CONSTRUCTION PLANNING WITH MACHINE LEARNING

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Over the next years, it is expected that machine learning will be widely implemented within fields in the construction context, such as construction planning. As construction projects tend to be influenced by interrelated issues resulting in cost and/or time overruns and lower performance, it has been continuously attempted to develop predictive planning methods and tools, in order to mitigate such issues. This study aims at investigating possible applications of machine learning for construction planning, noting their impact on project performance, and finally commenting critically on the issues of responsibility in action-taking, accountability in decision-making, and the still crucial need for human reasoning. Methodologically, a literature review on machine learning applications in construction project planning is carried out, and then two particular implementation cases are selected for a more in-depth analysis. The first case draws on a productivity survey of construction projects in Sweden, where the relative data is analysed to find the most influential factors behind project performance; then, statistical correlation is used to find the features that are strongly correlated with four performance indicators (cost variance, time variance, and client- and contractor satisfaction), and a supervised machine learning analysis is done to develop a model for predicting project cost, time and satisfaction. The second case elaborates on the appraisal of constructability of civil engineering projects through technical project risk analysis; the model utilizes both unsupervised machine learning for the understanding and pre-processing of data, and supervised machine learning for the development of the predictive system. Following the above analysis, it is argued that there is a need for human reasoning in construction planning, even more so after the introduction of machine learning. It is not enough to include human aspects in the machine learning modelling; it is also crucial to strengthen qualified reasoning in the decision-making for construction project planning and being responsible in action-taking and accountable in decision-making.

Keywords: information technology, machine learning, human reasoning

INTRODUCTION

Construction projects are usually affected by multiple and interrelated factors which have a direct impact on their performance (e.g. cost and time of delivery) and productivity, such as poor management practices, unclear goals and performance measure, and crises orientation (Forbes and Ahmed 2010). Construction projects suffer from scheduling problems related to the optimal sequencing of activities and resource allocation (Zhou *et al.,* 2013, Wauters and Vanhoucke 2014). There are also problems associated to uncertainties in design, construction management and decision making (Lu *et al.,* 2012). Among cases such as the aforementioned, and regardless of

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emerging performance measures (such as ones related to safety and environmental impact), delivery cost and time are still considered most important for construction planning and construction project performance evaluation (Chan and Chan 2004).

In tackling such issues within construction planning, as well as within the ongoing digitalization transformation of the construction sector, machine learning (ML) can play an important role both in research and practice (Kaplan and Haenlein 2019). Systems that utilize ML are “computer systems that automatically improve through experience” (Jordan and Mitchell 2015, Witten *et al.,* 2016, Portugal *et al.,* 2018). In this context “experience” means new data from the domain of the system. For ML to identify and verify any fundamental statistic, computational, and information theory laws that govern the respective learning systems in the relative contexts (Jordan and Mitchell 2015), it utilizes tools from, among other fields, data mining, statistics, and optimization theory (Jordan and Mitchell 2015).

ML is frequently classified in three types: supervised, unsupervised, and hybrid ML. Supervised ML (Jordan and Mitchell 2015) utilizes algorithms that are “trained” and validated using labelled datasets, within application domains with a known reasoning. ML algorithms “learn” based on real training data, produce certain results, and then, after the results’ validation, apply the gained knowledge on new instances (Portugal *et al.,* 2018). Unsupervised ML can be defined as “the analysis of unlabelled data under assumptions about structural properties of the data” (Jordan and Mitchell 2015). In unsupervised ML, the system is presented with data about a domain and has to find hidden patterns and develop relational models “on its own”, by running internal procedures (Portugal *et al.,* 2018). Counter to supervised ML, there are not pre-set assumptions about internals laws in the dataset; rather, unsupervised ML systems are supposed to find these. Hybrid ML involves mixing more than one approaches. These may include semi-supervised learning, or reinforcement learning (Jordan and Mitchell 2015, Portugal *et al.,* 2018).

ML can potentially provide powerful data-driven predictive models but is also exposed to scepticism on issues of accountability, surveillance, and direct impact on humans (e.g. fairness, bias, and discrimination) (Whittaker *et al.,* 2018). Currently, there is difficulty in recognizing the differences in the potential between earlier ML applications (i.e. expert systems), and the current systems; this is mainly related to the ability of ML systems to process large amounts of data and rules. However, such criticism does not prevent “intelligent machines” from being considered as the new means for effective construction management, utilized along knowledge management and organizational learning, and combining human learning with computational intelligence to solve the related construction planning problems (Zhou *et al.,* 2013).

