A systematic review on the requirements on BIM maturity and formal representation of sequencing knowledge for automated construction scheduling

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Abstract
Planning and scheduling is the centerpiece of every commercial and industrial building project. Despite significant effort that goes into planning and scheduling, still many projects end up behind schedule and are over budget. The reasons for this are myriad, and the ability to plan and schedule a project lies near the heart of them all. While research has focused on developing techniques for automated planning and BIM-driven schedule generation, these methods do not scale to real projects as they still require manual generation of work templates and do not intuitively account for all project constraints. This paper offers a close examination on the problems underpinning construction scheduling theory and practice such as sequencing logic and activity description by offering a systematic review on: 1) the way in which BIM-driven schedules are formalized; and 2) the challenges of tying in Building Information Modeling (BIM) with project schedules and/or BIM-driven schedule creation techniques. The requirement on maturity and granularity of BIM and a path forward for automated construction scheduling, purely based on machine learning and inference from BIM as well as historical schedule data, are presented in detail.

Keywords: Building Information Modeling, Automated Scheduling, Machine Learning, Natural Language Processing

1 Introduction
Construction planning and scheduling are fundamental to the timely execution of construction projects (Hendrickson et al 1989, Fischer & Aalami 1996, Fanghihi et al 2015). While planning is required in the planning phase to establish project duration, set major milestones, and identify required resources, rescheduling is often required during construction to accommodate for the inevitable changes that occur on construction sites on a daily basis. Hence, if project planning and scheduling is inadequate, it can lead to costly delays and budget overruns. For instance, McKinsey & Company reported that 98% of megaprojects around the world often suffer significant cost overruns, and more than 80% are delayed by an average of 20 months (Changali et al 2015). The

ability to plan and schedule a project is therefore the cornerstone of a successful project execution.

Today, most project scheduling still relies on the project scheduler's experience and knowledge. Relying on personal experience is prone to errors and biases as well as being limited by the ability of one individual to reason about all the complexities of construction operations. To assist human planners, many researchers attempted to automate the process of schedule generation by defining sequencing logics (Fischer & Aalami 1996) and automating activity generation (Aalami & Fischer 1998, Dzeng & Lee 2004, Koo et al 2007, Tauscher et al 2009, Mikulakova et al 2010) among other efforts.

With the prevailing implementation of building information modeling (BIM) in the architectural, engineering, and construction (AEC) industry, more attention is being paid to extending the capabilities of BIM into project planning. BIM has the ability to bridge the gap between the design phase and the planning phase by tying the 3D model to the schedule. Besides, BIM enables the exploitation of project information by making it available and easily retrievable using BIM authoring tools. Thus, BIM has facilitated and improved the planning and scheduling process (Liu et al 2015).

In this paper, the previous research on BIM-driven schedule automation is systematically reviewed. Based on underpinning construction scheduling theory and practice, this paper provides a close examination of the way knowledge is embedded into BIM. Subsequently, this paper (1) investigates the formalization and representation of BIM-driven schedules, and (2) identifies the challenges of tying BIM to project schedules. In addition, the paper offers a path forward for automating the generation of BIM-based construction schedules purely based on machine learning.

2 Automated BIM-driven Schedule Generation

The adoption of BIM in the construction industry is increasing (Büchmann-Slorup & Andersson 2010, Oraee et al 2017). However, the use of BIM has not yet fundamentally disrupted construction planning practices. Today, construction schedules are generated separately from the building model, and attempts to link the schedule to the model are performed manually using 4D planning solutions such as Syncro or Navisworks. As an open standard, Industry Foundation Classes (IFC) is used to allow BIM data exchange and shared among various software applications in construction industries (ISO 2018). Based on the IFC standard, previous researchers developed ontologies to support knowledge integration adding reasoning dimensions in the BIM model (Katranuschkov et al 2003, Rezgui 2006, Eynon 2016). With information in the BIM, existing research efforts to automate the BIM-based planning process focused on 1) using manually predefined activity sequencing rules, 2) applying case-based reasoning (CBR) methods, and 3) learning sequencing logic from existing data using machine learning and pattern mining methods and using it to reason about scheduling logic.

