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WEB BASED FIELD DATA ANALYSIS AND DATA-DRIVEN SIMULATION APPLICATION FOR CONSTRUCTION PERFORMANCE PREDICTION

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SUMMARY: *Field data acquisition, systematic data integration and applying data driven simulation models are current research topics in the field of architecture, engineering and construction (AEC). These research approaches are strongly linked together. The state of the art in construction simulation is to estimate model parameters by experience-based assumptions during the planning phase. Thus, construction project delivery is a one-of-a-kind production in a highly dynamical and volatile production environment. Occurring process variations during the construction phase cannot be foreseen beforehand and influence the simulation parameters. There is also a need to transform raw data from the construction site and provide the information to a simulation model. Prevailing approaches in construction research describe either methods for field data acquisition and analysis, or the application of data driven simulation environments. Therefore, this paper describes a web-based approach by integrating field data from construction equipment on site for the application in a data-driven simulation. The as-built process information allows the refining of the simulation parameters by linking the simulation with the as-built information in a web-based framework. Its main contribution is to evaluate prediction models of the remaining operation duration based on the current project performance and transfer the simulation results back to the framework. The evaluation is based on a real-world case study. The results allow a sufficiently accurate prediction of the task completion time which could serve as a basis for extended applications.*

KEYWORDS: *Field data acquisition and processing, Data-driven simulation, Near-real-time simulation, Web based application.*

REFERENCE: *Amadeusz Kargul, Willibald A. Günthner, Maximilian Bügler, André Borrmann (2015). Web based field data analysis and data-driven simulation application for construction performance prediction. Journal of Information Technology in Construction (ITcon), Vol. 20, pg. 479-494, http://www.itcon.org/2015/28*

1. INTRODUCTION

Production planning, monitoring and control of construction sites involves many actors and faces several challenges for the responsible project management. Due to, among others, unforeseen rework, disadvantageous geological conditions, machine/human failure, or weather during the execution phase, site management is often faced with project delays and deviations between the as-planned and as-built construction performance (Horenburg & Günthner 2013). Occurring process variations during the construction phase can hardly be foreseen and influence the simulation parameters (AbouRizk & Halpin 1992). The above mentioned circumstances lead to a lack of predictable future scenarios to secure the as-planned project schedule with on-site decisions. Therefore, it is necessary to update the simulation model with the actual construction progress, including changes in project scheduling and/or resource allocation (Hajian & Becerik-Gerber 2009). For this kind of near real-time simulation, reliable progress data sources need to be evaluated to provide current project progress and performance parameters with a sufficient granularity (Tavakoli et al. 2008) for supporting the decision making process during the execution phase and getting sharpened prediction models concerning the throughput time of a task (AbouRizk 2010). Simulation environments based on the current project status support the responsible actors in controlling the project performance and providing a possibility to exercise different "what-if" scenarios (Lu et al. 2007). The application, however, remains mostly limited to the academic and research environments. Furthermore, the application of data-driven simulation tools takes place at shop floor level where non-simulation experts need to update, run and evaluate the simulation results. Therefore, a framework that enables stakeholders to have accessible real-time control and feedback over as-planned versus as-built performance of the construction site is necessary. Especially for site managers, there is a need to update a simulation environment without expert knowledge. In the next step, the simulation results need to be prepared and visualized in a way that allows the user to compare the as-built status and the predicted project progress based on simulation adjustments done before. This paper presents an approach, called Project Control Center (PCC), for this kind of information system and focuses on heavy-equipped construction processes. The proposed method is shown to be effective by an extensive case study in a real-life construction environment. The main contribution of the paper is to describe a web based framework that integrates field data acquisition and the application of a discrete event simulation (DES) in a web-based framework.

2. LITERATURE REVIEW

The superordinate objective in data-driven simulation approaches is to integrate relevant project performance indicators of the construction operations on site into a modeling environment, refine the simulation parameters and increase the value of construction simulation applications (Song & Eldin 2012). Thus, several research areas are affected in order to monitor and control project delivery and generate extended knowledge by using data-driven simulation in construction.

2.1 Field data analysis and application in construction simulation

Akhavian et al. describe a methodology for data capturing and processing in a simulation environment. The gathered data is used for automated initialization and refinement of simulation models for construction equipment operations (Akhavian & Behzadan 2013). The statistical preparation of raw field data for selecting the best fitting distribution for the simulation parameters has been investigated, too. Law and Kelton describe three general approaches for adjusting samples for simulation models in general (Law & Kelton 1991). Xie et al. presented a graphical solution (Xie et al. 2011). A numeric solution is presented by Graham et. al using the Kolmogorov-Smirnov (K-S) test and the Anderson-Darling (A-D) test to evaluate the best fitting distribution function to a given sample (Darren Graham et al. 2005). Akhavian and Behzadan extend the numeric solution for raw data treatment by fitting sample data with three different goodness-of-fit tests (K-S; A-D, Chi-Square) (Akhavian & Behzadan 2014). Vahdatikhaki and Hammad describe a more general framework to contribute a methodology for multi-step data processing from different tracking technologies in near real-time simulation (Vahdatikhaki & Hammad 2014). Hamid and Burcin investigate to integrate different kinds of field data acquisition systems in a BIM to support real-time project information management (Hajian & Becerik-Gerber 2009). The description remained largely on theoretical considerations. The interaction of BIM with a simulation environment was also investigated in the past. Lu and Olofsson describe an approach of an integrated framework with BIM and a simulation environment. A discrete event simulation makes use of the product (e.g. quantities, geometry) and process information (e.g. start time, resources) of the BIM. The presented approach offers a framework for integrating this kind of data, but remains static concerning suboptimal assumptions in the planning phase or possible dynamic changes during the execution phase (Lu & Olofsson 2014).