This study aims at investigating possible applications of ML for construction planning, and especially noting their impact on the responsibility in action-taking, accountability in decision-making, and the still crucial need for human reasoning. After presenting the research method, a literature review on ML applications in construction project planning takes place, and then two particular implementation cases are selected for a more in-depth analysis. In the final two sections of this paper, the discussion emanating from the conducted analysis, as well as the relative conclusions, are respectively showcased.

METHOD

In the current study, a combination of interpretive sociological and mixed method is adopted as a research approach (Bryman and Bell 2011, Creswell and Clark 2011). This approach is applied to the literature review and the exposition of the two case studies included in the succeeding sections. The literature review is based on an explorative search on current ML applications for construction planning. Then, the two cases presented were chosen from the authors' own work (a master's thesis and a PhD) and represent current applications of ML in a construction management context, with an emphasis on construction planning as well.

The example findings are relatively few, but in a targeted manner, since the authors chose to mainly present cases with well-defined systems displaying a clear methodological and developmental process, and also having reached at least the technological maturity stage of prototype. It should be noted that the literature findings both satisfying the aforementioned broad criteria and also regarding construction planning more explicitly, are even fewer, with some of them shown in Table 1.

Table 1: Reported machine learning systems within construction planning

Case system /reference	Place	Algorithms	Data	Maturity
Litigation Site Disputes/ Mahfouz and Kandil 2011	Support	4	400 projects	Prototype - Internal validation
Cost Performance and use of technology/Chi *et al.,* 2012	Support	4	193 projects	Prototype - External validation
Productivity and environment/ Liu *et al.,* 2018	Planning	2	Projects/other sources	Prototype - Internal validation
Location on site resources/ Won *et al.,* 2018	Planning	1	192 data instances	Prototype - Internal validation

The limitations of the present contribution include the selective set of literature, and a reduced context appreciation in the two cases. The first presented case limitations include not using the nuanced distinctions highlighted in the data it was built on, and rather aiming at making a general comparison between projects. Moreover, the study only covered the Swedish construction market, as the applicability to other contexts (i.e. the construction sectors in other countries) was not known. In addition, cost, time and satisfaction were selected and considered as KPIs, and other possible indicators are disregarded. The second presented case limitations stem mainly from the limited, if diverse, training and validation dataset. Furthermore, while it strives for generalized results, the diversity of the model inputs may make its particularization in distinct construction project types and/or other special conditions cumbersome.

LITERATURE REVIEW

Central activities in construction planning is scheduling, optimization and resource leveraging. Zhou *et al.,* (2013) in their review map a series of existing pre-ML algorithms and claim that ML algorithms can present an optimal method to learn flexibly and automatically from sample data, and suggest that cost, time, risk, and quality were considered. Prayogo *et al.,* (2018) presented an ML application for solving the resource leveraging problem in construction projects. Zhou *et al.,* (2013) and Prayogo *et al.,* (2018) underpin a wide potential for use of ML in construction planning. When it comes to presented systems in the literature however, a much more limited sample is available at present. Table 1 juxtaposes four found examples, where only two are within planning in a strict sense. For each system, its place in the building process, number of used algorithms, data source, and technological maturity (i.e. is it a research model, prototype or product offered on the market?), is displayed.

The litigations of site disputes system (Mahfouz and Kandil 2011) aims at reducing site disputes through prediction of outcomes. Mahfouz and Kandil (2011) collected federal court data and separated the cases into the ones judged in favour of the client and the ones in favour of the contractor. Then, they deployed four ML algorithms on features such as project types and contract clauses and developed a model to predict the outcomes of such contractual disputes. Chi *et al.,* (2012) proposed a system for decision support, utilizing data on the degree of utilized technology and cost performance in construction projects. To process this data, they used four different ranking algorithms for project work functions. Then, they chose the highest-ranking attributes showcasing the best capability for predicting cost performance (e.g. including planning and execution, and project scoping). Liu *et al.,* (2018) proposed a system analysing scaffolding productivity and weather conditions. Liu *et al.,* (2018) claim that the relationship between outdoor ambient environment and construction productivity is nonlinear, thus a relative nonlinear model is proposed. Different nonlinear algorithms were used to study the ambient environment contributors on scaffolding construction performance factors. The collected and utilized data included performance factors (e.g. total planned hours), and ambient environment features and meteorological conditions (e.g. temperature and humidity).

