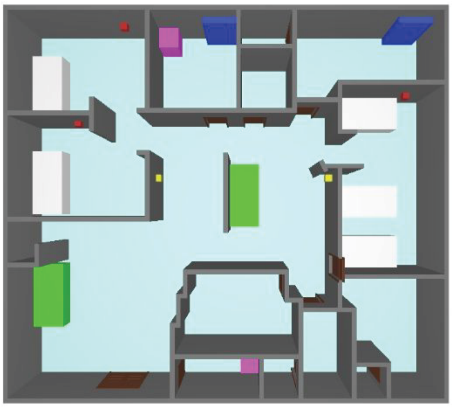


Figure 8: Clinic sample model

To evaluate the developed validation process pertaining to interoperability and model integrity of facility O&M data of BIM models, the authors implemented the several exchange requirements defined in the COBie model view on the IfcDoc application. Figure 9 shows the validation report of the clinic sample model represented in a user interface report and Figure 10 shows the validation report represented in the HTML format. These validation reports illustrate automatically identified errors in validation of the following red-colored concept templates: Metadata, Mappings, Typing, and Spatial Containment. Opposingly, the passed concepts as follows are represented in green: Composition, Quantities, and Units. In addition, users can identify the causes and the locations of identified errors when they click on a particular instance shown in the right-hand side of the user interface. For example, in Figure 9, the #66 IfcBuilding instance has an error in validation according to the Metadata concept because it lacks an IfcLabel value for the Name attribute.

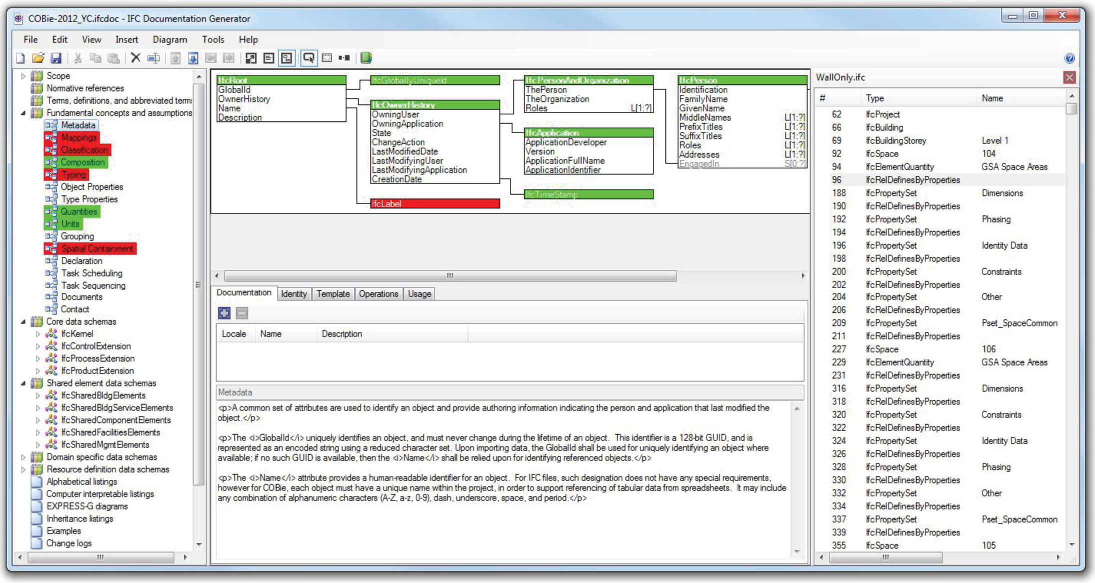
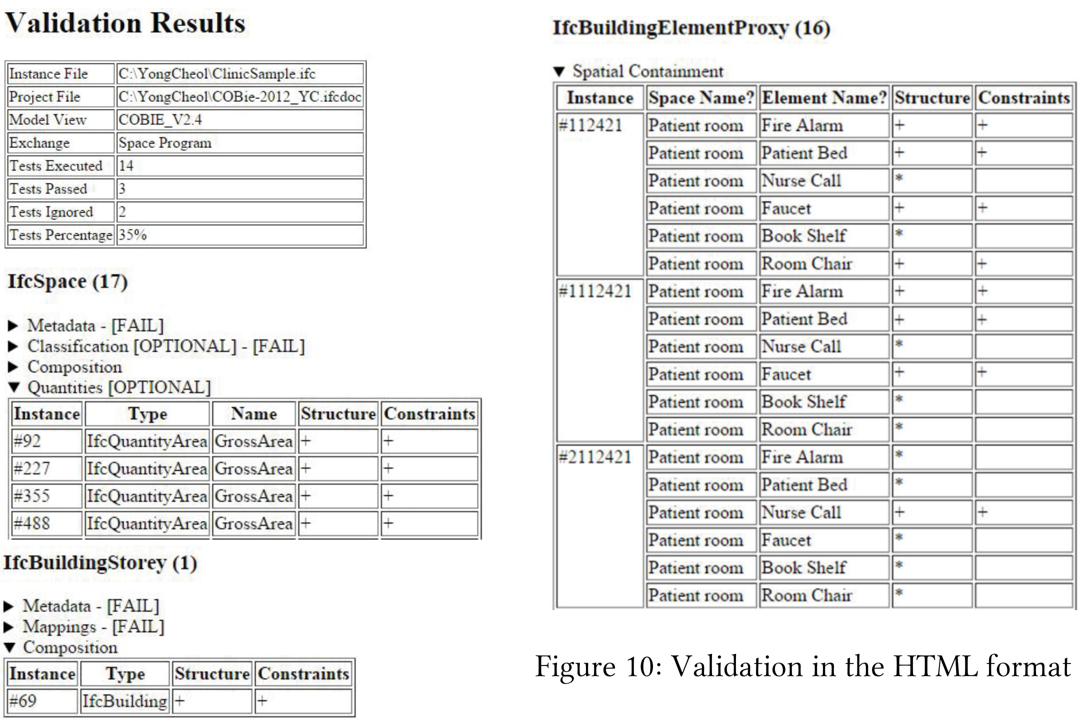


