Oprach, S., Steuer, D., Krichbaum, V., and Haghsheno, S. (2019). 'Smart Data – Dealing with Task Complexity in Construction Scheduling'' In: *Proc. 27th Annual Conference of the International. Group for Lean Construction (IGLC), Pasquire C. and Hamzeh F.R. (ed.), Dublin, Ireland. pp. 347-358. DOI:* https://doi.org/10.24928/2019/0155. Available at: <www.iglc.net

SMART DATA - DEALING WITH TASK COMPLEXITY IN CONSTRUCTION SCHEDULING

Svenja Oprach[1], Dominik Steuer[2], Viktoria Krichbaum[3] and Shervin Haghsheno[4]

ABSTRACT

Due to the numerous influencing factors, construction scheduling is a complex task. As construction projects are having a unique character, scheduling takes time and often uses high time buffers to cover uncertainties. Using historic project data with artificial intelligence applications show potentials to supportvalid and simple scheduling in the future. The construction industry already deals with large volumes of heterogeneous data and the amount of data is expected to increase exponentially with the Internet of Things (IoT). Smart data filters and analyses big data for useful information and creates a subset of information that is important and valuable. Therefore smart data sets a data management structure according to the lean principles.

Due to fragmented data management practices and a misunderstanding of the needed informationen in construction, data management practices in construction projects are far behind other industries. By adapting existing applications of artificial intelligence to construction scheduling, the gap of data management practices gets more visible. This paper identifies in three case studies relevant data (smart data) in and current challenges for construction scheduling based on historic data. Further research is needed to close the existing gap in construction data management.

KEYWORDS

Knowledge management, Smart Data, construction planning, digitalization, data analytics

INTRODUCTION

Defining the duration of a construction task is a complex activity. Factors such as the location, the size of the area, the experience or the motivation of the construction worker play an important role. Due to the unique characteristics of a construction project, time buffers are often added and the complexity in creating a valid schedule is very high. Good knowledge management practices are needed to reduce the existing complexity.

[1] Research fellow, Karlsruhe Institute of Technology, Germany, +49-721-608-43650, svenja.oprach@kit.edu

[2] Research fellow, Karlsruhe Institute of Technology, Germany, +49-721-608-44122, dominik.steuer@kit.edu

[3] M. Sc. Student, Karlsruhe Institute of Technology, Germany, +49-721-608-43650, svenja.oprach@kit.edu

[4] Professor, Karlsruhe Institute of Technology, Germany, +49-721-608-42646, shervin.haghsheno@kit.edu

Statistically more than nine out of ten companies rate knowledge management as very important according to a survey by the Fraunhofer Institute (Siegberg et al. 2006, p. 32). Knowledge can be reused repeatedly without losing value, in some cases even gaining worth with the amount of data. Studies have shown that the application of knowledge management correlates positively with revenue growth, market share, profit, innovativeness, competitiveness as well as the employee motivation (Pawlowsky et al. 2011, p. 22 f.).

