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A human touch? How machine learning can improve project performance

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Abstract

Construction projects are influenced by interrelated issues that may result in cost and/or time overruns, thus affecting the overall project performance. Therefore, a need to develop predictive models is widely highlighted, to aid in decision-making and offer guidance for corrective actions – especially when preparing for the production phase. Predictive models can utilize certain key performance indicators (KPIs). This study aims at investigating possible applications of machine learning (ML) for the development of such predictive models in construction projects, and the way these can impact project performance. Initially, a literature review about ML in the construction context is conducted. Following, two cases of developed ML predictive systems for construction project performance appraisal are presented. The first case is drawing on a productivity survey of 580 construction projects in Sweden, in which the most influential project performance factors are analyzed. The data encompasses project attributes, external influencing factors, and project organization. Statistical correlation is used to find the features that are strongly correlated with four KPIs: cost and time variance, and client and contractor satisfaction. Then, a regression analysis is performed to develop the prediction model. Technical complexity, like the level of prefabrication, are among the features affecting project performance. Moreover, human-related factors (e.g. client role, architect performance, and collaboration level), end up being highly impactful; it derives that they are the most suitable factors for predicting project success. The second case appraises a project's constructability combined with risk analysis, via a ML model utilizing a restricted dataset of 30 diverse civil engineering projects from several different countries and with very different character; a town square, a biogas plant, road bridges and sub projects from an airport. The development built on a literature study, expert interviews, and unsupervised and supervised ML. The ML-enabled strengths of this model lie more in the novel derivation of construction project risk sources from the related body of literature, as well as the computational and not just conceptual integration of constructability and risk analysis, rather than the system's coverage of the full corresponding context. It can be concluded that the human touch is still needed in preparing future construction projects – and even more so after the introduction of ML solutions. While ML includes human aspects, such as satisfaction and risk perception translated into concepts and variables, there is also a need for strengthening the human touch of qualified thinking for the related decision-making in construction project processes.

Keywords: Machine learning, Supervised and unsupervised learning, project performance, constructability, risk analysis

1. Introduction

Machine learning (ML) has become part of the recurrent wave of digital transformation technologies in research and a series of industry sectors (Kaplan and Haenlein 2019). Within the construction engineering sector, surprisingly Vinnova, a Swedish national funding body supporting innovation, concluded in the spring of 2018 that there was a wide implementation of ML solutions (Vinnova 2018). Yet, ML is also exposed to renewed skepticism regarding its potential and the challenges it faces. A prominent challenge of the new uses of ML is probably a lack of recognition of the differences between the potential of earlier applications, such as expert systems, and the present potential, which is mainly related to the ability of processing big data and complex attribute association rules. This challenge may also be a symptom of the "AI effect", which points to the fact that AI has a moving target of what machines have not been able to do yet. The outset of this contribution is therefore a more practical observation of the many aspects of construction project performance that could be improved by using ML techniques. We simply ask: what are the possible applications of ML in construction projects, and how could such applications impact on their performance? A literature review of recently proposed ML solutions for construction projects is carried out. Then, two cases are explored: a ML-based system for predicting construction project success, and a ML-based system for the evaluation of a project's constructability. This material is used to draw out some implications of the present developments, note their impact for construction engineering, and serve as the main basis for the discussion and conclusions sections of this paper.

2. Literature review

The specific application of ML within the construction context is rapidly developing, yet still draws on technologies and methods that come from more general ML research and practice. The literature review is therefore structured over the general ML categorizations available (Jordan and Mitchell 2015, Portugal et al 2018), simultaneously illustrated with recent construction examples. The latter include many promising systems for application the construction process (Cheng-Yang and El-Gohary 2018, Jebelli et al 2018, Le et al 2018, Petrova et al 2018, Siddula et al 2016, Wang and El-Gohary 2018).

2.1 Definition

ML systems are "computer systems that automatically improve through experience" (Jordan and Mitchell 2015: 255, see also Frank et al 2016, Portugal et al 2018, Sarkar et al 2013). A central challenge for the ML field is to identify and verify any fundamental statistical, computational, and information-theoretic laws that govern the learning systems in question (Jordan and Mitchell 2015). In trying to answer this question, ML scholars have adopted and mobilized tools from data mining, statistics (forms of regression analysis), and optimization theory among others (Jones and Mitchell 2015). The delimitation between artificial intelligence (AI) and ML is not clear. Some regard ML as a sub-discipline to AI (Jones and Mitchell 2015, Portugal et al 2018), while others as adjacent and overlapping. If one inspects a recent definition of AI namely "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein 2019), it is difficult to see the difference between AI and ML. Moreover the use of artificial neural networks, fuzzy logic, and genetic algorithms, that probably previously constituted the core of AI, in contrast to ML, are today approaches also widely adopted within ML. Neural networks are indeed used in some ML cases below (such as Jebelli et al 2018). The further implication of this blurred delimitation is not further discussed here.