Figure 9: Validation report in the user interface



Validation Results

Instance File	C:\YongCheol\ClinicSample.ifc
Project File	C:\YongCheol\COBie-2012_YC.ifcdoc
Model View	COBIE_V2.4
Exchange	Space Program
Tests Executed	14
Tests Passed	3
Tests Ignored	2
Tests Percentage	35%

IfcSpace (17)

▶ Metadata - [FAIL]
▶ Classification [OPTIONAL] - [FAIL]
▶ Composition
▼ Quantities [OPTIONAL]

Instance	Type	Name	Structure	Constraints
#92	IfcQuantityArea	GrossArea	+	+
#227	IfcQuantityArea	GrossArea	+	+
#355	IfcQuantityArea	GrossArea	+	+
#488	IfcQuantityArea	GrossArea	+	+

IfcBuildingStorey (1)

▶ Metadata - [FAIL]
▶ Mappings - [FAIL]
▼ Composition

Instance	Type	Structure	Constraints
#69	IfcBuilding	+	+

IfcBuildingElementProxy (16)

▼ Spatial Containment

Instance	Space Name?	Element Name?	Structure	Constraints
#112421	Patient room	Fire Alarm	+	+
	Patient room	Patient Bed	+	+
	Patient room	Nurse Call	*	
	Patient room	Faucet	+	+
	Patient room	Book Shelf	*	
	Patient room	Room Chair	+	+
#1112421	Patient room	Fire Alarm	+	+
	Patient room	Patient Bed	+	+
	Patient room	Nurse Call	*	
	Patient room	Faucet	+	+
	Patient room	Book Shelf	*	
	Patient room	Room Chair	*	
#2112421	Patient room	Fire Alarm	*	
	Patient room	Patient Bed	*	
	Patient room	Nurse Call	+	+
	Patient room	Faucet	*	
	Patient room	Book Shelf	*	
	Patient room	Room Chair	*	

Figure 10: Validation in the HTML format

In terms of the Quantities concept, each instance conforms to requirements for IfcQuantity. This concept allows element quantity to be represented by IfcQuantityLength named NetHeight and IfcQuantifyArea named GrossArea or NetArea. Since IfcSpace in an IFC instance file uses IfcQuantityArea and its name as GrossArea, this validation shows PASS. Similarly, the Unit concept restricts the possible unit types and measurement values. Such rule checking can be used to require a particularly customized format or unit system that facility managers or owners should use or FM-BIM tools can understand. In addition, the Spatial Containment concept enables validation of the relationships between objects and spaces. For example, given user-defined requirements, IfcSpace named Patient room can be validated as to whether it has a patient bed, a nurse call, a closet, medical equipment, or furnishing elements required for the corresponding type of space. Figure 10 shows the spatial containment validation, which shows which IfcSpace satisfies elements defined in the concept. In terms of the Mappings concept, to support automated mapping with a particular file or database, this validation evaluates whether an IFC instance file has persistent connections between IFC data and external ones such as tabular data format used to translate data.

6 Results and Discussions

Complete specification data aggregated during the design and construction phases is invaluable for facility managers who manage the complete building over the decades (Roper & Payant, 2009). To pass this impeccable data over to facility managers, BIM models must be accurately exchanged among project participants and automatically validated pertaining to implementable specifications defined for each exchange process. With increasing and complex requirements in building projects, binding processes between the COBie and native BIM objects can result in semantic errors, technical problems, and translation issues (William East et al., 2012). In addition, it takes tremendous time to debug errors incurred in the IFC exporting system. For end-users, currently there is no robust approach to evaluating IFC models in terms of the facility management handover and the COBie specifications.

This study proposed a new validation framework, process, and rule sets for validation of IFC models according to the COBie specifications. The formalized COBie requirements and rule sets defined in the IfcDoc tool can be easily executed by the public and software companies. In particular, such requirements and rule sets are able to be reused by other domains and electronically shared with pertinent domain experts. This improved data exchange procedure will reduce tremendous time and effort in managing and monitoring facilities after occupancy. Without these validation processes, the facility manager or operator is left with potentially inaccurate data and the benefits of BIM data become unreliable. The major advantage to having accurate, the reliable data at handover yields advantages in time, efficiency, and productivity during the long operational phase of a facility. COBie is only a format rather than a bi-directional data resource. The validation process for data turn-over should be embedded, resulting in automated, seamless transition of data from design though construction and into operations. Thus, this proposed validation process can resolve almost all of the exchange issues, delivering a clean and reliable set of data for operations. The limitations reside in that current validation only supports checking whether values and contents of an IFC instance file are the same or fulfil the defined rules of COBie. The more intelligent validation and diverse checking features such as a context analysis or a geometry-related rule would be required.

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BIM BIG DATA SYSTEM ARCHITECTURE FOR ASSET MANAGEMENT: A CONCEPTUAL FRAMEWORK

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Abstract: Effective decision making in the AEC/FM industry has been based increasingly on an exponential growth of data extracted from different sources and technologies. It has been argued that Building Information Modelling (BIM) can handle this information efficiently, acting as a data pool where data can be stored, managed and integrated. Indeed, a BIM platform based on cloud computing and Big Data can manage the storage and flow of data, as well as extract knowledge from Geographical Information Systems (GIS), Internet of Things (IoT), asset management, energy management and materials and resources databases. Furthermore, it can also provide an opportunity for multiple users to view, access and edit the data in 3D environment.