Construction data as the generated knowledge of each construction company is typically voluminous, heterogeneous, and dynamic (Aouad et al. 1999). This data can occur in forms of correspondence, schedules, contracts or pictures. It is often rarely structured (Bouchlaghem 2004, Manyika et al. 2011). Fully analysing this unstructured and big data for valuable information in construction scheduling makes the task even more complex. According to general data management studies so far just about 1% of all information is used for further analysis (Burn-Murdoch 2012) and approximately 80% of time is used to clean noisy datasets before embarking on analytics (Bilal et al. 2016, p. 518). Although chances in data management are high for construction industry; the way construction projects are organized has not changed much (Streule et al. 2016, p. 269). On the one hand, after a project, knowledge often continues to exist in the minds of certain employees and is not systematically available to all participants. On the other hand, the amount of collected data increases with the technological development in the construction industry. The data in construction is expected to increase as exponentially as technologies such as embedded devices, project management software, data from Building Information Modelling (BIM) and the Internet of Things (IoT) are commoditised (Bilal et al. 2016, p.500-501). Out of this big data, focus on relevant and valuable data (smart data) regarding construction scheduling needs to be taken. To handle data in general, in the 1950s researchers first used the term *intelligence* as part of artificial intelligence. In the 1990s the term *Business Intelligence* (BI), in the late 2000s *Business Analytics* as part of BI and afterwards *Big Data Analytics* (BDA) became popular (Davenport 2006). The systematic evaluation of certain data in construction projects can generate advantages for simple, valid and data-driven scheduling. This provides transparency and an interchange between different professional skills involved in a construction project. Construction planning based on an accurate foundation is a key to deliver a project on schedule and within budget (Chan 1996). If scheduling is based on realistic and already proven durations, trades do not have unnecessary capital commitment costs for their employees and machines due to the elimination of unnecessary buffers. Also time pressure upon employees with results in demotivation, security issues and a loss of quality can be prevented (Rogel, p.232). With these benefits in data management, it is worth investing time to aggregate and disseminate experiences in the form of documented data. This is the only way to link various construction projects. Such a connection gets more important as construction projects are becoming noticeably more complex, competition is getting tougher (Issa 2013 p. 699) and redundant information transfer is increasingly important due to the growth of international teams (Hari et al. 2005, p. 533).

Potential structures of databases storing the valueable construction information are already focused on in research (Bouchlaghem et. al 2004). The aim of this paper is to uncover challenges in scheduling construction tasks with historic smart data. The research question therefore is is: What challenges exist in scheduling construction tasks with smart data? By doing this, the above described benefits will be targeted. Three case studies will analyse the complexity of data management and identify possible solutions as a basis for further research.

METHODOLOGY

To uncover challenges in construction scheduling with smart data a three-stage process was done, following the method of value stream mapping (Rother et. al 1999).

First a target design was done in a real-world construction project. Identifiying requiredinformation of process and product features for construction scheduling to establis a Smart Data database. For this database further data out of IoT application were analysed. This derives in a visionary state.

Secondly, the current state of data management practices with the identified information features were analysed in detail. Three case studies demonstrate origings of failure with machine learning in construction. The cases studies orient on the needed data and essential data for construction scheduling: tasks, the duration per task orienting on the location. The three case studies reveal the task complexity existing in construction. To define the term “task complexity” in construction a literature research was done as first part of the second step.

Third and final, to overcome the task complexity possible solutions were identified in a discussion part to each of the three case studies. These solutions need to be analysed in further research project.

VISIONARY STATE: DEFINING SMART DATA

CASE STUDY 1: SMART DATA FOR CONSTRUCTION SCHEDULING

Smart data is a specification of big data. Big data generally has four attributes, also called big four V's of Big Data: Volume (terabytes, petabytes of data and beyond), variety (heterogeneous formats like text, sensors, audio, video, graphs and more), velocity (continuous streams of the data), and veracity or verification (quality, accuracy, truthfullness of the data documentation) (Beulke 2011). With the lean lenses it is important to review the value of the available data from the beginning, to reduce and eliminate waste in data documentation and usage. Smart data is like a filter on big data for needed and useful information. It creates a subset of information out of the available data that is important for companies and researchers (Triguero 2016, p.859). Smart data can be seen as the fifth ‚V’ with its value generation.

Smart data for construction scheduling can be seen as the aggregation of relevant product and process information. This includes documenting numerous project related product features (e.g. geographical location, required quality, contract model, building regulations, environmental construction constraints, functionalities within the construction project) and breaking down the process into single tasks with its work sections and their durations (process features). The tasks of the process are the fundamental structure. They are influenced by the product features and determine the sublayer of the overall construction process. By defining the detailed features of each construction work section, the resulting information stacks of different construction projects can be compared with each other and transferred to new construction projects (Siami-Irdemoosa et al. 2015, p. 88; Makarfi Ibrahim et al. 2009, S. 389). Smart data in construction scheduling is an information stack covering both process and product features. Figure 1 shows a real-world construction project. The project was a 30,000 sqm demolition of an industrial building from the 1960s in the UK. Here, a high-quality project database was established, documenting in short-cycle intervals process as well as product features. Defined process features were the work packages in sequence, with their duration, needed resources and a link to the product features. Product features are further information to the component, such as geometry, size, weight or location.