A combination of meteorological conditions was found to affect the construction performance of scaffolding in Darwin Australia. Won *et al.,* (2018) propose a system for locating on-site resources. The on-site locations of stocked and installed materials are sometimes determined by radio frequency identification (RFID) sensors, which are inefficient in terms of cost and time in large projects, especially if workers are manually carrying RFID radars to investigate tags on materials (Won *et al.,* 2018); this way, intensive labour working time is required. Won *et al.,* (2018) proposed a model for the unmanned aerial vehicle UAV-RFID, utilizing algorithms to analyse data regarding the received signal strength index (RSSI), or derived by real-time kinematic (RTK) GPS and the gyro sensors mounted on the vehicle. This model was considered to be more efficient than previous methods for locating resources in outdoor sites, such as RFID, GPS, and ultra-wide band (UWB).

Summing up, there is a variety of systems and prototype applications of ML within the construction context. The purpose of the development of such systems covered various aspects of the construction field, but only a handful of the ML solutions related more explicitly to construction planning. For these systems to be developed, different ML algorithms, interfaces, and connected interoperable systems were used. The technological maturity of those is generally low (prototype stage), and their validation largely utilized internal processes (e.g. cross-validation with instances of the training dataset), rather than extensive testing through new cases. What can be underpinned is that while there is a still growing interest and promise in the research literature regarding ML applications for construction, more ground has to be covered for this interest to transform into actual established knowledge fully integrated within the construction context.

Cases

Performance prediction for Swedish construction projects

Machine learning algorithms were used to extract and analyse project performance data from a productivity survey of n = 580 construction projects in Sweden (Koch and Lundholm 2018). This data included answers from 324 main contractor representatives and 256 clients, both of whom participated in a questionnaire survey. A main ambition of the investigation was to measure productivity as something more than just cost per square meter. Process-related and soft aspects were considered, such as disturbances during construction production, and the performance of the project organization members (i.e. clients, consultants, contractors, and suppliers). The questionnaire included a set of questions that mostly had pre-given categories for answers in Likert scales. Such categories included technical project complexity, preparation work, blasting work usage, level of prefabrication, and chosen structural engineering technology (e.g. concrete, steel, or timber). In addition, project organization questions were included, such as ones about the clients' and contractors' evaluation of the consulting engineers, the architect and supplier performance, and the level of collaboration throughout projects. There were also questions where facts and figures were demanded, as well as some open questions related to stated definitions (e.g. client costs and partnering). Finally, a few questions were open without stated definitions, including ones on satisfaction, disturbances and lessons-learned. The design and operation of data collection was conducted in the autumn of 2014.

The focus was on four key performance indicators (KPIs): cost, time, and client- and contractor satisfaction. The data was related to several factors, including project attributes, external factors, and the project organization. For the ML analysis and modelling of the factors affecting project performance, several algorithmic tools were used, with the relative computational processes performed via WEKA (Waikato Environment for Knowledge Analysis), a data mining and ML software (Witten *et al.,* 2016). In the first part of the modelling, the features of time variance, cost variance and satisfaction of the contractor during the pre-construction and construction phases, as well as the cost variance and satisfaction of the client during the pre-construction and construction phases, were selected. By this feature selection, the number of input variables used to build the prediction model was reduced, and the attributes with the most distinctive predictive capability in relation to the output were identified (Witten *et al.,* 2016). Next, an analysis was performed using the selected features, so that the prediction model could find the correlation between those features and the level of project performance in terms of the four aforementioned KPIs. The error estimate used in this analysis was the root mean square error (standard deviation of residuals), namely the root of the square value of the difference between the predicted and the actual value (Witten *et al.,* 2016).

Among other features, project technical complexity, the use of blasting work, and the level of prefabrication were recognised as important factors that affect project performance within construction planning. However, despite external factors and technical aspects of a building being considered important, the most recurring factors behind project performance were human-related (such the role of the client and the level of the architect's performance). The data shows high variation in cost and time variance, and the analysis highlights that in extreme cases (which actually constitute a minority within the dataset), the performance of projects that show high cost overrun or extreme savings is harder to predict.

Constructability appraisal through risk source identification and assessment
The second case of a ML-enabled predictive system for construction planning, appraises a project's constructability through technical project risk source analysis. The constituents of this system were developed using both unsupervised ML (Kifokeris and Xenidis 2018) and supervised ML (Kifokeris and Xenidis 2019a). Constructability can be here understood as the optimal use of construction knowledge and experience in planning, design, procurement, and field operations to achieve the overall project objectives of time, cost, quality and client satisfaction, and it is an integral construction management framework implemented through the initiation, execution, and delivery project lifecycle phases (Kifokeris and Xenidis 2019a).

Firstly, the development of the system encompassed an extensive literature study on constructability and technical project risk analysis. In this review and among other findings, the definitional discrepancy regarding the notion of risk, as well as the current research trends promoting the use of risk sources (rather than risks themselves) for building and construction projects, were identified (Kifokeris and Xenidis 2018). Then, this data was used for the derivation of risk sources via unsupervised ML; it was extracted from the respective body of literature and was processed with a semantic and linguistic clustering algorithm. This resulted in the identification of 129 general technical project risk sources, organized into ten contextual overhead clusters.