This paper describes the requirements and different components of a BIM Big Data platform for facilitating management of building assets. This is achieved by firstly, conducting a critical peer review to ascertain Big Data definitions and stages, and also to define the critical BIM requirements for the Big Data platform. At the crux, this paper presents a conceptual framework for developing a Big Data platform for BIM which incorporates suitable tools and techniques needed to export, store, analyse and visualise BIM data.

Keywords: Building Information Modelling, Big Data, Asset Management.

1 Introduction

The era of Big Data Analytics (BDA) has emerged mainly due to the need to deal with the huge volume, complex and growing data generated by social media, sensors, instruments and a plethora of digital sources. Currently, nearly every sector of the economy including accounting, tourism, transportation, education and construction is affected by Big Data. This has mainly been due to the noticeable Big Data capabilities in storing, processing and analysing big volume of diverse data.

At the same time, Building Information Modelling (BIM) has become the new international benchmark for better efficiency and collaboration in design, construction and building operation and maintenance. BIM can act as a data pool during all phases for all data of the building, even from other technologies such as Geographical Information Systems (GIS), Radio Frequency Identifications (RFID), Internet of Things (IoT) and Augmented Reality (AR). Furthermore, Data from different sources such as asset management, energy management, and materials and resources databases can be

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integrated and linked within a BIM environment. As a result, BIM can deal with large volumes of heterogeneous data which would more often than not, result in an interoperability barrier. This massive accumulation of data in BIM platforms has pushed the implementation of Big Data in the construction industry, especially in BIM applications and platforms. However, although Cloud computing and Big Data analytics can improve interoperability, the adoption of Big Data in BIM for asset management remains at a nascent stage lacking clear frameworks and guidelines. The benefits of asset management database based on BIM and BIG Data can include improved financial performance, informed asset investment decisions, improved services and outputs, managed risks, and demonstrated compliance (Spilling 2016).

To address this, the paper firstly presents the Big Data definitions and the different stages the data passes through, as well as the critical BIM requirements for the Big Data platform. Then, taking into consideration BIM requirements and armed with available researches and tools dealing with the problem, a conceptual framework of the Big Data platform for BIM in asset management is proposed.

2 Big Data for BIM

2.1 Big Data Definitions

The term “Big Data” was coined in 2005 by Roger Mougalas of O’Reilly Media (Sangeetha and Sreeja 2015). He used the term to refer to a huge set of data that is almost impossible to manage and process using traditional business intelligence tools. In the same year, the open-source Hadoop - one of the most-used platforms for Big Data- was created by Yahoo based on Google File System and MapReduce. Big Data can be described and defined by several characteristics. The V’s definition started in 2001 in the META group (now Garnter) (Laney 2001). Actually, the Gartner report did not use the term “Big Data” and predates the current trend. However, the report has since been chosen as a key definition for the term 'Big Data'. Laney (2001) proposed a threefold definition encompassing the “three Vs”: Volume, Velocity, Variety was proposed. Volume focuses on the size of the data set, velocity indicates the data processing and variety describes the range of data types, schemas and sources. IBM (2012) expanded this definition and introduced a fourth V, Veracity. Veracity corresponds to the extent to which data can be trusted. Moreover, Biehn (2013) extended the definition to include a fifth V, Value. Value refers to the monetary worth that an organisation can derive from processing Big Data. Besides, other V’s such as variability, virtual, visualisation and viability are also mentioned in the literature serving complement characteristics of Big Data (Van Rijmenam 2014, Wang et al. 2016).

2.2 Big Data Stages

Generally in data processing world, the data goes through the process of capture, store, process, analyse, and produce results (Casado and Younas 2015). Accordingly, Big Data can be carried out in four stages including Big Data capture, Big Data storage and processing, Big Data analytics, and Big Data visualisation and interpretation. However, the data life cycle does not strictly follow this sequence (Casado and Younas 2015).

Big Data capture stage is the stage where data is received from different technologies in heterogeneous formats. This data can be classified into three categories namely, structured, semi-structured and unstructured data. Structured data refers to the tabular data in spreadsheets or relational databases which can be stored in structured query language (SQL) databases. Semi-structured data refers to data that does not reside in a relational database, nevertheless has associated information. Extensible Mark-up Language (XML), a textual language for exchanging data on the Web, is classified as semi-structured data. Unstructured data is available as audio files, images, videos, presentations, and amorphous texts such as email, and blogs. Depending on the data format and classification the data storage and processing stage differs.

Big Data storage and processing refers to the storage and management of large-scale datasets and accomplishing availability for this data (Chen et al. 2014). A data-storage system consists of two main components, hardware infrastructure and data-storage methods/techniques. The data-storage methods are deployed on top of the hardware infrastructure to handle the data. Traditionally structured relational database management systems (RDBMS) based on SQL cannot handle and maintain the variety of Big Data. Different systems and databases have been developed to meet the demands of Big Data storage such as consistency, availability and partition tolerance (Chen et al. 2014). This Big data storage consists of distributed file systems and NoSQL databases. Distributed file systems is a method of storing and accessing files in one or more central servers. These files can be accessed, with proper authorization rights, by any number of remote clients on the network. In the market there are different competing distributed file systems such as Hadoop distributed file system (HDFS), Parallel virtual file system (PVFS), Google file system (GFS) and ZFS Lustre (Shvachko et al. 2010). While NoSQL database stands for not only structured query language database. NoSQL database systems provide a mechanism to store and manage data in a non-relational data model (semi-structured and unstructured data) without prohibiting relational data. DB-Engines lists 309 different database management systems (DBMS) classified in relation to their database model (Solid 2015). Currently, the most popular NoSQL databases include graph DBMS, document stores, wide column store, search engines, and Key/Value DBMS (Solid 2015).