2.1 Rule-based method

To generate a construction schedule, predefined rules derived from physical laws or construction knowledge are used to automate the sequencing process. To define the construction sequence, the geometrical and topological position of the building components can be used to infer sequencing rules (Borrmann & Rank 2009). Based on the geometrical and topological position in the 3D model, de Vries & Harink (2007) formalized an algorithm to generate construction sequencing order. Likewise, Kim & Cho (2015) proposed a Construction Spatial Information Reasoner (CSIR) system to support automated construction planning. They defined algorithms to detect geometric relationships in BIMs, however, their geometric reasoning is applicable only to rectangular and planar surfaces.

On the other hand, researchers formalized the constraints that govern sequencing dependencies. For instance, Echeverry et al (1991) categorized the factors governing sequencing logic into physical relationships, path interference, trade interactions, and code regulations. Building on the work of Echeverry et al (1991), Koo et al (2007) refined the formalization of sequencing logic into the physical component relationship, trade interaction, and code regulations and introduced their roles and flexibility for rescheduling. For example, 'Form, Rebar & Place Columns' is the predecessor of 'Form, Rebar & Place Deck'. These two activities are linked by the physical component relationship where the deck is supported by the columns. From the predefined sequencing logic, Kim et al (2013) proposed a framework to automatically generate a schedule from BIM. They extracted IFC data such as geometry and material information from BIM, and their proposed system then aligned building components to a predetermined activity set. For activity sequencing, they applied structural rules using four different sequencing logic constraints such as '*supported by', 'covered by', 'embedded in'* and '*distance to support*'. Likewise, Mohammadi et al (2016) extracted building information such as elements, quantity, location, and their topological and structural relations from BIM. They identified activities based on building elements and generated activity sequences based on predefined rules given topological and structural relationships. Although rule-based methods are able to leverage available building information, they still require hard-coded sequencing rules and work templates to be manually defined, and they are unable to cover undefined rules (Wang 2018).

2.2 Cased-based reasoning method

The CBR method does not require predefined rules. As knowledge-based process planning, building elements are defined as execution tasks with constraints. For example, a wall should be built on a slab. These building elements are used to define task sequences as constraints. Likewise, knowledge captured in former project schedules is stored in the Case-Based Reasoning (CBR) system, and the CBR system linked to a BIM enables retrieval of them to reuse scheduling knowledge from the similarity assessment. Hence, the CBR method has mainly four steps; information retrieval, reuse, revise, and retain.

In Tauscher et al (2009), they interpreted building elements as constraints using IFC data. For example, the wall erection activity was represented by the building element *IfcWall* and its attributes. They interpreted the building element *IfcWall* as constraint and found all cases that have a wall as CBR to retrieve similar cases. Among similar cases, they calculated an overall similarity and adapted the most similar case for sequencing activities. Similarly, Mikulakova et al (2010) used the CBR system for the schedule generation and further presented a decision-support system for evaluating construction alternatives. To rank schedule alternatives and make a decision, they considered qualitative criteria such as know-how requirement, error sensitivity, personnel' s qualification using fuzzy logic and probability distribution. As more advanced research, Hartmann et al (2012) extended the BIM-based scheduling concept for the schedule generation using additional elements called abstract elements. Abstract elements not stored in the currently used IFC model are also used to define constraints of processes and integrate them into the BIM-based scheduling logic. For example, they considered element states such as completed, non-existent, 80%, and so on. From the flexibility of the states, they can consider all possible constraints splitting cases. Wang and Rezazadeh Azar (2019) also presented a BIM-driven schedule generation system using the CBR system. They extracted building objects and attributes from BIM models, and work-packages were created from the extracted data and validated by the predefined rules. They utilized the CBR system to generate and retrieve activity sequences.