Secondly, the data used for the integration of constructability and construction risk analysis via the training and validation of supervised ML, was collected through unstructured interviews with experts. The latter dataset, consisting of constructability class- and risk analysis-related data, consisted of 30 civil engineering projects. These included, among others, a biogas power plant (Greece), two bridges (Greece and Romania), the expansion of a municipal primary school (Greece), reconstruction of a municipal road axis (Greece), sustainable public installations (including a public square, Greece), four road infrastructure projects (Estonia), three renewable technology projects (Greece and Albania), four municipal electrical lighting projects (Greece), and 10 subcontracted projects forming parts of the Midfield Terminal megaproject, in the Abu Dhabi Airport. The supervised ML system that was developed utilized a variety of algorithms and auxiliary mathematical and programming tools; it linked the previously found 129 risk sources with the risk-related real data from the latter 30-project dataset, and then correlated the outcome of this linking with the constructability class-related data of the 30 projects (Kifokeris and Xenidis 2019a). As a result, and after the simultaneous training and validation of the utilized algorithms, a classification scheme able to predict the constructability of a construction project when given the values of the identified general risk sources affecting it, was produced (Kifokeris and Xenidis 2019a). Finally, the software prototype RISCONA (RIsk Source-based CONstructability Appraisal) was created (Kifokeris and Xenidis 2019b), which offered a simple graphical user interface for using the predictive model, while the computational supervised ML apparatus is running in the background.

DISCUSSION

ML has been tested in several activities related to project performance, productivity and planning. The ML literature shows that relative solutions are covering problems in scheduling, uncertainties, cost and time planning issues in construction. Scheduling and resource leveraging are urgent issues related to adequate planning of construction projects, the schedule optimization (Prayogo *et al.,* 2018, Zhou *et al.,* 2013), and the ranking of project work-related functions (Chi *et al.,* 2012). The function ranking model provides a flexible tool for prioritising work functions, which facilitates the decision-making of construction managers by scoring identified key project elements and evaluating project management practices (Chi *et al.,* 2012). ML for the localization of resources (Won *et al.,* 2018) and the appraisal of the effect of the outdoor ambient environment on the productivity of construction tasks (Liu *et al.,* 2018) can also offer solutions for construction planning-related issues (such as the optimization of task efficiency, and project delivery time and cost); this is due to the respective models being related to success factors such as site conditions, follow-up and on-site supervision, and productivity during construction. ML models for predicting the litigation of disputes (e.g. related to site conditions) (Mahfouz and Kandil 2011), can aid in solving problems related to economic and external factors. There is a direct correlation between these factors (also affecting construction project performance) and effective construction planning, and the prediction results of the former can affect the latter. Regardless of the advancement of ML models supporting construction planning (which influences and is influenced by the level of project performance), there are dimensions that still need to be investigated and realized into practical solutions for the related problems - such as uncertainties in design (Lu *et al.,* 2012). It is also a common point in the literature that there are limitations in validating the reliability and efficiency of ML models developed for descriptive and predictive purposes within construction planning; there is a need for more diverse project outcomes and project management practices to be considered, and for the investigation of the user-friendliness of the implemented models (Chi *et al.,* 2012). In problems related to time and cost overruns, aspects of uncertainty regarding the time of activities and the acquisition of resources are important for future research studies (Prayogo *et al.,* 2018).

The extraction of more data is also recommended for better model training and validation, especially in cases where data were limited on the outset (Won *et al.,* 2018). These limitations illustrate that accountability in decision-making is still an issue to be addressed in the development of ML models for construction planning. The reliance on the quality and quantity of the training and validating data, the relative ambiguity in the selection of the related factors that are addressed for each application, and elements of uncertainty that are difficult to be considered and/or quantified, may result in an unbalanced relationship between the level of informative support that a ML model for construction planning can offer to the decision-making construction managers, and the actual results that the decisions of those construction managers will yield in reality. The aforementioned issue is also directly related to the responsibility accepted by construction managers using ML models for construction planning in their action-taking - an issue also illustrated in the aforementioned limitations, but drawing more on the scope of practical application, rather the understanding of the results of such ML models.