Big Data Analytics is the process/stage where advanced analytic techniques operate on Big Data to reveal hidden patterns, unknown correlations and other useful information. Like Big Data itself, the analytics evolution has been made possible by a number of key innovations mainly related to advances in capturing, storing, and processing data capabilities (Berson et al. 2004, Marr 2015). This stage is focusing on finding patterns in Big Data. As the world grows in complexity and overwhelming data is generated, data mining becomes the only process for clarifying the patterns that underlie this Big Data (Witten and Frank 2005). Data mining process applies methods from many different areas including computer science, artificial intelligence and mathematics in order to identify unknown patterns in already stored data (Witten and Frank 2005). These methods could include statistical algorithms, machine learning, content analytics, and time-series analysis. In the market, the two main stacks of horizontal scaling are Hadoop Big Data Analytics Stack and Spark Big Data Analytics Stack.

Big Data visualisation and interpretation stage is the stage of human-computer interaction where the data is presented in a pictorial or graphical format. This stage is important because the analysed data/information generated from the Big Data Analytics stage must be standardised, interpreted, and visualised to help users to extract knowledge and make decisions (Zhong et al. 2016). However, Big Data visualisation could make information more expressive. However, due to the complexity of the Big data, data visualisation is more challenging than traditional cases (Wang et al. 2016). Different visualisation approaches can be used to visualise the Big Data such as object-oriented, location-based (interactive maps), and network visualisation. Generally, open-source and web-based data visualization tools are preferred by end-users for free application which could be easily interoperate and integrate with existing systems (Bughin et al. 2010). From this perspective, cloud computing has been emerged in the Big Data visualisation and interpretation stage and even in further stages like storage, processing and analysis.

2.3 BIM Requirements in the Big Data platform

The identification of BIM requirements is the first step in choosing the appropriate Big Data platform. These requirements can be categorised according to the three phases where the raw data is transformed to information, knowledge and wisdom enabling better decision making in the design, construction, operation and maintenance of building facilities. The three phases are data to information, information to knowledge and finally knowledge to wisdom.

Data to information stage: A huge volume of input data is present in the BIM platforms during design, construction and operation. These data have to be handled, managed and categorised to generate information. Meanwhile, further data from different technologies such as Geographical Information Systems (GIS), Internet of Things (IoT), energy sensors, and materials and resources databases have to be engaged and integrated with the BIM data. However, this data has to be firstly extracted from their authoring tools in a proper format to integrate with other surrounding data. Industry Foundation Classes (IFC) format is the most common schema for exporting BIM data. Still, different schema has to be taken into consideration as IFC is not a suitable choice for real-time queries (Solihin and Eastman 2016). A suitable schema that allows fast and efficient queries, and deals with graphical information and geographical reference location is required. Once the data is exported, it has to be stored and managed in a database which can handle large volumes of data, stream data, integrated geometry and unstructured data.

Information to knowledge stage: The data stored in the database from different sources has to be smoothly and rapidly integrated to reach the knowledge related to all building aspects. The platform has to be able for high-performance read. In other words, the data is written once and read many times. The platform has also to accumulate massive BIM data and other technologies data, and run multiple services concurrently for access by multiple users (Chen et al. 2014). Furthermore, the platform needs to provide techniques and tools to find the pattern/relation between the data from the different sources. Consequently, the data is managed and categorised based on object instead of source criteria.

Knowledge to wisdom: Once the data is integrated, efficient visualisation and secured access are required in a user friendly platform for user interpretation. Cloud computing environment is also a requirement to allow better collaboration between stakeholders.

3 CONCEPTUAL FRAMEWORK

Conceptual system framework provides an important foundation for the system software development. Based on Zachman's framework (2002), the proposed conceptual framework can be classified as an application architecture framework where the principle perspective is designer's perspective (Row 3) and the abstraction is function (Column 2). The proposed framework is formulated by synthesizing concepts from peer-reviewed papers and integrating four empirically tested and proven research developed prototypes. These models are a tender price evaluation system (Zhang et al. 2015), cloud-based online system for big data of massive BIMs (Chen et al. 2014), construction waste analytics system (Bilal et al. 2016), and a simplified BIM model server on a Big Data platform (Solihin and Eastman 2016). Figure 1 illustrates diagrammatical overview of the BIM Big Data system framework for asset management in its four levels. This is based on Big Data phases which include extracting, integrating, analysing and interoperating data.