2.2 Web based construction management

Abanda et al. predict in their work a shift in construction industry from conventional desktop applications to semantic web applications in the next decade (Abanda et al. 2013). Despite the advantages concerning integrated project delivery with a new form of collaboration, the usage in the field of AEC remains limited (Hassan Ibrahim 2013). Four key factors were identified why the industry is struggling with the application of new web technologies (cultural barriers, technological and security barriers, generational differences, no one-size-fits-all models) (Klinc et al. 2009). Viljamaa and Peltomaa have presented an intensified methodology for real-time project management. They describe a construction control system where different stakeholders of the project were integrated into the different construction stages (e.g. planning, execution and maintenance phase) to share all project-relevant data on a main contractor semantic server by intelligent information integration (Viljamaa & Peltomaa 2014). A framework for data collection and management in order to monitor and control construction operations is described, too. The tool supports the decision-making process on site by processing sensors data from pavers and rollers (Vasenev et al. 2014). Thus, the on site-decisions are not considered to be supported by simulation models. Another web-based approach for field data analysis and application of earthmoving operations is described by Montaser and Moselhi (Montaser & Moselhi 2014). Truck+ captures and processes real-time data of the hauling trucks, provides the as-built information as reports to the user and uses the data within a DES to forecast the future truck productivity. However, the forecasting overview is summarized in an Excel sheet and not transferred back to the web-based system as the forecasted construction schedule. This impedes the user to compare the as-planned and the as-built respectively the as-forecasted construction schedule. Web-based approaches for collaborative BIM platforms for different kinds of stakeholders in project delivery are also a subject in the current research. A cloud-based BIM framework has been discussed by Redmond et al. to enable better access and communication among the different actors in the construction industry (Redmond et al. 2012). Matthews et al. discussed an approach for real time progress management with a cloud-based BIM (Matthews et al. 2015). There, the as-built status of the buildings components can be manually captured and updates the general BIM.

2.3 Review summary

The discussed approaches show evident progress in the relevant research areas. However, a web-based management framework for field data acquisition, analysis and visualizing the current project progress linked with a DES environment has not been investigated yet to the best of the authors knowledge. More specifically, no approaches were published where simulation results are transferred back to an information system to compare the current as-built with the as-predicted status of the DES environment to support the decision-making processes on site.

3. PROPOSED METHOD

The paper discusses an approach for a framework named Project Control Center (PCC). The framework is web-based in order to provide an information platform for different kinds of actors on site. The PCC stores necessary as-planned data and processes, and integrates as-built data during the execution phase in two separate views. The application visualizes the task information in the project plan view and also in the 3D model view. Further, there is a link provided between the database of the PCC and a data-driven simulation environment for adjusting the simulation parameters. For evaluation purposes, the results of a simulation run are transferred back to the PCC. The integration of field data into a web-based framework and, additionally, the synchronization of the framework with a DES environment represent the main focus of the discussed work. FIG. 1 shows the proposed framework.