While empirical knowledge is still the main driving force in construction management (even when aided by digitalized tools and techniques such as ML), construction managers rely more and more on the automated results of quantitative data- and qualitative information-driven systems (Bilal *et al.,* 2016). However, the past historic knowledge, best practices, and lessons-learned from which such systems extract, process and utilize data for their training and validation, may in several cases approximate the reality of future predictions in a satisfactory manner, but might also fall short on providing solutions for unprecedented bottlenecks, difficulties and/or potential disasters. Over-relying on and being over-confident about the prediction results of ML models for construction planning, can lead construction managers to shed some of their responsibility for the actions they actually take following their decision-making; in addition, such an attitude could also weaken their criterion and ability for a quick and out-of-the-box thinking for solving paradoxes and wicked problems.

Such paradoxes and wicked problems may not only be project-specific, but also reflect a more generalized situation apparent in the whole organizational structure of e.g. a construction firm; there is thus even less room for non-sharp thinking on the side of construction managers. The two cases explored in more detail, illustrate the implementation of supervised and unsupervised ML for aspects of construction planning, and build on an assumption of generalizability, i.e. that construction project success, as well as risk and constructability, can have a relationship of causation (and not only correlation) with a set of generic parameters. However, the mentioned limitations in the generalization of the results of the respective models, still hinder the full deployment of such generic solutions. Therefore, future research should focus, among others, on the tackling of problems in generalization, validation and user interface experience - which will, in turn, address more adequately the issues of accountability in decision-making and responsibility in action-taking for construction managers. Expert knowledge is crucial for knowledge inference in ML models within construction planning, especially in complex elements associated with the concepts of stakeholder collaboration and satisfaction, as well as correlated causes behind project efficiency and productivity. Therefore, and despite the capabilities of ML models in providing valuable assistance as auxiliary tools for construction planning, human reasoning - driven by targeted education, tacit knowledge, accumulated experience, and taking-up of current and future challenges in an emergent manner - should continue being cultivated and relied upon. ML models for construction planning should be decision-making helpers, not the decision-makers.

CONCLUSIONS

The implementation of machine learning (namely, systems that algorithmically "learn" by themselves and form predictive systems based on existing datasets) within the construction context, and especially for construction planning, is expected to become even more pronounced in the near future, also following the paradigm shift of digitalisation in construction. As construction projects tend to be influenced by interrelated issues resulting in cost and/or time overruns and lower performance, there has been a continuous attempt to mitigate such issues by developing predictive construction planning systems. ML can offer such a capability. In this research effort, and after a targeted literature review investigating possible applications of ML for construction planning, as well as a more detailed exposition of two application and development cases, certain deductions and identified limitations led to a discussion addressing the issues of responsibility in action-taking, accountability in decision-making, and the still crucial need for human reasoning when it comes to construction managers using such ML systems. Accountability in decision-making may be hindered by the reliance on the quality and quantity of the training and validating data, the relative ambiguity in the selection of the related factors that are addressed for each application, and elements of uncertainty that are difficult to be considered and/or quantified. Such hindrance can result to an unbalanced relationship between the level of support that a ML model can offer to the decision-making construction managers, and the actual results that the decisions of those construction managers will yield in reality. Also, and through a more practical lens, the responsibility accepted by construction managers using ML models for construction planning in their action-taking, can be affected. Construction managers still rely heavily on their empirical knowledge (even when aided by digitalized tools and techniques such as ML), but also draw more and more on the automated results of quantitative data- and qualitative information-driven systems. However, such systems, however satisfactory their general approximation of the reality of future predictions is, may still fall short on providing solutions for unprecedented situations.

Over-reliance on and being over-confident in the prediction results of ML models for construction planning, can lead construction managers to shed some of their responsibility for the actions they actually take following their decision-making; in addition, their ability for a quick and out-of-the-box thinking for solving paradoxes and wicked problems may be weakened. Furthermore, experience is crucial for knowledge inference in ML models within construction planning, especially in complex elements associated with the concepts of stakeholder collaboration and satisfaction, as well as correlated causes behind project efficiency and productivity; the assumption of generalizability of the prediction results is centrally tied to this knowledge inference process, as the actual applicability and utility of such generalizations can be linked to the reasoning of the construction manager and user of the respective ML system.

As a continuation of the current work, there should be a conduct of research focused on tackling problems in generalization, validation and user interface experience - which will, in turn, address more adequately the issues of accountability in decision-making and responsibility in action-taking for construction managers. In addition, empirical research can be conducted, to address the impact of the such issues in practice and investigate the interfaces between data-driven methodologies used in the training and validation of ML models for construction planning, and the cognitive processes followed by construction managers in their reasoning and problem-solving. As a general conclusion, it is not enough to include human knowledge inference aspects in ML modelling; it is also crucial to strengthen qualified reasoning in the decision-making and accountable action-taking for construction project planning.

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