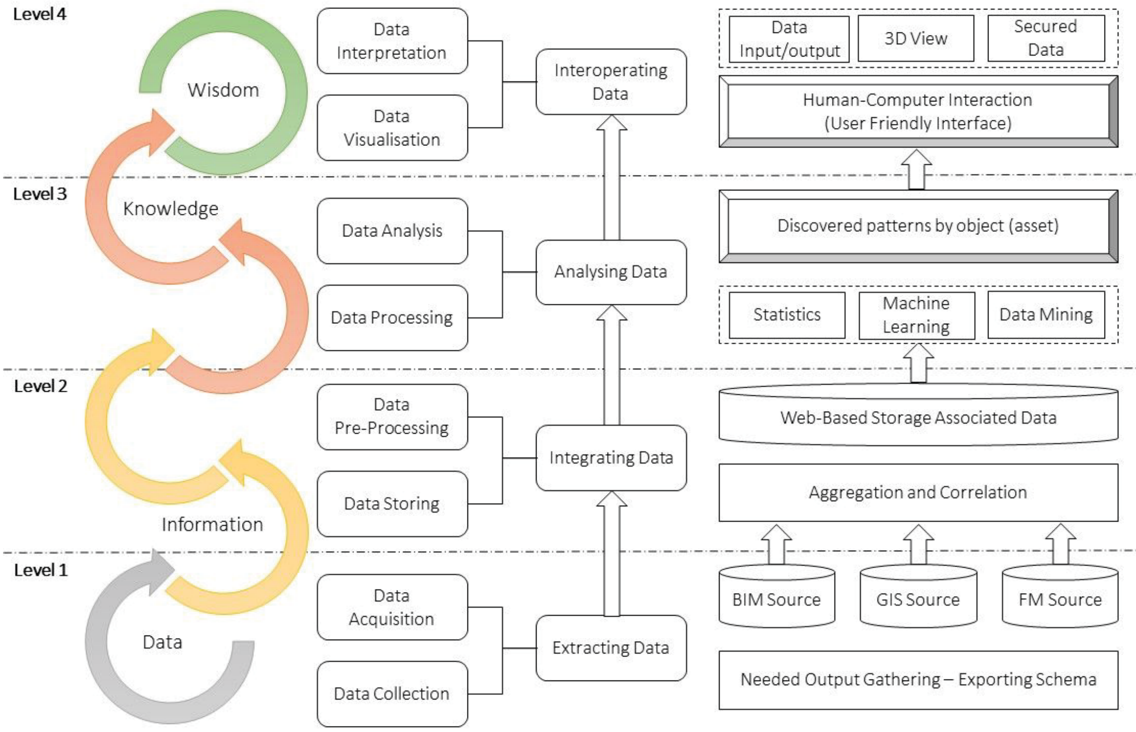

Figure 1: BIM Big Data framework for asset management

3.1 Level 1 - Extracting Data

This is the foundation level of the system and the most important stage. It mainly focuses on data collection and acquisition related to building assets. Data from the BIM model, GIS and sensors are included. Structured, semi-structured and unstructured data are extracted from the different sources through automatic data extraction mechanism (suitable schema). This level also includes data cleaning and quality assessment based on the required output.

Generally for BIM data extraction, the first choice of BIM exporting tool is the Industry Foundation Classifications (IFC), mainly because IFC is an open, vendor-neutral BIM data repository for the semantic information of building object and supported by plenty of platforms. However, the IFC language is significantly large and complex and its definition of IFC includes 327 data types, 653 entity definitions, and 317 property sets which would result exporting asset data which is not required (Steel et al. 2012). Each individual data exchange specifies a compulsory dataset which is covered by a small part of the whole IFC model. Implementation of the model view definitions (MVD) concept can overcome the IFC generalisation (Venugopal et al. 2015). MVD is the international standard concept of model (Hietanen and Lehtinen 2014) and referred as Building Compliance Model (Dimyadi et al. 2016). Based on the platform requirements and needs from the BIM model, the exported BCM subset can be defined as Asset Compliance Model (ACM) (Hietanen and Lehtinen 2014). BIMQL (developed operators for query languages) could be a promising solution for MVD (Dimyadi et al. 2016, Ying et al. 2016). Other query languages can be used such as Java, SQL, EDMexpressX, EQL, PMQL, and ProMQL (Ying et al. 2016). Also in this stage, a meaningful list of what data/information is needed to operate the assets has to be specified. An additional requirement is the development of a taxonomy for the required data in order to facilitate exporting the data (Love et al. 2014, Mayo and Issa 2015, Ibrahim et al. 2016).

3.2 Level 2 - Integrating Data

After data extraction, it is necessary to store, process and manage building assets data extracted from various sources. This data is stored and managed in a web-based storage for massive associated data where aggregation and correlation of data occurs. In other words, this level aims to transform the raw extracted data to data stored according to certain rules and form Big Data centre/pool (Zhang et al. 2015).

The chosen/required database requires dealing with various relationships supported in the BIMRL or other query languages (Exporting query language in level 1). Meanwhile, the database has to deal with other data such as tabular data (from Sensors and GIS) and documents (asset specifications). Nowadays, there is a variety of non-relational sequence query language (NOSQL) databases which are suggested to be multi-mode NOSQL databases (Solihin and Eastman 2016). Graph database stores data in vertices and edges and it is the most suitable NOSQL database for our purpose as it allows the relationship/pattern to be directly linked through its edges. The most popular graph databases used with BIM data are Neo4J (Bilal et al. 2016) and OrientDB (Dimyadi et al. 2016). Meanwhile, a key-value store database is required to handle the stream simple structured data received from the sensors (Solihin and Eastman 2016).

3.3 Level 3 - Analysing Data

Further data processing and analysis are continued by using mathematical and statistical methods, data mining and machine learning algorithms. This stage can provide the correlation law discovered from the asset data (integrated from different sources) for facility managers' decision making. At the same time, simple data visualisation techniques are considered a requirement for presenting the results effectively.

Horizontal scaling stack is required to analyse the data and find a pattern to integrate the data coming from the different sources and stored in the NOSQL database. Horizontal scaling platforms distribute processing across multiple serves and scale out by adding multiple machines to the cluster to increase the speed and performance. The selection is mainly influenced by the requirements for achieving interoperability between BIM, GIS and FM data which would include iterative algorithms, compute intensive tasks and near real-time visualisation. Based on the research finding, the most popular two stacks of horizontal scaling able to achieve the requirements are Hadoop Big Data Analytics Stack and Spark Big Data Analytics Stack.

3.4 Level 4 - Interoperating Data

The top level is the human-computer interaction level, including data input, data output, secured data, results of statistical analysis, 3D view, etc. in a user friendly interface. This level is crucial as the analysed data/information generated from level 3 must be standardised, interpreted and visualised to help facility managers and other end-users to extract knowledge and identify new patterns from visualised information (Zhong et al. 2016). A secured web-based software as a service (SaaS) is required, where the users are provided access to enterprise applications using multiuser architecture via the internet. In literature, different technologies were emerged to serve display of BIM in 3D viewer on browser such as WebGL and HTML5 (Chen et al. 2014), Gaming Engines like Unity 3D web player (Lee et al. 2016), and DWF and PHP (Nakama et al. 2015).