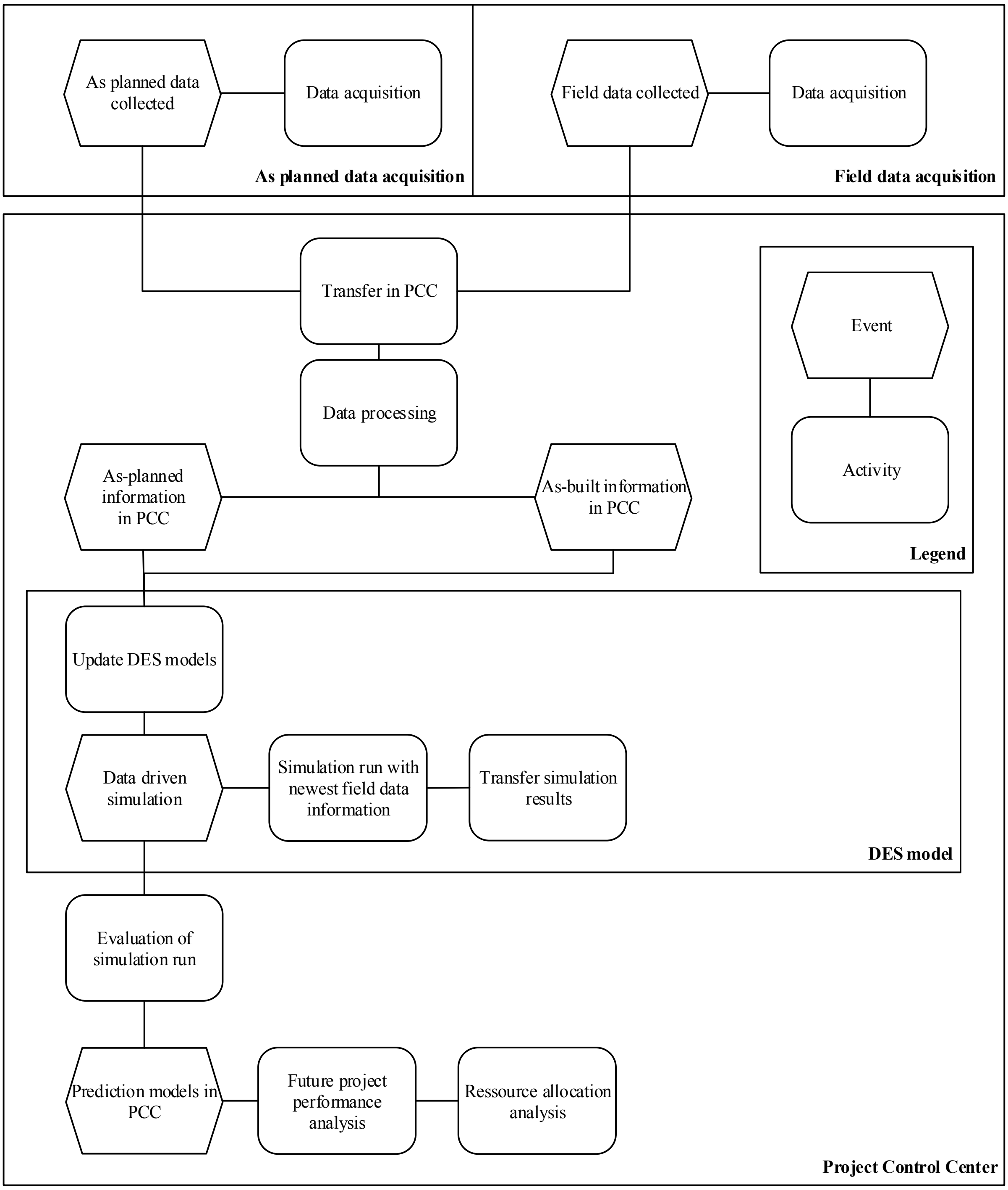

FIG. 1: Proposed workflow

The key framework of the presented research is the PCC. In general, the PCC serves as a collaborative web service for different kinds of actors in a site environment. The PCC represents the as-built building information model with the relevant project and process parameters and visualizes the necessary information. The database of the PCC is linked with a DES environment where a bidirectional data flow is enabled. The DES receives all relevant project data from the PCC and sends the simulation results back to visualize the prediction models in the PCC. The PCC consists of four core modules as shown in

TABLE 1.

TABLE 1: Main modules of the PCC

Dashboard	Core modules	Main focus	Information flow
Project	Overview	General project information	- start/end date of project - mean work hours per day - setting of project and supplier location - calculating of cycle times between site location and supplier
	Project plan	Gantt chart visualization of project tasks	- import of as-planned / as built data - start/end date task (as planned/built) - duration task (as planned/built) - type/amount/cost resources task - current status of task (not started, done, in progress)
	5D-model view	three-dimensional view of components with relevant task information (3D + cost + time)	- start/end date component (as planned/built) - duration component (as planned/built) - type/amount/cost resources component - current status of component (not started, done, in progress)
	Experiment	Gantt chart visualization of project tasks and select of tasks to be simulated	- start/end date task (as built) - duration task (as built) - float task - type/amount/cost resources task - duration task (as built)

The web application uses standard Java EE technologies and is deployed on a JBoss server. The business logic is encapsulated in stateless Enterprise Java Beans. The presentation logic of the application is mostly developed with standard JavaServer Faces 2.0[1] components. Two third-party open source UI components libraries are used for the project timeline. These libraries are Prime Faces 3.5 and Prime Faces Extensions 0.7.1[2]. They are built on top of the JavaServer Faces 2.0 specification and provide a richer user experience. A relational MySQL database is used for data storing and management. The connection between the database and the web application is realized with Hibernate[3] – an object-relational mapping framework and an implementation of the Java Persistence API specification. Every task in the project plan is linked with the relevant components that have to be delivered in the project. FIG. 2 shows the module **overview** of the PCC. After setting the location of the project (big flag) and the location of the supplier/disposal (small flags) the mean arrival time is requested via a Google Maps API. This information is later necessary in order to set the cycles times of the transport entities in the DES. In this particular case, the supplier "concrete" delivers the necessary amount of concrete to the site and the supplier "dump" carries the removed soil to the recycling site.

[1] http://olex.openlogic.com/packages/jsf/2.0
[2] http://www.primefaces.org/downloads
[3] http://hibernate.org/