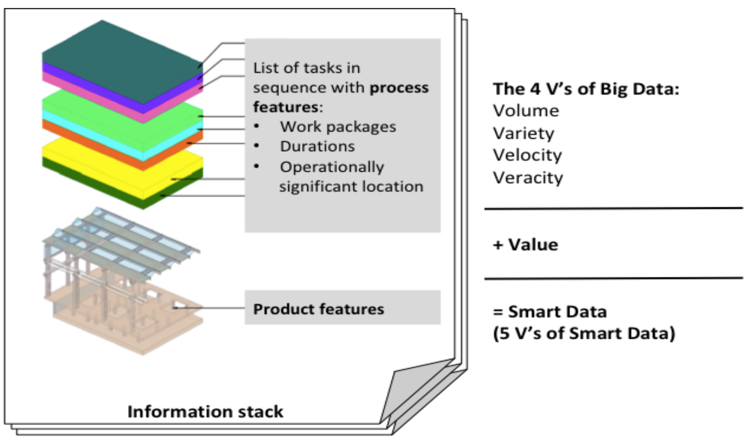

Figure 1: Smart Data information stack for scheduling in construction

Further on, by adding e.g. following data sets to the information stack the 5 V's of Smart data are increased by sensor data and picture of trades, machines and equipment, open data pools like building regulations and local standards and available information in the internet like environmental construction constraints

Birrel stated in 1980: '... the fact that any construction process is made up of a finite set of tasks from an existing feasible set of tasks came out by the construction industry'. Hence, tasks in general are comparable but the complexity of the process features has a direct influence on the volume, variety, velocity, veracity and value of the construction data. Analysing the complexity of the process features is therefore relevant in reducing existing barriers in data management.

CURRENT STATE: TASK COMPLEXITY

THEORETICAL BACKGROUND

Construction projects are often planned under uncertainty. Uncertainty is defined as 'the difference between the amount of information required performing a particular task and amount of information already possessed by the organization' (Galbraith 1973 p. 5). Missing information creates uncertainty. This uncertainty derives from the complexity of construction tasks. The task complexity in construction can be further defined according to Norvig (p. 69-72):

Fully observable or partially observable tasks: A fully observable environment means that data is recorded at any time by Internet, sensors or knowledge management methods. However, construction projects often contain gaps in their documentation due to the high number of influencing factors and non-recordable manual processes. As a result explicit knowledge is only documented incompletely. Also, the 2004 NIST report (Gallaher et al. 2004, p. 2-7) identifies most stakeholders reticent to convert to electronic systems. Implicit or personal knowledge is very high in construction. This kind of knowledge is difficult to articulate and is based on experience, intuition, feelings and subjective views. A complete documentation about the project duration in short cycle intervals about all process steps and their influencing factors is not given at present. However, electronic systems based on IoT strives to a continuous recording of data.

Deterministic or stochastic environment: If the prospective state is clearly triggered by the current state, the environment is called deterministic. Many real situations appear to be stochastic because they are influenced by many input factors. For reasons of simplification, also in construction, a theoretical deterministic situation is solved in a stochastic environment due to the high number of influences.

Episodic or sequential tasks: In episodic environments, current decisions have no direct influence on the following tasks. In contrast, in sequential environments decisions have a direct influence on all further processes and short-term actions can lead to long-term effects. Also a decision in construction planning can have a far-reaching effect in the execution process. Potential challenges and decisions must therefore be documented by a clear structure for follow-up projects.