2.2 Types of machine learning

ML is frequently classified in three types: supervised ML, unsupervised ML, and hybrid ML. *Supervised ML* (Kotsiantis, 2007; Zhang & Tsai, 2006) utilizes algorithms that are "trained" and validated using labeled datasets, in a context where it is assumed that the reasoning of the application domain is known. The task of the ML algorithm is to learn based on the real training data, and then, after its validation, to apply the knowledge that was gained on new instances (Portugal 2018). Algorithms used in supervised ML include decision trees, decision forests, logistic regression, support vector machines, kernel methods, and Bayesian classifiers (Portugal 2018). More recently, deep learning system have received attention. Deep learning systems make use of gradient-based optimization algorithms to adjust parameters throughout sa multilayered network, based on errors at its output (Jones & Mitchell 2015). Within the construction sector, one group of systems using supervised ML intends to support the bidding process of contractors (Le et al 2018, Xu and Cai 2018, Zhang and El-Gohary 2018). Le et al. (2018) present a system for analyzing construction contract texts for relevant requirements. The system uses a supervised ML approach with Naïve Bayes algorithms, and a test with around 1100 statements showed a very high accuracy over 90%. in the analysis (Le et al., 2018). Zhang and El-Gohary (2018) developed a ML system for compliance checking using semantic role labeling of building code sentences. Their proposed method combined multiple subsequent ML algorithms: (1) capturing the syntactic and semantic features of the building code sentences with natural language processing techniques, (2) using external training data selected by data similarity techniques for the ML system, and (3) performing semantic role labeling using a conditional random field model (Zhang and El-Gohary (2018: 561). The proposed approach was tested on a corpus of annotated text from the International Building Code encompassing 300 sentences, and achieved promising precision, (0.71) according to Zhang and El-Gohary (2018). Yet, the use of an external dataset of linguistic origin appears problematic in a building code domain. Xu and Cai (2018) present a study of a possible compliance code checker based on natural language processing and ML. As their system is tested on one semantic frame only, it is far from being generally applicable in bidding processes. Petrova et al. (2018), used data collected from sensors in a building in operation to make the prediction of building design outcomes more accurate, by reducing the occurrence of design errors; the data was processed through a combination of data mining and semantic modelling techniques. Cheng-Yang and El-Gohary (2018) present a system based on web image processing, for the detection surface cracks on roads. Their proposed method incrementally retrieves and classify crack images; in it, a weak Convolutional Neural Network classifier first models and sorts data from a limited set of Web images, and then acts as a ML annotator and further labels a larger size of data. The proposed method was according to Cheng-Yang and El-Gohary (2018:553) "able to retrieve and label a set of images with 95% labeling recall". *Unsupervised ML* can be understood as "the analysis of unlabeled data under assumptions about structural properties of the data" (Jones & Mitchell 2015). In unsupervised ML, algorithms do not operate on a training set. The system are presented with some data about a domain and have to develop models of relations from that data "on their own", by running internal procedures (Portugal et al 2018). Unsupervised ML algorithms are mostly focused on finding hidden patterns in data. Counter to supervised ML, there are not preset assumptions about internals laws of the dataset. Rather, the relative ML systems are supposed to find these. In construction, examples of unsupervised ML implementation are few, but we provide an example in the second case (constructability appraisal through risk sources).

Hybrid ML algorithm types involve mixing more than one approaches. These include semi-supervised (Jordan and Mitchell 2015, Portugal et al 2018) and reinforcement learning (Jordan and Mitchell 2015, Portugal et al 2018). Many studies and prototypes use a combination of machine learning algorithms (Amasyali and El-Gohary 2018, Portugal et al 2018). Amasyali and El-Gohary (2018) test a series of algorithms for developing energy performance prediction system, including the Gaussian process regression, support vector regression, Artificial Neural Networks, and linear regression. It is not so clearly described in these studies what are the implications of the hybridization regarding the validity of the algorithms in an actual domain.