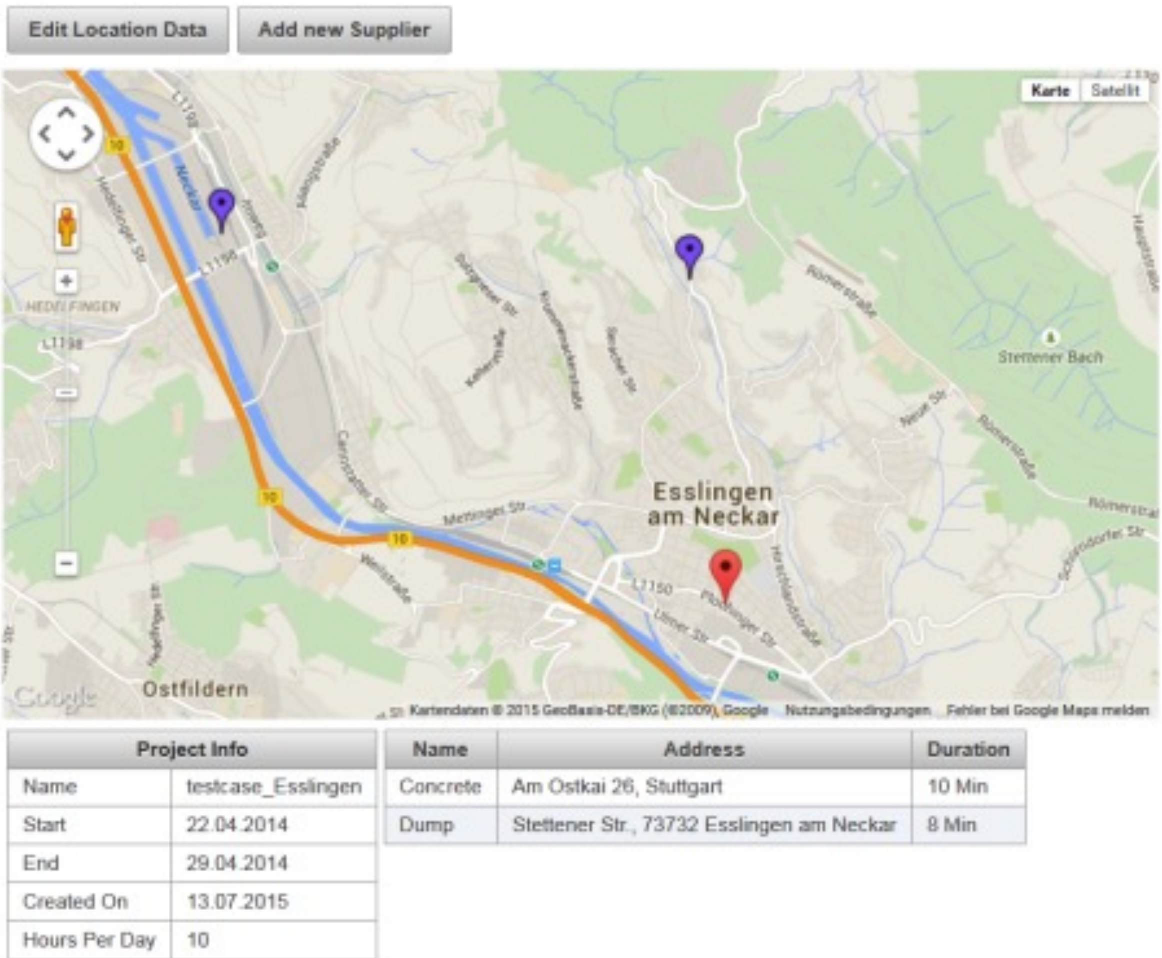

FIG. 2: Overview of the project in the PCC

4. DATA ACQUISITION AND ANALYSIS

Our approach enables the usage of common commercial ERP software (RIB iTWO 5D) for construction management as a data source for the as-planned information of the project (RIB 2015) . Therefore, a multi-model container is exported (Scherer & Schapke 2011) which contains several sub-models of the project. Each sub-model represents a different kind of project information needed. The link model is necessary for understanding the connections between these sub models. Each task of a project plan is linked with the information acquired by the multi-model container. The 3D view enables the user to visualize the as-planned building information model in 3D with the same relevant task information. Each component represents a sub task in the project plan view and can be selected in the model view. So far, the as-planned information is set up in the PCC and allows for control of the project during the construction phase. TABLE 2 shows the relevant project data that is obtained via an xml file via export from the ERP software. The data format of the sub-models is a standard xml-format which is parsed by the PCC and imported into the database.

Field data processing is used to provide two types of information in the presented approach. First, the data is used to process field data in order to update the current project progress and visualize the task performance in the PCC for the relevant component group. Further, there is need to continuously update the key performance parameters based on the processed performance data for each component. The presented approach does not depend on the granularity of the captured data. However, the processing steps are universally valid if field data from one or several data sources is available. It is just a matter of the field data granularity how many sub-processes can be determined for further processing. The PCC is able to either import an individual data snapshot or to group together several data snapshots, e.g. for an entire day. In the presented case studies the raw data is available in text format, which a parser logic can read and process.

TABLE 3 shows sample data in a simplified form, captured during the equipment operation for the case study that is evaluated in this paper. The current steps of the statistical processing are calculated with sample data from a real-world field data analysis.

TABLE 2: Multi-model container for as-planned data

multi model container	**sub-models**
Link model	objects
	bill of quantities
	activities
	calculation
	equipment
	materials

TABLE 3: Simplified sample of data capturing

id	**task_nr**	**sub-process1_start**	**sub-process1_end**	**sub-process2_start**	**sub-process2_end**
30	110	08:53:32	09:01:47	09:02:18	09:11:55
31	114	09:13:38	09:22:23	09:22:59	09:32:58

Due to the highly volatile nature of construction operations on site, the field data is widely scattered. This has to be taken into account for further processing by eliminating outliers which would otherwise distort the simulation results. Therefore, the logic eliminates outliers that are outside the range between the mean added plus/minus three times the standard deviation. Further, commonly used standard probability distributions (Exponential, Gamma, Lognormal, Normal, Weibull) are fitted to the sample data and the specific numerical parameters for each distribution are calculated. FIG. 3 shows the graphical representation of the fitted standard theoretical probability distributions to the sample data.

Further, an evaluation is performed using three common goodness-of-fit tests (Chi-Square test; Kolmogorov-Smirnov (K-S); Anderson-Darling (A-D)) to evaluate the best fit for the sample data based on the calculated parameters. These tests compare a null hypothesis, H_0, and an alternate Hypothesis, H_1, and evaluate if the sample corresponds to a certain distribution function. The alternative hypothesis corresponds to the exact opposite, claiming that the empirical distribution function does not correspond to the standard theoretical distribution function.Finally the test statistics of the three goodness-of-fit test are evaluated with a rank-sum test. The rank of each goodness-of-fit test is summarized in order to evaluate the best fit for the sample data. TABLE 4 shows the result of the calculated rank-sum test for the sample data. The best fitting distribution for the sample data is Weibull.

Further, TABLE 5 shows the general information parsed and processed in the database. The as-built task duration is summarized about the overall duration of all field operations. The mean and standard are calculated over the sample data excluding the outliers. The mathematical parameters (distribution; distribution_mean; distribution_std / alpha; beta) depend on the chosen distribution function.