Static or dynamic tasks: A static environment is one in which the environment does not change during decision-making. Due to the strong fragmentation in construction projects, parallel decisions can be made that influence each other. Therefore, we speak of dynamic task environments in construction projects.

Discreet or constant tasks: Discreetness or continuity refers to the temporal state of perceptions or actions. Construction planning units and construction trades move in a space of constant values.

Known or unknown tasks: Unknowingness refers to the level of knowledge of the involved people and to the rules of their environment. In an unknown environment, the effects of decisions about time must be learned. The rules may or may not be known depending on the knowledge management approach and repetitiveness of the project.

Single agent or multiagent environment: A single agent is someone who can solve a problem in its overall context on his own. Multiagent environments contain multiple agents that make decisions based on each other. In many construction projects, the number of participants quickly exceeds 100. There are typical dependencies between construction planning, execution, owner user groups, the owner's purchase, the facility management, etc. Due to strong fragmentation, construction projects are in a multi-agent relationship. These agents compete or cooperate to some extent.

Due to the partially observable, stochastic, sequential, dynamic, continuous and often unknown tasks, it is complicated to document all the process features within an information stack. This restricts the volume, velocity and variety of the data. The multi-agent relationship, on the other hand, generally limits the veracity of the data. Therefore, it is highly important to define valuable information in the beginning.

Within stationary production, the Methods-Time Measurement (MTM) was developed for the standardised documentation and evaluation of performance factors on basis of the constant framework conditions within stationary production. Here, simple elementary movements were classified out of the contractor's work. Standardized activity durations are also already documented in construction and can be compared with the MTM values. In addition to these classified activity durations, Lowry, Maynard and Stegemerten developed the LMS method (named after the inventors), which determines the worker's performance on the basis of MTM. The MTM values are based on the effort of a medium-well-trained person who is able to perform this work in the long term without work fatigue. Further factors influence the performance of the worker. According to LMS these are dexterity, effort, uniformity of movement and independent influences such as weather, lighting, odours, noises, heat, etc. According to the LMS Performance Rating Table, a maximum range of -60% to +38% of the respective activity duration can be achieved, depending on the design of the factors. For each category there is a subdivision of six to 16 states, which leads to a percentage increase or decrease in the rating. (Karger, p. 31) Eventough, stakeholders are known in the stationary industry and production processes are inside and under same conditions, big variations in time may exist. Still, detail obersverations of work steps are done to analyse influencing factors and eliminate wastes. As conditions in construction are different, new methods are needed in documenting process and product features.

Each of the following case studies will focus on one of the information dimensions described in the visionary state: Tasks with their duration (process feature) and the location (product feature). The first case study is based on a construction project data evaluation. The second and third case studies are based on a broader literature research in comparison to the stationary industry.

CASE STUDY 1: NAMING OF WORK PACKAGES

Projects are structured in a work breakdown structure (WBS) as a list or diagram (DIN 69901-5:2009-01, 3.82) with subprojects, work packages and activities as well as the relationships among themselves (DIN 69901-5:2009-01, 3.79). In the first case study 66 construction time schedules of an industrial fit-out of an internationally active client were analysed and compared.

In table 1, the example of the electrician illustrates the different naming

between different projects. In the work package 'First Fix ELT' ('ELT' = electrician) a total of nine different naming's were found, in the work package 'Second Fix ELT' seven naming's for the same work content were found. 'First Fix ELT' often is used for raw installation in the electric trade. 'Second Fix ELT' is the final installation of the electrician. Hence, different projects use a different naming and just human experience can compare and understand with the gained knowledge similarities.

Table 1: Different naming of the work packages of an electrician

First Fix ELT	Second Fix ELT
Electrical installations I	ELT Installations, Light fixture
ELT Cable duct	ELT-Final installation
ELT Assembly/Installation of trays	Lights/Sockets
Wiring	ELT Precision assemblies
Basic installation electro	

The data differs often from project to project in terms of naming and also in the level of detail. Consequently, without any prior knowledge and accurate data construction projects cannot be compared (veracity). Reasons for the different naming are the multi-agent environment and the missing rules for it. Due to international activities with varying project participants, a different language is used for the naming of work packages depending on the project and the experience of the site manager. This results in a multitude of different sequences without including linguistic differences from the respective country.