Although the CBR method can retrieve knowledge gained from previous projects, it does not always guarantee the best optimal solution and is not completely effective. Considering the CBR method provides a solution for a similar experience, this method might not be able to provide solutions for new problems (Sigalov and König 2017, Wang 2018). Additionally, in the CBR system, previous cases for the retrieval are manually stored by human hand.

2.3 Pattern-based method

A pattern-based approach for knowledge reuse is suggested to solve the problem of redundancy and storage space. Capturing knowledge on the schedule and removing duplicate cases, process patterns are stored into templates. Given templates generate individual processes and interdependencies, Wu et al (2010) integrated a hierarchical level-of-detail (LoD) approach for a bridge construction schedule generation. Building components were assigned to construction methods implying a fixed set of activities and precedence relationships by means of process patterns. In their approach, starting on LoD 1, the planner selects a certain construction method for Construction Bridge among the available methods. Likewise, this hierarchical approach in the template enables the generation of schedules at different levels of detail for a 3D model simulation system. König et al (2012) presented reusable templates by storing interdependencies between activities for handling modifications and different alternatives. They manually assigned a single pattern or multiple process patterns to building elements and extended their template according to topological and spatial properties. As an example, a process pattern to construct in-situ concrete walls is assigned to every building component, *IfcWall*. Benevolenskiy et al (2012) presented a Process Configurator system to support the schedule generation with the process patterns. For the BIM model, IFC data was used and the taxonomic relations between the elements were modeled. For example, a process pattern can be searched by the defined object and an object property *hasSubTask* can be used to build a process hierarchy. They adapted their system to a real-world high-rise office building project. Otherwise, Sigalov and Konig (2017) introduced the application of reusable process templates based on graph-based methods for the process pattern recognition in schedules. process patterns. Given schedules have nodes (activities) and directed edges (dependencies), features are small fragments of the schedule graph. Sub-schedules were used for pattern recognition based on the feature-based similarity, and the subschedules with the highest similarity value form a process pattern.

As such, template-based scheduling is able to improve the efficiency of the scheduling process. Nevertheless, this method still needs manual work such as assigning construction methods and tasks to building elements or hard coding spatial constraints or properties of processes. Hence, fully automated learning from historical schedule data is rarely conducted in the scope of work. Considering the increase of construction complexities, manually assigning the interactions between systems and components is still inefficient. Given the availability of a large amount of historical schedule data, machine learning is able to learn sequencing knowledge and capture their relationships between activities in the future.

3 Challenges of tying in BIM with schedule data

Real-world schedules are becoming more complex and are easily affected by various factors such as construction approaches, knowledge, and constraints. Given the nature of the schedule itself, schedules can be changed and it is hard to examine their correctness. BIM-driven schedules are generated by hard coded rules or templates based on the BIM model, hence, BIM-based schedules are prone to producing incorrect sequencing rules when the drawings or the 3D models are inaccurate (de Vries & Harink 2007).

While the previous research has been presented for schedule quality assessment (PMI 2006, GAO 2009, DCMA 2012, Farzad Moosavi & Moselhi 2014), these assessments rarely check the correctness of the sequencing logic in project schedules (Moosavi & Moselhi 2014, Zhao et al 2020). Also, the previous research for the BIM-driven schedule automation was verified to only a few specific projects such as bridges, residential or concrete-framed buildings (Fanghihi et al 2015, Mohammadi et al 2016, Sigalov and Konig 2017, Wang et al 2019). To guarantee the feasibility of BIM-based schedule generation as well as extend their application, automatically learning construction knowledge from various historical schedule data might be necessary given the activity and its logical dependencies.