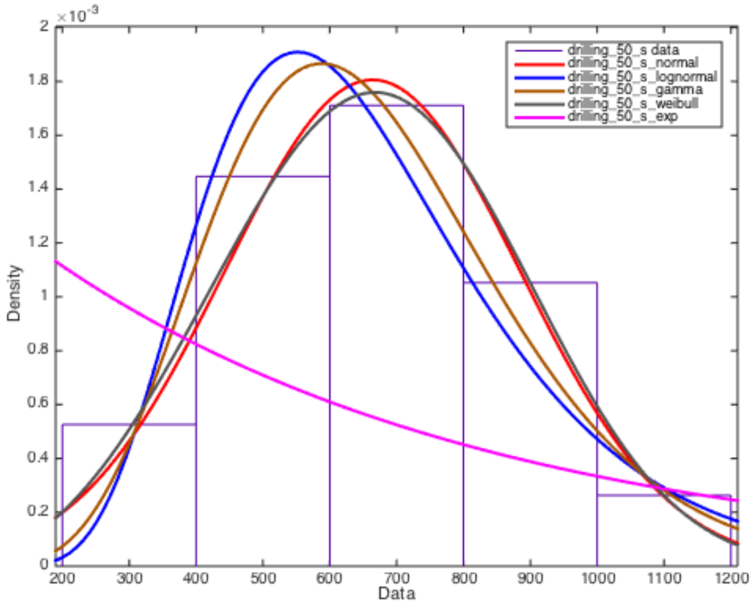

FIG. 3: Graphical representation of the sample data distribution fittings

TABLE 4: Rank-sum test of the fitted sample data for sub-process drilling

	Exponential	Gamma	Lognormal	Normal	Weibull
Rank Chi-Square test	5	1	2	4	3
Rank K-S test	5	3	4	2	1
Rank A-D test	5	3	4	1	2
Total Rank	15	7	10	7	6

TABLE 5: Processed field data parameters

as-built task	task_nr
	as built task duration [h]
Field data parameter	number_of_valid_data_points{sum}
	field_data_values_{1..n}

	field_data _performance_{mean; standard deviation (std); min ≥ mean-3*std; max ≤ mean+3*std}
	field_data _performance_{distribution; distribution_mean; distribution_std / alpha; beta}

5. DATA DRIVEN SIMULATION

The presented approach uses discrete event simulation to generate prediction models based on the field data generated and further processed. Although the common understanding that construction project delivery represents a single-unit production we can subdivide the activities into repetitive work tasks on site to represent the engineering system in a simulation model. The simulation model is developed within the Technomatix Plant Simulation environment (Siemens 2015). The process standard modules (PSM) are the key framework of the data driven simulation and represent the standard logic of a specific construction operation. The PSM is based on the identified process patterns that were evaluated on site with the restriction that the patterns strictly follow the generated field data. Thus, only sub processes of a construction operation with available field data are represented in the DES. Each process of the operation is processed by a trigger that follows the logic of the process standard for all remaining tasks. At the beginning, the necessary as-planned information for the processes in the PSM are synchronized with the database of the project. Further, each operation has a specific amount of time that is calculated based on the processed field data. FIG. 4 summarizes the process and information flow between database of the PCC and the simulation environment. The figure follows a simple sequence of task in order to describe the conceptual structure within the PSM and the DES in general. Thus, the main objective is to describe a framework where all kind of construction operations can be linked with field data and evaluated within the simulation results.