2.3 Application areas

In the general literature on ML, a large and quickly growing number of applications are developing, many of which are still not widely adopted in the construction context. Examples of those are: Smart assistants (Bruss 2018) and recommender systems (Portugal et al 2018). Conversely, a case where a system could indeed be considered as a smart assistant in the construction system, is BIMbot, proposed by Mutis et al. (2018). BIMbot is intended to be a so-called cognitive assistant to a BIM team (Mutis et al., 2018). Large-scale deep learning systems (Jones & Mitchell 2015: 258), which have yielded, in recent years, large-scale major improvements in the performance of computer vision and speech recognition, when compared to previous approaches.

However, other ML systems have indeed been applied in the construction context: Image recognizion (Cheng-Yang and El-Gohary 2018, Siddula et al. 2016, Tixier et al. 2016). Tixier et al. (2016) review several examples of image analysis applications in construction surveilling issues, such as concrete quality and workers' movement. Siddula et al. (2016) present a ML system for analyzing pictures of roofs to prevent occupational accidents. Cheng-Yang and El-Gohary (2018), as also mentioned earlier, present a surface crack detection system for roads, using Web images.Amasyali and El-Gohary (2018) present a model for energy consumption prediction, consisting of three base models: (1) a ML model that that learns the impact of outdoor weather conditions from simulation-generated data, (2) a ML model that learns the impact of occupant behavior from real data, and (3) an ensemble model that predicts cooling energy consumption based on weather-related and occupant behavior-related factors predicted by the first two models. In doing so, several ML algorithms were tested: Gaussian process regression, support vector regression, Artificial Neural Networks, and linear regression. The predicted energy consumption levels showed agreement with the actual levels. Nevertheless, the impact of the simulation-generated data on the model results is unclear. Similarly, Wang and El-Gohary (2018) propose a classification of energy consumption in office buildings, using multiple ML algorithms. The classification sorts the buildings in three energy consumption levels, using as criteria the building characteristics, occupant behaviors, and geographical, and climate attributes. To support this, ML algorithms like support vector regression, naïve Bayes, decision trees, and random forests, were used (Wang and El-Gohary 2018:757). Jebelli et al. (2018) developed an electroencephalography (EEG)-based stress recognition framework by applying deep learning algorithms and a neural network to recognize construction workers' stress while performing different tasks at actual construction sites. They experimented with a different number of layers to optimize the efficiency of the system. Yet, the connection to the practical domain appears weak, as alternative forms of coping with stress on a building site are not evaluated along this proposed technical solution. Tixier et al. (2016) use construction site accident reports to categorize safety outcomes, with a natural language processing tool and two ML algorithms: random forest and stochastic gradient tree boosting. The model is claimed by Tixier et al (2016:102) to be able to predict the relative injury type, energy type, and body part, with "high skill". An important discussion topic lies in the criteria for ML application. In their review, Jordan and Mitchell (2015) underline the need for "function approximation" when making ML systems, and attempts have been made to categorize ML algorithms based on the purpose for which they are designed (Kulkarni 2012, Shalev-Shwartz and Ben-David 2013); however, categorization by purpose does not assure "fitness" with the domain. Portugal et al. (2018) identify another aspect of difficulties in accommodating ML algorithms into a context, namely the large number of algorithms described in the literature. But as a general observation, ML studies and prototypes are not well described when it comes to criteria for application.

2.4 Summary

Summarizing, the literature review has identified two main types of ML; supervised and unsupervised. Yet, much current ML development involves hybrids of both these and other intermediate types, as well as elements from data mining, statistics and AI (Amasyali and El-Gohary 2018, Jordan and Mitchell 2015, Portugal et al. 2018). This combination of several algorithms and the ability to derive relations (if not causalities) out of large datasets are central characteristics of ML (Portugal et al 2018).

A common weakness of ML approaches is the lack of full understanding of their possible applicability to particular practices or domains which characterized by a particular knowledge structure, decision practice and reasoning processes. Not all proposed system prototypes are equally promising, and some appear to have a weak connection to the context they are intended to support. It is commonplace that researchers provide their own evaluation as basis for presenting the estimated performance of the systems; these estimations are usually quite promising.