CASE STUDY 2: ACTIVITY DURATION

The number of different influencing factors on the execution time and the activity durations of each trade lead to further uncertainties. The definition of the activity duration seems to be stochastic and makes a complete manual documentation of the durations from area to area as well as from construction project to construction project difficult.

Table 2: Additional time for individual performance and non-value adding activities (Karger, p. 31; Boenert and Bloemke 2013)

Individual performance (LMS)		MUDA 1		MUDA 2	
Skills	-22% to +15%	Transports	0% to +19,8%	Disturbances	0% to +3,5%
Effort	-17% to +13%	Ways	0% to 5,6%	Personnel stops	0% to +10,3%
Consistency	-4% to +4%	Searching materials	0% to 1,1%	Absence	0% to +8,9%
Conditions	-7% to +6%	Cleaning & sorting	0% to 5,8%	Others	0% to +14,1%
Sum	-60% to +38%	Sum	0% to 32,3%	Sum	0% to +36,8%

Example of a potential variation of the activity duration
*= Activity duration * (1 + 0,38 LMS + 0,323 MUDA 1 + 0,368 MUDA 2)*
*= activity duration * 2,071*

To the LMS Performance rating table non-value-adding activities need to be added. They can be divided into MUDA type 1 (unavoidable, but reducible work) and MUDA type 2 (eliminable work). In the Lean philosophy ‘MUDA’ is a Japanese word for waste. In construction industry there are seven typical kinds of waste: transportation, inventory, motion, waiting times, over-processing, over-production and defects. According to Boenert and Bloemke (2013), they can be broken down as shown in table 2. If LMS values as well as MUDA 1 and MUDA 2 are added to the individual performance, durations can differ by about twice as much. A calculation of the construction schedule with the expected value can lead to a considerable underestimation of the project. 'It is well known that replacing random durations with their expected values always results in underestimating the expected duration of the project' (Elmaghraby 2005, p. 310). Furthermore, the pure activity duration can depend on weight, material, quality, diameter, size or length as well as the available manpower.

However, with complete information, these values are calculable but the large quantity of influencing factors makes a systematic recording complex and therefore stochastic methods must be used. A wrong calculation can have fast effects on the subsequent trades. Here, the partially observable environment and continuous development of the construction project are decisive.

CASE STUDY 3: OPERATIONALLY SIGNIFICANT LOCATIONS

By breaking the construction project in smaller areas, the value of the client can be planned more precisely. As every area with a different functionality (e.g. sanitary areas and office areas) produces different work packages and activity durations, information stacks are different and for further analysis they need to be classified according to their function. There are several planning methods in construction using the space as a main dimension in the time schedule. The location breakdown structure (LBS) is the planning basis (Kenley and Seppänen 2010). The four best known methods are: Line of Balance (LOB), flowline technique, Location-Based Management System (LBMS) and Takt Planning and Takt Control (TPTC).

Nevertheless, general project scheduling software like Microsoft Office Project (Microsoft Corporation), Primavera Project Planner (Oracle Corporation) or PS8 (Sciforma Corporation) are widely used but regarding data analytics not up to date (Demeulemeester and Herroelen 2009, p. 17; Kolisch 2001). These schedules specify start-finish relationships of individual activities and are usually planned over the entire project or larger subproject sections. Although the trades are constantly moving, durations are converted into discrete values to simplify the scheduling. It is not possible to extract single independent areas out of these schedules. Data is therefore only available on the aggregated level within the schedule and the total gross floor area. Here the veracity of an accurate documentation or the volume of space-related data instead of project-related data is missing.