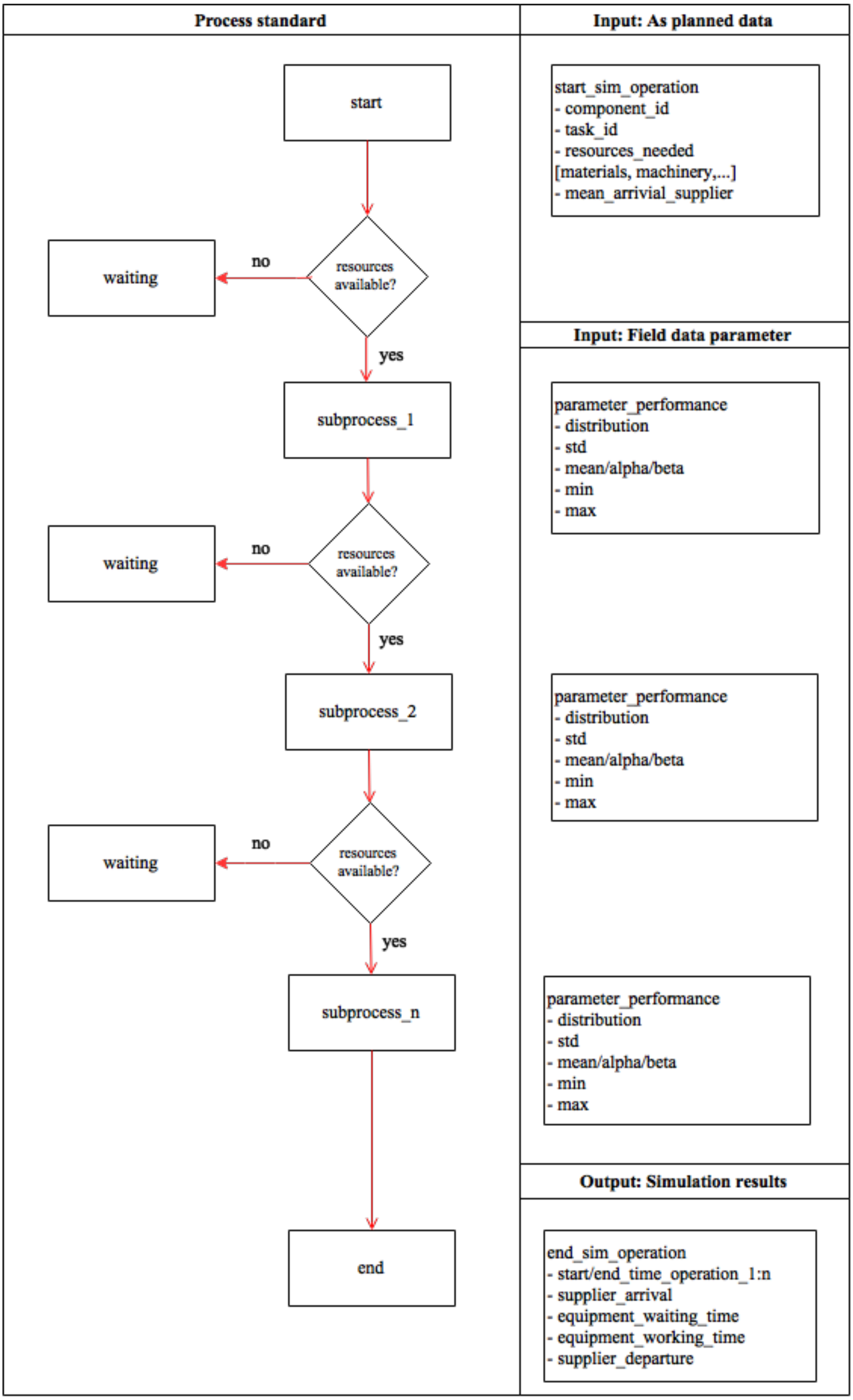

FIG. 4: Schematic PSM

6. CASE STUDY: BORED PILE WALLS

The main focus of the case is the production of a series of 77 bored piles. These are cylindrical concrete bodies drilled and concreted into the ground. Basically, there are three sub processes for manufacturing these kinds of bored piles. First, the equipment drills with a rotary auger to a defined depth. After reaching the final depth, concrete is pumped from bottom to the top by the hollow stem auger. The third sub process involves moving and setting up the drilling rig for the next defined pile coordinates, which is summarized as idle time. The following description is based on field data automatically captured by internal sensors of construction equipment and made available by the responsible contractor. The main focus of the case study is to present the different steps of the framework based on a simple sequence of construction task. The approach of the field data analysis is evaluated by refining the simulation environment with the current simulation parameter of the different sub-processes. Three simulation runs during different completion grades of the project are carried out. The results of the prediction models are compared with real-world results to evaluate the presented approach. The following description is based on the upload of field data from 19 bored piles as described in the corresponding section "Data acquisition and analysis".

6.1 Data acquisition, analysis and visualization

The series of 77 bored piles is clustered in three constructions tasks (pilewall_1, pilewall_2, pilewall_3). Each task represents a specific component group with different topological parameters. The tasks have a total of 77 sub tasks that represent each bored pile as a single task/component that has to be manufactured. The heavy equipment operation investigated in the case study consists of three single-production units (sub-processes): drilling, concreting and idle, which are implemented in a PSM. As already mentioned in the section field data acquisition and analysis the field data is processed in a multi-level procedure. First, outliers are eliminated and five standard probability distributions were fitted to the field data. Further, an evaluation is performed using three common goodness-of-fit tests (Chi-Square test; Kolmogorov-Smirnov (K-S); Anderson-Darling (A-D)) to evaluate the best fit for the sample data based on the calculated parameters. So far, the approach represents the current project progress, which was automated generated through field data processing via field data acquisition and analysis and stored in the database of the PCC. FIG. 5 shows the as-built construction progress in the project plan view and 3D view with the as planned and as built tasks respectively components (highlighted in green). The popup window "Task Details As Planned" shows the imported as planned information.

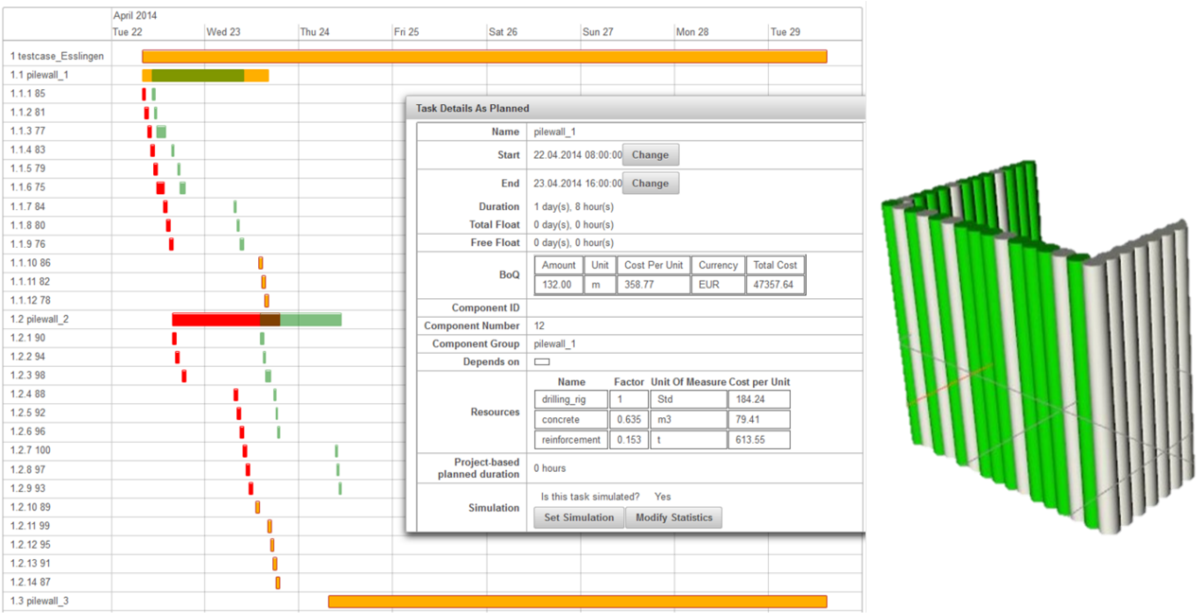

FIG. 5: As-built view in the PCC

As mentioned earlier, the as-built data import corresponds to 25% of the entire project delivery. The tasks pilewall_1 and pilewall_2 already started. The as-planned (orange bars) and as-built tasks (green bars) are visualized in the project plan view in the same row. If there is a delay, the as-planned tasks are highlighted (red color) in the project plan view. Each task can be individually selected for exporting the field data parameters to the DES. By clicking on the as-built task, the relevant field data parameters that are synchronized with the simulation environment are displayed as shown in FIG. 6.