4 Conclusion and Further Work

This study proposed a BIM Big Data based system framework for capturing, storing, analysing and visualising data from BIM, GIS, sensors and asset databases for data integration in order to enable improved asset management decisions. The proposed system framework can provide online services (cloud computing) that allow facilities managers, BIM users and asset managers to interact with asset data in a 3D environment. The system, which can be defined as a BIM platform that facilities integration of data from different systems, consists of four main modules in four different levels. Module 1 is responsible for extracting the needed/required data from the BIM model through a schema such as BIMRL. Module 2 is the NOSQL database (Graph database) where the different data is stored, managed and integrated. Module 3 is the Big Data analytic stack (Hadoop or Spark) where advanced analytic techniques operate on Big Data stored in Module 2 to reveal hidden patterns and categorise the data based on the object (asset) instead of the source. Finally, Module 4 is the Human-Computer interaction where the integrated data is presented as 3D components through a gaming engine (Unity 3D) or web programming language (WebGL and HTML). This study is part of an ongoing research which aims to develop a BIM Big Data system for asset management. Further work will involve developing the system and evaluate it on real-world case studies.

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USE OF AUGMENTED REALITY TO ENHANCE COMPREHENSION OF STEEL STRUCTURE CONSTRUCTION

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Abstract: The future of the construction industry is highly dependent on the competence of new employees. Therefore, it is very important for new employees to enter the industry with the abilities required to resolve the intricate complications inherent in the construction process. However, inadequate exposure of Construction Management students to in-situ construction processes and procedures can be detrimental to their early success and ability to effectively solve problems. In this regard, students often lack comprehension of the complex spatial and temporal constraints which exist during the construction process, thus limiting their productivity. The goal of this study is to determine the value of advanced construction technologies for improving spatial-temporal comprehension of construction processes in construction management students.

This study uses Augmented Reality (AR) and a layer of computer visualizations to simulate and enhance the environmental context and spatio-temporal constraints of steel structure erection to determine if learners are able to better comprehend the elements and hidden processes which exist during construction. The positive effects of AR are demonstrated in this study, warranting future research and consideration for construction management education.

Keywords: Augmented Reality, Construction Management, Education, Structural Steel, Construction Assemblies, spatio-temporal constraints

1 INTRODUCTION

It is very important for new employees to enter the construction industry with the ability to solve intricate and complex situations inherent in the construction processes. The future of the construction industry is highly dependent on the competence of these new employees as they begin their professional careers. However, the prevalent situation in higher education leads to an inadequate exposure of students to many construction processes and procedures. This results in a comprehension deficiency of the spatial and temporal constraints which exist during construction. Advanced teaching techniques that can provide greater insight to students are needed to enhance the educational experience of construction management students. This study uses Augmented Reality (AR) combined with a layer of artificial visualizations to simulate the environmental context and spatio-temporal constraints which exist during steel construction.

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As this technology continues to gain popularity it is crucial to study and understand its ability to enhance educational experiences. This study aims to assess the impact of AR, as a mechanism to simulate the environmental context of construction processes, on construction management educational experiences, and evaluates the impact of AR on learning outcomes in construction management education. The results of this study provide a basis of understanding for educators seeking to integrate a new instructional tool for the improvement of their students' educational experiences and comprehension of the construction industry.

1.1 Problem Statement

Construction management students today are inadequately exposed to many construction processes and procedures, and therefore lack experience related to the multitude of complex processes which exist in construction. Sole dependence on traditional teaching techniques, such as field trips, can fail to deliver the contextual details required to fully grasp the complex nature of every aspect of a construction project. Furthermore, this can lead to a comprehension deficiency of the spatial and temporal constraints which exist during construction. The resulting lack of experience and understanding renders the students inadequately equipped for entry into the workforce. The scope of this study focuses on improving the spatial and temporal skills of construction management students through the use of AR, with efforts directed at meeting the needs of industry.

1.2 Research Goals and Hypotheses

The primary objective of this research is to determine whether the use of AR can enhance the educational experience of construction management students and improve their spatio-temporal comprehension of specific construction processes. This study builds upon previously published work (Blinn et al. 2016, Blinn et al. 2015) and expands the research area to structural steel erection and assemblies. In this regard, identical methodologies were utilized for the development of AR-enabled content and data collection. The hypotheses that the use of augmented reality will enhance the students' comprehension of the spatio-temporal constraints prevalent in steel structure construction projects was tested. In this regard, this study postulated that the combination of visually documented jobsite experiences superimposed with virtual enhancements will enable students to gain a more thorough understanding of the documented construction process.

2 AUGMENTED REALITY IN THE CONSTRUCTION INDUSTRY

AR is a discipline that merges the real-world, computer generated (virtual) world and computer-generated data (Izkara et al. 2007). The study of the applications for AR has spanned across many industries, including the construction industry, and continues to evolve. However, the full potentials for augmented reality applications have yet to be achieved. AR is an emerging technology in the architecture, construction, engineering and operations (AECO) industry and it demonstrates promise for a variety of applications. The AECO industry has begun to explore applications for AR in the areas of as-planned to as-built progress monitoring, training, dynamic site visualization, construction defect detection and integration with various building information modeling (BIM) workflows (Rankohi and Waugh 2013).

The majority of research for augmented reality in AEC industry has focused on the use of AR in the field. A review of AR based research completed by Rankohi and Waugh (2013) found that 5% of research conducted focused on education and training in the AECO industry. However, applications of AR in the field can be extended to educate and train students in preparation for joining the workforce. A case study that highlights this was the use of a building information model (BIM) and mobile augmented reality (MAR) device to provide virtual data and information about actual building components and systems to facility managers on their mobile devices (Gheisari et al. 2014). A similar design can be employed as an educational tool to enable the improvement of learners' spatial-temporal skills by tailoring the augmented experiences to what is being taught in the classroom, thereby providing a more effective learning experience.