3. Method

The overall research approach adopted in the current study for the attainment of the stated research goal, is an interpretive sociological one, combined with a mixed method (Bryman & Bell 2011, Creswell and Clark 2011). This method applied to the literature review presented in the previous section, as well as the exposition of the two case studies in the fourth and fifth sections. The literature review is based on several explorative searches on ML and AI in construction, carried out during the spring, autumn and winter of 2018. This encompassed scientific publications as well as professional coverage in the IT and the construction press. This including the studying of all ML-related contributions at the recent CIB W78 conference (Mutis and Hartmann 2018). The two cases presented are chosen by convenience from the authors own work. They represent current work on ML in a construction management context. The first case of ML-enabled predictive system draws on project performance data from a productivity survey of 580 construction projects in Sweden, conducted in 2014 (Shayboun & Schenström 2018). The study that is analyzed in this research includes answers from 324 main contractor representatives and 256 clients that participated in the survey. A main ambition of the investigation was to measure productivity as something more than just cost per square meter. Processual and soft aspects are entered, looking at disturbances during the process, and the performance of the project organization members, i.e. the client, the consultants, the contractor, and the suppliers. The design of the questionnaire led to a set of questions, where most had pre-given categories for answers in Likert scales. These included technical project complexity, such as preparation work, the use of blasting work, the level of prefabrication, and the structural engineering technology (e.g. concrete, steel, or timber). In addition, they included a series of project organization questions, such as the clients' and contractors' evaluation of the consulting engineers, the architect and supplier performance, and the level of collaboration throughout projects. However, there were also a series of questions where facts and figures were demanded, as well as some open questions related to stated definitions, such as client costs, and partnering. Finally, a few questions were open without stated definitions, including questions on satisfaction, disturbances and lessons-learned. The design and operation of data collection was conducted in the autumn of 2014. After given access to this data in the form of Excel spreadsheets, the development of the ML model was culminated in the M.Sc. thesis by one of the authors. The second case of ML-enabled predictive system appraises a project's constructability through construction risk analysis and was developed within the Ph.D. thesis by one of the authors in Greece (Kifokeris and Xenidis 2018). Firstly, it encompassed an extensive literature study on constructability and construction risk analysis. Then, the data used for the derivation of risk sources via unsupervised ML, was extracted from the respective body of literature, and 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 limitations of the present contribution include a highly selective set of literature, and a lack of context appreciation in the two cases. On the one hand, the first presented case does not use the productivity study's distinction between project type, building type, and geographical location – it is rather aimed at making a general comparison between projects. Moreover, it only covers the Swedish construction market, as the applicability to other contexts (i.e. the construction sectors in other countries) is not known. In addition, cost, time and satisfaction are selected and considered as KPIs, and other possible indicators are disregarded. On the other hand, the limitations of the second presented case 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.

4. Case: construction performance prediction through KPIs

The need for a model which predicts the level of construction project performance is highlighted both in the literature and amongst practitioners. Project performance, the outcome of a construction project, can be measured by using KPIs. Performance mainly consists of two different dynamics: the general project conditions, and the project organization. The general project conditions consist of the contract type, the building size, the level of prefabrication, and external factors considering market conditions, weather, regulations and requirements. The second dynamic, project organization, is a process embodied by the characteristics and performance of the client, main contractor, engineers, subcontractors and consultants. ML algorithms were used to extract and analyze project performance data from the productivity survey described in the previous section. The data covers the aforementioned dynamics of project performance, and it was chosen to focus on four KPIs; cost, time, and client and contractor satisfaction. The factors covered by the data included project attributes, external influencing factors, and aspects of the project organization. The tool that was used to perform the ML processes of linear regression and attribute selection was Weka (Waikato Environment for Knowledge Analysis), a data mining software (Frank et al., 2016). Weka contains ML algorithms, including tools for data processing, and feeding data into learning schemes. Moreover, the software contains a variety of methods for common data mining problems, such as regression, classification, clustering, association rule mining, and attribute selection (Frank et al., 2016). The statistical correlation method was used to extract the features that were strongly correlated with four KPIs described above. Then, a regression analysis was performed to develop a model for predicting project cost, time and satisfaction. For example, to generate insight in the client satisfaction KPI, a process of clearing and organizing the data related to the client's perspective was extracted from the respective productivity survey Excel sheet covering the clients' answers. The client's satisfaction is conceptualized to be the integration of the three questions regarding first the corresponding question on the client's satisfaction, but then also the questions on success and expectations of the results of the project. To evaluate if these three questions are representative of client satisfaction, a correlation test was performed. Backward stepwise linear regression was carried out, starting with the full set of data and systematically deleting irrelevant attributes, one by one, until reaching the final attribute set. The final set of input variables was evaluated as having the highest capability of producing accurate predictions. An attribute was considered as irrelevant when its value did not change systematically in relation to the output class. It was also important to remove redundant attributes that were characterized as being correlated with one or more of the other attributes. N-fold cross-validation and quantile - quantile plot analysis was used to test the ML system. The error rates in the outcome showed that the best prediction error was the one associated with the prediction of the contractor cost variance of construction (9.79%). The prediction for construction cost based on the pre-construction predictor variables also performed better than other models, with a root mean square error of 10.06%. Predicting satisfaction was the hardest. This was quite expected, since it is harder to know what constitutes satisfaction. In the results, project technical complexity, the use of blasting work, and the level of prefabrication, were showcased, among other features, to be important factors that affect project performance. Human-related factors in the project lifecycle, such as the client role, the architect performance and the level of collaboration throughout projects, were found to be of high impact. It was also derived that these factors were the most suitable for predicting construction project success. The conclusion was that, although external factors and the technical aspects of a building were important, the most recurring factors behind project performance can be linked to human-related aspects. The method proved to be successful in testing the shared assumptions in the Swedish construction sector. The study provides statistical evidence for the factors that are important to consider and use in building capable prediction models.