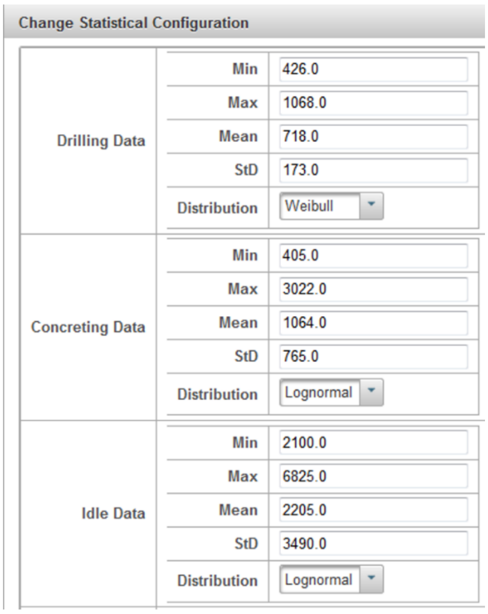

FIG. 6: Processed field data parameter

6.2 Performance prediction

The main focus of the case study is to estimate the further project performance, which is represented as throughput time of a specific task in the project plan. To evaluate the presented approach, three simulation runs are carried out as shown in TABLE 6. Due to the field data processing rules, some raw data points are eliminated within the implemented logic of the PCC (see column adjusted data points).

TABLE 6: Test case evaluation

Experi-ment	as-built database.	as-built duration	Raw sample [drilling/concreting/ idle]	Adjusted sample [drilling/concreting/ idle]	Probability distribution function [drilling/concreting/ idle]
1	25%	21.25h	19/19/19	19/17/16	Weibull/Lognormal /Lognormal
2	50%	35.26h	38/38/38	38/35/34	Weibull/Lognormal /Lognormal
3	75%	44.4h3	58/58/58	58/56/53	Lognormal/Lognor mal/Lognormal

The first experiment is carried out after the completion of 25 percent of the total task delivery and estimates the probable completion time of the investigated task. The prediction of the remaining duration is clustered into minimal duration, mean duration and maximal duration by 10,000 observations for each simulation run. In our case, a simulation run needs approximately 60 seconds, which is sufficient enough for daily analysis. FIG. 7 shows a screenshot of pile wall 3 in the experiment view of the PCC after transferring the simulation results to the PCC. The predicted simulation results are highlighted in grey and compared to the as-planned tasks. The statistics section of the pop-up window visualizes the simulation results, for instance machine utilization and waiting times, and compares the as-planned and predicted performance of the task.

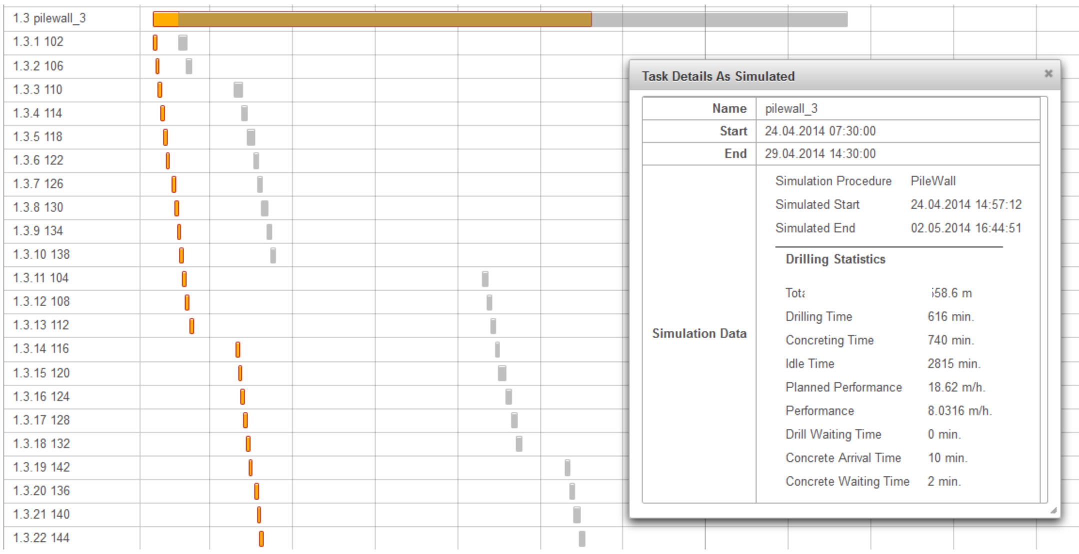

FIG. 7: Experimental results of a simulation run in the PCC

The results of the different simulation runs were compared in TABLE 7 with the real duration (55.93h) of the investigated tasks. Positive values in the row deviation to as-built 100% imply that the predicted duration is longer than the real duration and negative values imply that the predicted duration is shorter than the real task duration.

TABLE 7: Result experiments

	as-built database 25%			**as-built database 50%**			**as-built database 75%**		
	min	**mean**	**max**	**min**	**mean**	**max**	**min**	**mean**	**max**
Prediction duration 100%	64.10h	75.67h	87.45h	55.80h	61.64h	69.66h	52.93h	55.92h	62.00h
deviation to as-built 100%	12.75%	26.09%	36.05%	-0.22%	9.28%	19.72%	5.66%	0.05%	9.80%

The first simulation based on the database of 25 % of the task delivery were suboptimal and within the range of 12.75% to 36.05% far away from the real task duration. FIG. 8 depicts the result of the simulation runs.