3 AUGMENTED REALITY TEST CASE

The methodology used for the development of the AR-enabled content and data collection for the structural steel construction is the same as previously published work (Blinn et al. 2016, Blinn et al. 2015), upon which this study is built upon. In order to obtain the necessary data required to conduct this research, a test case was developed and learning assessments were conducted to determine the understanding of the students related to steel erection. The project selected for use in this study was a multi-story academic classroom and office building being constructed on the University of Florida campus. Construction on the site of the sample project commenced in the fall of 2013 and image and video data were collected from daily site visits throughout construction. The structural steel assembly system was singled out as the primary focus for this phase of the study and was utilized for the remaining part of the study during the classroom assessments. The scope of the structural steel assembly for the selected sample project included foundation footings, structural columns, structural framing, angle bracing and metal decking.

3.1 Sample Population

The selected population for this study was undergraduate students enrolled in an accredited Construction Management program. For the purpose of this research, the data analyzed is based on a sampling of students enrolled in the Rinker School of Construction Management at the University of Florida (UF). The study was conducted with students in the second semester of their junior year in the program. The Estimating I course, a required introductory estimating course for all construction management students, was selected for the implementation of this study. A total of 55 students, from spring 2015 (29 students) and spring 2016 (26 students) semesters, completed the experimental procedure and provided viable data for use in this study.

4 AR DEVELOPMENT

4.1 Augmentation Procedure

The development of AR-enabled site documentation for the steel structure assembly of the sample project was a crucial step in this research. To achieve the process of augmenting a virtual model onto construction site visualizations, a variety of software packages were used. The research team identified the major elements of the structural steel assembly, as students tend to have difficulty identifying individual steel components. These elements were enhanced and highlighted through the augmentation of BIM components into the real-world visual documentation, both still photography and video based. Portions of the augmentation related to the erection of the structural steel are shown in Figure 1. The virtual model shows the assembly and installation sequence in-situ, to allow for an understanding of the process. This is an example of the augmentations which were superimposed over real-world visuals capturing the entirety of the steel erection process for that portion of the sample building.

Upon completion of augmentation, the developed video was packaged as a standard video file and hosted on a secure server, which the students were provided access to as needed during the appropriate phases of the study. The completed steel erection video, with augmentation, was 8 minutes and 37 seconds in length and showed a range of structural erection processes. During the test phases of the study, students were permitted to view the video and progress through it as they saw fit, with no involvement from the proctors. In order to eliminate any excessive influence on the students' individual learning and comprehension experience, text and sound were not incorporated with the visualizations in any way.

Figure 1: Augmentation of steel structure over existing as-built site conditions

5 EXPERIMENTAL PROCEDURE

All participants in the study were initially required to complete a demographic and background questionnaire to determine their contextual experience. The rest of the study was conducted in two phases, with the participants being split into three testing groups, designated as Groups A, B and C. Phase 1 was developed to accurately assess the participants' base knowledge of steel erection processes, after which Phase 2 was implemented to assess the impact the various instructional tools had on the students' knowledge and contextual understanding. The participants in each group were randomly selected and provided with varied combinations of information regarding structural steel assembly based on the group they were assigned to. The information that was made available to each of the three groups is shown in Table 1. In addition to this information, each participant received an identical document set for each of the two phases of the experiment. The Phase 1 documents included the test questions along with an image, derived from the BIM model, of the area and assembly being studied. The Phase 2 documents included a full drawing set, also derived from the BIM model, of the study area including; dimensioned plans, sections, and 3D views.

Table 1: Group designations and associated information streams

Testing Groups	Group A	Group B	Group C
Information Provided	AR Video Only	Lecture Only (Control)	Lecture and AR Video

Phase 1 involved a pre-learning test (pre-test) and was completed at the beginning of the semester, prior to any instruction on the topic. Phase 2, the post-learning test (post-test), was completed during a later class towards the end of the semester when the curriculum reached steel assemblies. Group A completed Phase 2 of the study prior to receiving any formal instruction on the topic from the course instructor. For the integrity of the study, the three groups were separated during Phase 2 and those in groups A and group C were brought to a computer lab where they were provided access to the AR enhanced steel video. The participants in groups A and C had access to the AR video, through a web-based access portal, on individual computer terminals for the duration of the assignment. In addition, the participants were not permitted to discuss their work with one another or ask questions of the proctor.

6 RESULTS

Both the pre-test and post-tests had the same problem-solving skills questions which were designed to accurately assess the participants' knowledge of steel erection. The tests were used to determine whether there was a change in each participant's knowledge or spatio-temporal understanding of the structural steel assembly process, as well as to assess the impact of the various instructional tools used. An analysis of the test questions follows.

6.1 Installation Sequence of Tasks Required to Build the Structural Steel Assembly

The responses to this question provided information on the ability of the participants to identify the necessary tasks required for the structural steel construction process, as well as the sequencing of these tasks. Table 2 shows the suitable installation sequence for the structural steel assembly that was introduced in the estimating class, along with the number of students that listed each item in the answers. The null hypothesis (H_o) postulates that there is no significant difference between the sample proportions, while the alternate hypothesis (H_a) postulates that there is a significant difference between the sample proportions. Equations (1) and (2) show the null and alternate hypotheses used in the 95% confidence level analyses.

$$H_o: \hat{p}_1 - \hat{p}_2 = 0 \tag{1}$$

$$H_a: \hat{p}_1 - \hat{p}_2 < 0 \tag{2}$$

The sample proportions were compared using the MS Excel (2013) statistical analysis add-in. Equations (3) and (4) were used to determine the test statistics of both the pre-test and post-test sample proportions for each element. To test the hypothesis, the p-value, which is then derived from the z-statistics, is used and the null hypothesis is rejected for p ≤ 0.05.