DISCUSSION

Additional analytical methods are needed to get an understanding of the mechanism behind the complex data structures of construction. 'High value-added products (and services) are characterized by complex production processes and are complex themselves - the credo of simplicity is a manifesto for economic decline' (Rycroft and Kash, 1999). Construction projects will continue to contain complex relationships. Statistical methods cannot solve the complexity to its full content. Many simple statistical case studies show the high potential in failing as there are more influencing factors involved in project prediction (Magnussen et al. 2006, Potts 2005, Walker 1995, Flyvberg et al. 2002). Hence, Smart data structures as well as advanced data analytics in form of artificial intelligence are needed. Establishing artificial intelligence methods in the building industry has increased significantly in recent years (e.g. Fox et al., 1983; Hendrickson et al., 1987; Chevallier and Russell, 2001; Navinchandra et al., 1988; Dzeng and Tommelein, 1993; Darwiche et al., 1988; Fischer and Aalami, 1996). By using methods such as data mining and machine learning existing data is analysed in order to transfer findings for further projects.

A possible solution is the **naming of work packages.** Choo et al. (1998) propose a standardised working catalogue for construction projects as a solution. The work packages are stored with a code, a standardized description, deposited costs and further relevant information. Within the stationary production a standardized description of work packages is already common practice. The standard worksheets represent a user guide for the employees on site to optimise work processes and train new employees (Traeger 1994, p. 14). The standardised work catalogue in the form of content management systems, groupware systems, or project databases falls into the area of knowledge management of semantic knowledge. As a standardized naming structure can be a solution for a single company, globally work packages will be named differently regarding content and detail level. A possible solution is establishing a semantic wiki to classify and compare the naming of the work packages. With text mining methods, letters of the work package naming are compared in accordance to the semantic wiki and filtered to the clusters. With doing this, further on methods of (sequential) pattern mining can detect unknown rules in sequences. Pattern mining is for example done when analysing a market basket of a customer with the target to predict the next product item or most brought items together. These product items are comparable to construction work packages. As with the FP-Growth algorithm most possible package sequences are at any time detected and proposed to the scheduler and construction workers. AliceTechnologies is an example Software, detecting sequence alternatives and comparing them regarding time and costs.

Another solution is the improvement of **activity duration** data. The first option is to reduce non-value adding activities as reason for high variations by outsourcing these activities to logistic experts. Secondly, with electronic devices and especially using sensor data the volume of data, the velocity and veracity can be increased. Also, robotos and drones can observe and documents the construction progress (see for example Doxel, www.doxel.ai). Lastly, when having high-quality and accurate informations stacks available, influences can be analysed and categorized with applications of machine learning. Available software solutions like NPlan or Lili.ai analyse the information stacks according to their patterns. With decisions trees and random forest documented informations can be clustered. Neuronal networks further on, detect and include information not visible for scheduler.

The third presented solution is the definition of **operationally significant locations**. Besides using the described location-based schedules, also Building Information Modelling (BIM) is a possible exchange platform that supports spatial data documentation. Here, the components with additional information (geometry, weight, location) can be derived during planning stage and linked with the construction schedule. Also construction scanner can scan and identify during construction with applications of image segmentation single components and their location (see Doxel).

In total, increasing data volumes and adding data analytics lead to various implications that need to be taken into account. The filtering, storage and evaluation of Smart Data causes hardware and software costs to be carried by the construction companies. Internet must be available on the construction sites. Finally, the question of data security and ownership needs to be clarified. As with data collection across business units and along partners even more benefits can be analysed (Bilal et. al 2016, p. 518).

CONCLUSIONS

The creation of time schedules in construction projects is currently made under great uncertainties: The documentation of construction projects is often chaotic and the quantity of influencing factors makes the documentation complex. The cause of the uncertainty is the complexity in the construction process features. Construction projects are only partially observable, stochastic, sequential, dynamic, continuous, and rules are often unknown. Although a large amount of data is already collected during the life cycle of a construction project, data losses in terms of volume, velocity and variety exist. The multi-agent environment makes data veracity difficult. A complete and accurate data collection, analysis and use of all this data can bring great advantages for construction projects, such as revenue growth, market share, profit, innovation capability, competitiveness and employee motivation.