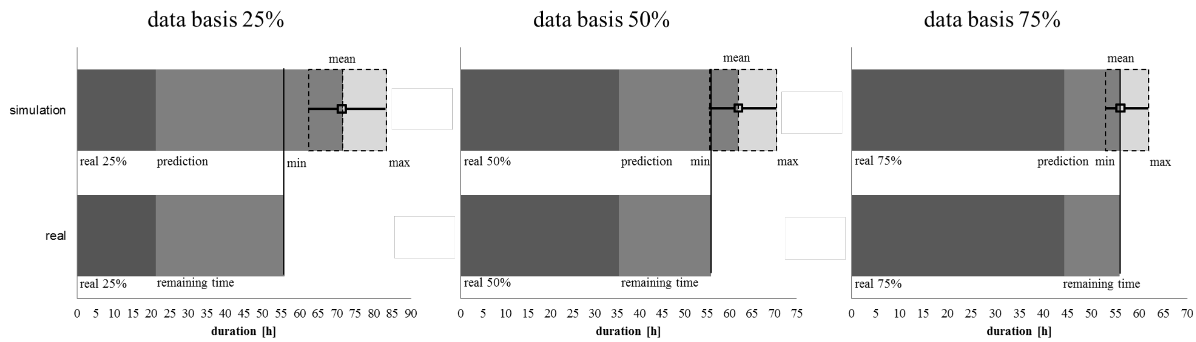

FIG. 8: Simulation results

The notable deviations appear to have several reasons has several reasons. The database for the simulation parameters, drilling, concreting and idle, was low with less than 20 values for each parameter. Thus, the occurring extreme values, particularly in the max range, falsify the results, which cannot be balanced by the sample. The results of the simulation runs, based on the database of 50% and 75% as-built data, show a much better prediction time range. The as-built duration of the complete task is within the prediction of the remaining task duration for both experiments, which improves the result significantly. For the second experiment the real task duration is already in the range of the predicted remaining duration based on the as-built database of 50 % even though the real task duration is indeed close to the minimum value of the predicted time duration range. Thus, the experiment shows a considerable improvement in the predicted results compared to the first experiment. Due to the richer database, which substantially refines the different simulation parameters, a better estimation of the remaining time is ensured. The simulation results, based on the as-built database of 75 % (predicted mean time remaining), differ only by 0.05 % of the real task duration, which conclude that the predicted mean in simulation run 3 almost reaches the real duration of the investigated task exactly. This allows a nearly optimal prediction of the remaining 25 % of task delivery. Furthermore, the range between the extreme values decreases in the second and third experiments, which also reduces the volatility of the predicted task duration and allows a more precise statement as shown in FIG. 9.

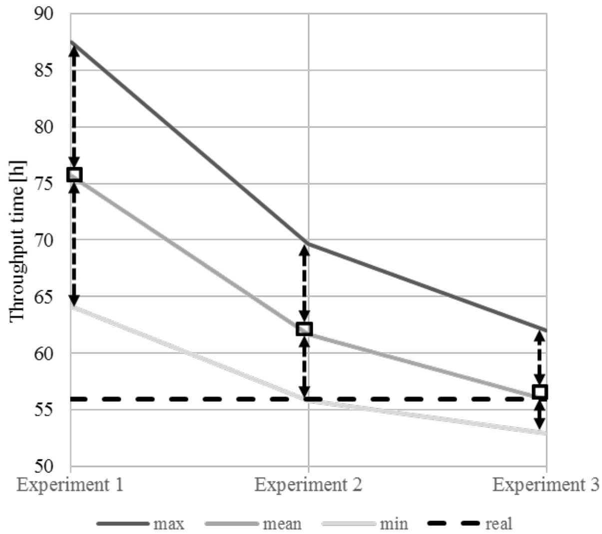

FIG. 9: Deviations of extreme values for each experiment

7. CONCLUSION

Field data processing and data-driven simulation have played a superordinate role in construction research over the past decade. The captured raw data needs a processing logic to generate reliable project and process information. Data driven or near real-time simulation represent a tool that eliminates the pitfalls of a limited simulation environment based largely on assumptions for the input parameters in the planning phase. The presented web based framework combines the advantages of field data analysis and data-driven simulation for advanced construction management purposes. Process-specific production data ensures process quality in near-real time. The equipment performance data facilitates the evaluation of the process parameters in detail. The major research gap in the paper was to link the above mentioned research areas and integrate them into a framework to provide an approach for construction production control and re-planning. A simulation environment was linked with database of the web based framework to transfer the necessary as-planned and as-built information in order to initialize the simulation model. For evaluation purposes, three experiments were carried out with a data basis of different task completion degrees. The focus of the simulation experiments was to predict the throughput time of the investigated project task based on the current process performance by considering interdependencies in the supply chain (concrete truck arrival times). The results based on the first experiment with a data basis of 25% were suboptimal and not able to forecast the completion of the real engineering system. The next experiments based on the data basis of 50% and 75% indicated improved results. The second experiment allowed a sufficiently accurate prediction of the task completion time. The simulation results based on the process information after 75% of the task completion offered a nearly optimal estimation of the remaining time for the last quarter of task completion.

7.1 Research limitations and future work

As mentioned earlier, main focus of the research was the link between field data analysis and data-driven simulation to state out the proof-of-concept. Nevertheless, the presented web-based framework allows the responsible stakeholder on site to use the PCC as a tool for construction management and control. These advantages (e.g. project schedule control, quantity take-off) were not discussed in order to keep focused on the main objectives of the paper. An approach to improving the results in the early stage of task completion would be to consider a learning curve factor to the logic of the simulation environment. Therefore, more case studies need to be performed to investigate the learning impacts during task execution. Further, more the complex sequence of construction tasks needs to be considered, too. However, the general usability allows the authors further evaluations concerning construction operation optimization (e.g. changes in resource allocation) and risk assessment in future studies.

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