3.1 Formalization of activities

Although the ability to extract information from BIM has been improved to support object-oriented and other downstream processes, it is not fully utilized to automate schedule generation. In the real-world schedule, the representation of the activity itself is complex and unstructured. To decode semantic information in activity descriptions, Darwiche et al (1988) introduced semantic object-oriented representation with the {Object, Action, Resources} tuple (OAR). Fischer & Aalami (1996) expanded the OAR representation to the {Constituents [Objects], Actions, Resources, Sequencing Constraints} schema. Amer & Golparvar-Fard (2019) presented a formal representation of activity, the ALOR set: {Action, Location, Object, Responsible Party}

(Figure 1). Likewise, a formal representation can assist to define and decode construction activities functionally. Existing research for BIM-driven automated scheduling leveraged BIM-object oriented structure to assign BIM elements with activities.

Furthermore, the activity description in the schedule can be written using different expressions but still refer to the exact same meaning. For example, '*frame slab level 1*' activity can be represented differently as '*f/r/p slab lvl 1*' (which stands for form/reinforce/place). Also, curtain walls can be described as '*cw*' or '*curtainwalls*' or '*curtain walls*'. These expressions use construction-domain abbreviations and synonyms which are not common in standard English. Given this variety of expressions, BIM-based scheduling methods that use hard coded sequencing logic might fail to decode activity descriptions and therefore fail to link them to the right objects. To decipher activity descriptions and learn construction knowledge from activities, Natural Language Processing (NLP)-based approaches might be useful.

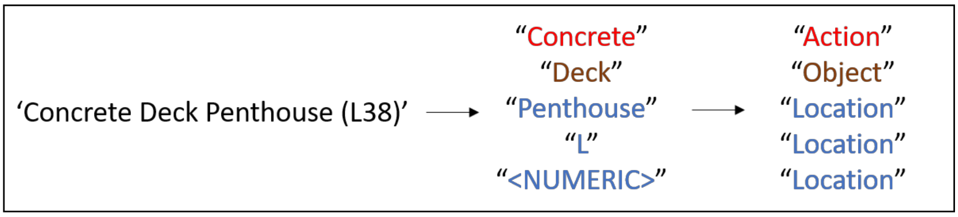

Figure 1. ALOR representation of the activity from the real-world schedule (Amer & Golparvar-Fard 2019)

3.2 Formalization of sequencing logic

Schedules are composed of activities and their relationships. Planners define the predecessor activities required to enable an activity as well as the successors that are enabled by it. For example, Echeverry et al (1991) formalized the representation of sequencing dependencies such as *Physical Relationships, Trade Interactions, Code Regulations, and Path Interference*. Within each dependency factor, constraints were categorized such as *supported by, covered by, embedded in, relative distance to support, relative distance to access, and weather protected by*. Each constraint was given a *flexibility* attribute depending on whether this sequencing was modifiable or not. Building on the formalization of Echeverry et al (1991), Koo et al (2007) revised the formalization of sequencing logic. In particular, they defined activities roles to be *enabling* or *impeding*. Enabling means an activity enables the successor activity to take place, and impeding means an activity prohibits the execution of the successor. Then, the role and flexibility of each activity allow the scheduling system to generate logical sequences as well as rescheduling.

BIM-based systems can fundamentally infer sequencing logic from the relationships of activities to BIM model components. Hence, BIM-based schedules are prone to producing incorrect sequencing rules when the drawings or the 3D models are inaccurate. However, many researchers focused on the retrieval of sequencing knowledge using hard-coded templates or rules, especially physical relationships. Therefore, in order to prevent incorrect sequence patterns, the system needs to consider the underlying reasons among activities.

Considering all, the current system might not guarantee the correctness of sequences despite the availability of BIM information. Furthermore, manual work is still required in the system. In order to automatically generate a BIM-driven schedule, several things remain challenges of tying in BIM with schedule; (1) deciphering the activity description, (2) decoding sequencing logics with underlying reasons. To do so, the formal representation of activity and sequencing logic can help computers to interpret the planning knowledge itself, and machine-learning methods can learn the knowledge without any human input or hard-coded systems. In the following section, machine learning-based methods for fully automated schedule generation are introduced.