Table 3: Challenges and possible solutions in construction scheduling with Smart Data

Challenge	Solution	Solution with Smart Data (Analytics)
1) Work packages	Standardized naming	Clustering with sematic wikis, (Sequential) pattern mining, Data recording with electronic devices
2) Activity duration	Outsourcing of non-value adding work	Data recording with robots and drones, analysing with applications of machine learning
3) Operationally significant location	Using location based schedules	Documentation with Building Information Modelling (BIM)

Table 3 summarizes potentials solutions to overcome the challenges in low data quality in construction industry. Here, smart data focuses on relevant information compared to big data. Therefore, in construction projects, the customer value and the goal of the data evaluation must be clarified. Considering construction scheduling, the work packages, the activity duration and the locations are relevant. Introducing electronic devices with IoT applications and BIM to construction supports the data collection (table 3). Artificial intelligence supports analysing influences and with the support of pattern mining methods the construction sequence can be predicted. By doing this, smart data management can reduce uncertainties in a complex environment and close the gap to other industries in this area.

REFERENCES

Aouad, G., Kagioglou, M., Cooper, R., Hinks, J., Sexton, M. (1999). "Technology management of it in construction: a driver or an enabler?", *Log. Inform. Mgt.* 130–137.

Beulke, D., (2011). "Big Data Impacts Data Management: The 5 Vs of Big Data", (online: Jan 20, 2019).

Bilal, M., Oyedele, L.O., Qadir, J., Munir, K., Ajayi, S.O., Akinade, O.O., Owolabi, H.A., Alaka, H.A., Pasha, M. (2016). "Big Data in the construction industry: A review of present status, opportunities, and future trends" *Adv. Eng. Informatics,* 500- 521

Boenert, L., Bloemeke, M. (2003). "Logistikkonzepte im Schlüsselfertigbaz zur Erhöhung der Kostenführerschaft". *Bauingenieur*, Springer VDI Verlag.

Bouchlaghem, D., Kimmance, A.G., Anumba, C.J. (2004) "Integrating product and process information in the construction sector", *Industr. Mgt. & Data Sys.*, 218-233,

Burn-Murdoch, J. (2012). "Study: less than 1% of the world's data is analysed, over 80% is unprotected", (online: Jan 20, 2019).

Chevallier, N.J., Russell, A.D. (2001). "Developing a draft schedule using templates and rules". *Journal of Construction Eng. and Mgt. 127(5),* 391–398.

Choo, H. J., Tommelein, I. D., Ballard, G., Zabelle, T. R. (1998). "Workplan: Database for work package production scheduling". *Proc. IGLC '98*

Davenport, T. H. (2006). "Competing on Analytics" *Harvard Business Review (84:1),* 98-107.

Darwiche, A., Levitt, R., Hayes-Roth, B. (1988). "Generating project plans by reasoning about objects, actions and resources". *AI for Eng. design, analysis and manu.*169–181.

Demeulemeester, E., Herroelen, W. (2009). "Robust Project Scheduling. Foundations and Trends in Technology, Information and Operations Management", *Inc.*, Delft, Boston.

Dzeng, R.J., Tommelein, I.D. (1993). "Using Product Models to Plan Construction". *Proc. 5th Intl. Conf. on Computing in Civil and Building Eng.*, ASCE, 1778–1785.

Elmaghraby, S. E. (2005). "On the fallacy of averages in project risk management". *European Journal of Operational Research, 165*, 307-313.

Fischer, M., Aalami, F. (1996). "Scheduling with Computer-Interpretable Construction Method Models". *Journal of Construction Eng. and Management, 122(4),* 337–347.

Flyvbjerg, B.; Holm, M.S.; Buhl, S. (2002): Underestimating cost in public works projects: error or lie?, *Journal of the American Planning Association* 68(3) 279–295.