$$\text{z-statistics} = \frac{\hat{p}_a - \hat{p}_b - (\hat{p}_a - \hat{p}_b)}{\sqrt{[\hat{p}\,(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})]}} \tag{3}$$

$$\text{z-statistics} = \frac{\hat{p}_b - \hat{p}_c - (\hat{p}_b - \hat{p}_c)}{\sqrt{[\hat{p}\,(1-\hat{p})(\frac{1}{n_2} + \frac{1}{n_3})]}} \tag{4}$$

Table 2: Number of observations and sample proportions of installation sequence

Installation Sequence within the construction process.	**GROUP A OBSERVATIONS (VIDEO ONLY)**				**GROUP B OBSERVATIONS (LECTURE ONLY)**				**GROUP C OBSERVATIONS (VIDEO AND LECTURE)**			
	n = 19				**n = 20**				**n = 16**			
Installation Sequence	Pre-Test	p̂	Post-Test	p̂	Pre-Test	p̂	Post-Test	p̂	Pre-Test	p̂	Post-Test	p̂
Fabrication	2	0.11	1	0.05	0	0.00	0	0.00	2	0.13	2	0.13
Excavation	3	0.16	7	0.37	2	0.10	3	0.15	2	0.13	2	0.13
Delivery	1	0.05	2	0.11	2	0.10	3	0.15	3	0.19	0	0.00
Concrete Footings	14	0.74	16	0.84	14	0.70	14	0.70	9	0.56	8	0.50
Columns	10	0.53	14	0.74	13	0.65	14	0.70	9	0.56	8	0.50
Structural Framing	11	0.58	14	0.74	14	0.70	13	0.65	8	0.50	10	0.63
Metal Deck	2	0.11	5	0.26	1	0.05	1	0.05	0	0.00	2	0.13
Welded/ Bolted Connections	12	0.63	13	0.68	9	0.45	14	0.70	6	0.38	8	0.50

The collected data showed with 95% confidence that there were no significant differences (p-value > 0.05) between the control group and the experimental group's answers in regard to fabrication, excavation, delivery, structural framing and metal deck. Table 3 shows the results of the pre-test and post-test null hypothesis testing completed for the data sets of the suitable installation sequence within the structural steel construction process. Significant differences were observed between the control and the experimental groups' answers in regard to concrete footings, structural columns, and connections.

For the "Concrete Footings" item, the post-test sample proportions showed a significant difference between the groups A and B (p-value = 0.011 < 0.05) and groups B and C (p-value = 0.000 < 0.05). Therefore, the null hypothesis for the post-test sample proportions between groups A and B and groups B and C can be rejected, indicating the groups have significantly different proportions after the experiment. Furthermore, for the "Structural Columns" item, the post-test sample proportions showed a significant difference between the groups B and C only (p-value < 0.001) as opposed to the pre-test p-value of 0.074. For the "Connections" item, the post-test sample proportions were found to be significantly different between groups B and C only (p-value < 0.001) as opposed to the pre-test p-value of 0.068.

Table 3: Test results for difference in task sequencing (PS-3)*

Elements	Difference Test	Phase	z-statistic	p-value
Concrete Footings	$\hat{P}_A - \hat{P}_B$	Pre-test	0.610	0.271
	$\hat{P}_A - \hat{P}_B$	Post-test	2.276	0.011*
	$\hat{P}_B - \hat{P}_C$	Pre-test	2.229	0.013
	$\hat{P}_B - \hat{P}_C$	Post-test	3.322	0.000*
Structural Columns	$\hat{P}_A - \hat{P}_B$	Pre-test	2.257	0.012
	$\hat{P}_A - \hat{P}_B$	Post-test	0.610	0.271
	$\hat{P}_B - \hat{P}_C$	Pre-test	1.446	0.074
	$\hat{P}_B - \hat{P}_C$	Post-test	3.322	0.000*
Connections	$\hat{P}_A - \hat{P}_B$	Pre-test	3.452	0.000
	$\hat{P}_A - \hat{P}_B$	Post-test	0.266	0.395
	$\hat{P}_B - \hat{P}_C$	Pre-test	1.494	0.068
	$\hat{P}_B - \hat{P}_C$	Post-test	3.322	0.000*

* $p < 0.05$; H_o is rejected.

7 CONCLUSIONS

The implementation of AR in the construction industry is swiftly progressing and developing in many ways. However, studies have indicated that AR research is not yet widely explored for education in the AECO industry (Rankohi and Waugh 2013). AR has great potential as a possible solution to the comprehension deficiency of construction management students in grasping the complexity of construction processes.

From the analysis of the tasks sequencing question asked during this study, results show that the augmentation video significantly increased the understanding of the students on the identification of concrete footings, structural columns and connections related tasks. This can be attributed to the fact the construction sequence of the structural steel assembly was highlighted and demonstrated in the AR video. The group that had access to the lecture and video had the highest statistical benefits, as they were able to apply the knowledge from the instructor to an accurate visualization of how the structure was erected. It can be inferred from this study that the AR video helped buttress the elements and concepts which were introduced in class and focussed on in the AR content.

The world is undoubtedly changing and moving increasingly towards immersive technology in many industries. As AR tools continue to improve and develop there are increasing opportunities for innovative utilization. This study is a first step in determining the effectiveness of AR for enhancing construction education experiences by introducing the augmentation video as a supplement in the classroom, thus preparing students for successful careers in construction. Further study in this area will aid in the development of effective pedagogical techniques instructors can use to improve the contextual understanding and construction knowledge of their students.

8 ACKNOWLEDGMENTS

This study is based on work funded by the National Science Foundation (NSF) under grant number: 1245529. The opinions, conclusions, and recommendations conveyed in this paper are those of the authors and should not be interpreted as the opinions of the NSF. Additionally, the members of the research team would like to express their gratitude to Ajax Construction and James Marini for their cooperation with the research team and willingness to participate in the study. Without their collaboration, the research team would have been unable to capture the substantial bulk of visual construction data which were paramount to the completion of this study.

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