5. Case: constructability appraisal through risk sources

There have been many calls for the better preparation and management of construction projects. Two main aspects of such a preparation is constructability and risk analysis and management. The need for the implementation and integration of such frameworks is corroborated by the existing division of the as-design and as-build project states. The ML system of the present case was thus an attempt to address these preparation issues, by integrating these two frameworks. Constructability was in this context understood as (paraphrasing CII 1986); the optimal use of construction knowledge and experience throughout the construction project lifecycle until its delivery (e.g. planning, design, procurement, field operations etc.), so that its performance objectives (cost, time, quality, client satisfaction) can be optimized (CII 1986). Risk was conceptualized noting: (i) the prevalence of non-standard risk definitions, with different cases putting their emphasis on the uncertainty of the culmination of a potentially harmful event, while in other cases it is on the magnitude of the consequences if that event happens, and (ii) the definitional discrepancy between risk, hazard, impact, defect, and other risk-related notions. This was tackled by discussing sources of risks, rather than risk itself. An unsupervised ML algorithm was used, which performed semantic processing and clustering of linguistic data organized in lists. This data covered aspects of risks found in an extensive part of the literature research on risks; 3434 risk elements were initially identified. They were then sorted alphabetically and according to their notions and fields of application of the risk elements, as they were given within the literature sources (due to the definitional discrepancy, similar elements were differently defined, resulting in the iteration of linguistically same, but differently designated, elements). Modelling was then carried out, with the aim to develop and algorithm which could extract a concise list of general construction project risk sources from the constructed database. This was done by first performing semantic processing to find the “roots” of the risk elements (i.e. the risk sources), and then linguistic clustering for the robustification of the list of the semantically processed elements. The tools used were “stop word removal” by utilizing suitable libraries, word suffix stemming by using the Porter stemmer to reduce inflected and derived words to their basic word stem or root form, and the k-means++ unsupervised ML algorithm, performing vector quantization and then clustering of linguistic elements. This led to an initial clustering in ten overall themes, and then a second-level clustering into 129 centers. The contexts of the ten overall clusters were: technical design and drawings, productivity in construction, economy, cost and finances, time and schedule, construction process, environment, site safety and accidents, project management, contracts and procurement, and sociopolitical factors. Then, the second main step in the model development was the development and tool-ification of an algorithm using supervised ML for the derivation of a classification equation, which characterizes the constructability class of a new construction project when given the values of the identified general risk sources affecting it. This ML system was trained and validated with the use of real risk- and constructability class-related data from civil engineering projects, using WEKA (Frank et al. 2016). The trained algorithm was soft-margin support vector machines, solved with an optimized version of the sequential minimal optimization process, and was simultaneously validated with n-fold cross-validation with an accuracy of (86.67%). The project data was derived from the 30 civil engineering projects delineated earlier in this paper. Two main results of this development are an extensive if not fully defined analysis and systematization of risk sources and the design of a risk source-based constructability ML-based prototype that is intended to assess and predict the constructability of a project based on an assessment of risk sources.