4 Machine Learning-based Schedule Automation

Given a large amount of historical data available, machine learning-based methods can suggest a potential solution for addressing scalability issues. For information extraction and retrieval from an input document, Natural Language Processing (NLP) techniques such as Part-of-Speech (POS) tagging are widely used to identify and recognize the syntactic and semantic features in the construction domain (Zhang & El-Gohary 2014, Bilal et al 2016). Considering activities in schedules are unstructured, Amer & Golparvar-Fard (2019) presented an NLP-driven pipeline for deciphering construction activity with a formal representation, namely the ALOR set: {Action, Location, Object, Responsible Party}. To capture semantic similarities among words in construction schedules, they trained three real-word projects using word embeddings with ALOR tagging. As an example, 'pour' and 'slab' are not similar in English, but their model can capture similar words of 'pour' such as 'slab', 'deck', 'shearwalls', and 'form'. Hence, construction knowledge can be automatically learned from the formal representation of activity. Likewise, Zhao et al (2020) used NLP techniques such as POS tagging to extract construction methods and dependency logic from construction schedules and detect errors in the description of schedule activities.

To automatically capture the sequencing patterns in the schedule data, Alikhani et al (2020) presented a Bidirectional Long Short-Term Memory Recurrent Neural Network (LSTM) model to learn the sequences of activities in highway projects and predicted the next and the past chain of activities. Amer & Golparvar-Fard (2021) proposed Dynamic Process Templates (DPTs) where construction sequencing knowledge was leveraged with LSTMs and NLP techniques querying the predecessor or successor of the input sequence. Consequently, machine learning methods are capable of learning construction planning and sequencing knowledge across different real-world projects and supporting project schedulers with flexibility.

From NLP and machine learning-driven research, many of the points mentioned in the third section can be solved. First, the formal representation of activities can help ensure activities are deciphered considering syntactic and semantic features. Second, the formal representation of activity is able to assist interference from BIM. Third, querying the sequencing patterns automatically from the real-world schedule data without any predefined rules or templates. Finally, construction schedule knowledge from the previous records can be utilized to examine the feasibility of the generated schedule. Hence, a path forward for automated construction scheduling purely based on machine learning and inference from BIM and historical schedule data has enough potential to solve the gap of knowledge between BIM and automated scheduling systems.

5 Conclusion

This paper systematically reviews the previous approaches to automate BIM-based schedule generation. The enriched source of data in the BIM model has facilitated the scheduling process, but this paper revealed that existing systems cannot handle the complexity of real-world projects. Utilizing BIM elements (e.g., IFC data) for the schedule generation, the existing approach still required strict hard-coded rules, manually stored cases, or structured templates. These methods are rigid in automatically generalizing knowledge from existing projects to new projects. For modeling activities and sequencing logic, the existing methods consider only a predefined set of activities or operations despite the variety of them. Therefore, they do not enable decipher semantic representations in real-world schedules and do not verify on real-world projects. Moreover, BIM-based systems are prone to generating incorrect sequencing results when the 3D models are inaccurate. Consequently, there are still limitations in tying BIM with schedule generation; 1) too rigid to generalize knowledge, 2) decoding sequencing logic, and 3) not verifying on real-world projects.

To solve these knowledge gaps, a new formalization of activity and sequencing logic is recommended. By interpreting unstructured activities functionally, a formal representation of activities can assist in leveraging BIM to activities. Given the variety of expression of activities, the NLP-driven approach can decipher syntactic and semantic representations as well as infer construction knowledge from historical data. In addition, the formal representation of sequencing logics can consider the underlying reasons among activities. With decompiled data in the BIM model and historical schedule data, the machine learning-based approach has the ability to learn the sequencing knowledge without any human input. Therefore, the approach based on machine learning and NLP techniques has potential to fully automate schedule generation typing with BIM.

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