Fox, M.S., Allen, B.P., Smith, S.F., Strohm, G.A., Surnniary, S., Fos, R.S. and Smith, S.F. (1983). "ISIS: a constraint-directed reasoning approach to job shop scheduling".

Galbraith, J. (1973). "Designing complex organizations". Addison-Wesley, Reading, MA.

Gallaher, Michael P., O'Connor, Alan C., Dettbarn, John L., Jr., and Gilday, Linda T. (2004). „Cost Analysis of Inadequate Interoperability in the U.S. Capital Facilities Industry". *U.S. Department of Commerce Technology Administration National Institute of Standards and Technology.*

Hendrickson, C., Zozaya-Gorostiza, C., Rehak, D., Baracco-Miller, E. und Lim, P. (1987). "Expert System for Construction Planning". *J. of Comp. in Civil Eng., 1(4),* 253–269.

Issa, U. H. (2013). "Implementation of lean construction techniques for minimizing the risks effect on project construction time". *Alexandria Eng. Journal, 52(4*), 697–704.

Karger, D. W., Bayha, F. H. (1987). “Engineered Work Measurement: The Principles, Techniques, and Data of Methods-time Measurement Background and Foundations of Work Measurement and Methods-time Measurement”. *Industrial Press*.

Kenley, R., Seppänen, O. (2010). “Location-based management system for construction”. *London: Spon Press*.

Kolisch, R. (1995) “Project Scheduling under Resource Constraints - Efficient Heuristics for Several Problem Classes”. *Physica*, Springer, Heidelberg.

Magnussen, O.M.; Olsson, N.O.E. (2006): Comparative analysis of cost estimates of major public investmentprojects, *Intl. Journal of Project Mgt. 24*, S. 281–288.

Makarfi Ibrahim, Y., Kaka, A., Aouad, G., Kagioglou, M. (2009). “Framework for a generic work breakdown structure for building projects”. *Con. Inno. 9* (4), 388–405.

Manyika, J., Chui, M., Brown, B., Dobbs, R., Roxburgh, C., Hung Byers, A. (2011) “Big Data. The next frontier for innovation, competiotion and productivity” (Jan 20, 2019).

Maynard, H. B., Stegemerten, G.J., Schwab, J. L. (1948). “Methods-time Measurement”. *McGraw-Hill Book Compony*, New York.

Navinchandra, D., Sriram, D. und Logcher, R. D. (1988). “Project Network Generator”. *Journal of Computing in Civil Eng.*, ASCE, Band 2, 239–254.

Norvig, R. (2012). “Künstliche Intelligenz”, *Pearson Verlag*

Potts, K. (2005): “The New Scottish Parliament Building—a critical examination of the lessons to be learned”, *CITC-III Advancing Eng., Mgt. and Tech*., Athens, 534–539.

Rogel, D., Osebold, R. (2013). “Exploring Uncertainity”. *Springer*, 209-244

Rother, Mike, Shook, John: “Learning to See – Value-stream mapping to create value and eliminate muda”. *Lean Enterprise Institute.*

Rycroft, R., Kash, D. (1999). “The Complexity Challenge”. *London: Pinter.*

Siami-Irdemoosa, E., Dindarloo, S. R., Sharifzadeh, M. (2015). “Work breakdown structure (WBS) development for underground construction”. *Auto. in Con. 58*, 85–94.

Traeger, D. H. (1994). “Grundgedanken der lean production.“ *Springer* Wiesbaden.

Triguero, I., Maillo, J., Luengo, J., García, S., Herrera, F. (2016). “From Big Data to Smart Data with the K-Nearest Neighbours Algorithm”. *2016 IEEE Intl.Conf. iThings, IEEE GreenCom and IEEE Cyber, IEEE SmartData*, Chengdu, 859-864.

Walker, D.H.T. (1995): “An investigation into construction time performance”, *Construction Mgt. and Economics 13*, 263–274.