6. Discussion

The literature review showed that there are many places and occasions in construction projects where ML can improve performance; there are possibly even more that have not been explored yet. It was also revealed that ensemble ML systems (namely systems using more than one ML algorithm) are recurrent, and possibly also in need of a further conceptualization, as combinations of algorithms might have an unclear impact on the generated predictions. The two cases presented are both prototypes developed in a university context, and they are still to be tested in practical processes. This also means that little can be said about their actual impact on construction project performance. Nevertheless, the two systems address some recurrent and important factors in construction projects. The first case develops some interesting insights in factors that affect Swedish construction projects, such as the contract form. The utilized dataset is large when the typically low data availability in its domain is considered, and it covers various attributes of Swedish construction projects, such as geographical, project size, construction company, project time and other types of typical variance. Human-related factors in the project, such as the client role, the architect performance and the level of collaboration, stand out as being of high impact; it could be assumed that this is probably a general result, evident even beyond the Swedish context. Nevertheless, this result can also resonate with the Swedish construction culture of mutual trust and willingness to cooperate. The second case appraises a project's constructability through construction risk analysis, via a ML model utilizing a restricted dataset of 30 diverse civil engineering projects. The development built on a literature study, expert interviews, and unsupervised and supervised ML. The ML-enabled strengths of this model lie more in the novel derivation of construction project risk sources from the related body of literature, as well as the computational and not just conceptual integration of constructability and risk analysis, rather than the system's coverage of the full relative context. Both cases presented systems built on an assumption of generalizability; construction project success and risk and constructability are result of sets of generic parameters. Yet the results can in a sense be considered to contradict this assumption, as the testing is done on limited data sets and from specific domains. When discussing the limitations of ML systems for construction, few if any contributions have systematically elaborated on them. Therefore, to highlight such limitations it makes sense to draw on the more general literature available. At the basis of ML lies a quantification of certain parts of a domain; but there is a risk of missing out on an organic complexity in issues such as "collaboration" and "satisfaction" through quantifying them (Power 2004). Stilgoe (2018: 31) points out that that designers of contemporary ML systems have loose control over the content the ML systems actually learns from, i.e. the model attribute relations are too many and too complex to be properly modelled even by their designers. Mackinsey (2015) problematizes the willingness to generalize, and analyzes four main ML techniques, namely logistic regression, Naïve Bayes, K-nearest neighbor and decision trees., and then claims that their commonality is an unsolicited assumption about stable and distinct categories. Mackinsey (2015) notes that ML data can consist of not only variables in the classic statistical sense, but also images, videos, and sensor signals. The critical question according to Mackinsey (2015), is how the actual combination of all these elements in ML comes about. Prediction comes about through approximation, and ML tends to attempt overcoming the messy and the unforeseen and substitute it with order. Therefore, for the assessment and/or prediction of construction project performance, a human touch in ML is needed both in the ML content itself (like including soft parameters in the modelling, as done in the two cases), and in the infusion of ML with the required reflection and reasoning needed in the subsequent decision-making in construction project processes.

7. Conclusions

This contribution started with a practical observation of the many aspects of construction project performance that could be improved by using ML and pointed to what the possible applications of machine learning in construction projects could be and how they might impact on construction project performance. A literature review of recently proposed ML solutions for construction projects was carried out. It was found that when it comes to construction projects, there are a lot of instances where ML can improve performance – and many more that have not been explored yet. ML is not anymore about using a single algorithm; it is rather systems using more than one ML algorithms that are recurrent. These types of systems should be further researched and conceptualized; combinations of algorithms still have unclear impact on the generated predictions, and their relation to the application domain's particular body of knowledge and reasoning is largely under-illuminated. Then two cases were explored: a ML-based system for predicting construction project success, and a ML-based system to assess the constructability of a project. Both of the two presented cases were prototypes. They were developed in a university context and have not been tested in a practical context yet. This also means that their impact on construction project performance is of an envisioned character. But the two systems were mainly developed to improve some recurrent and important occasions in construction projects, such as the preparation of the production phase. Both presented systems were built on an assumption of generalizability; it is posited that construction project success and risk and constructability are results of sets of generic parameters. And in this respect usable in the global construction industry. This should be challenged in the future however to assure strong tools in a particular context (for example Sweden and Greece). Moreover, the approach in the two cases can in a sense be said to contradict this assumption, as the testing is performed on limited datasets and from specific domains, most evidently in the performance prediction example, whereas the risk and constructability project case covers a broad variety of civil engineering projects. The human touch in future preparation activities in construction project is therefore needed even more after the introduction of ML. It is relevant, yet not enough, to introduce human aspects like satisfaction and risk perception, as factors in the content of the ML. There is also a need for strengthening the human touch of reflection and reasoning in the subsequent decision making in construction project processes.

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