ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20170627195003
Original scientific paper

The Simulation Model for Predicting the Productivity of the Reinforced Concrete Slabs Concreting Process

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Abstract: This paper presents an approach to predicting the productivity of the concreting process based on a conducted quantitative research involving the recording of concreting at building construction sites in the city of Nis, Serbia. In the period of 20 months, 81 recordings of reinforced slabs on eight construction sites of buildings were observed and recorded. The total amount of poured concrete was 11951 m³ and the total consumed time was 503 work hours. The factors that could impact productivity have been identified and a simulation model for predicting the productivity of the concreting process has been developed using Discrete Event Simulation and Agent Based Modelling. AnyLogic software package was used to develop the simulation model. Experiments were carried out and based on the obtained parameters the models are estimated. The proposed models can be useful in the planning stage and allow for more precise prediction of concreting productivity, thus benefiting the decision making and work flow prediction and improving the concreting process management in order to increase productivity, shorten the delays, and reduce costs.

Keywords: concreting process; predicting; productivity; reinforced concrete slab; the simulation model

1 INTRODUCTION

During building construction, concreting is very important in terms of cost and amount, especially if skeleton construction is used. In the dynamic plan of construction work for such buildings, concreting is a critical activity. Therefore, it is important to devise a realistic construction plan by properly harmonizing all influences and by ensuring the required productivity.

In domestic practice, planning of concreting is usually reduced to experience, without involving any of the factors that influence the productivity of the process. This often leads to delays or queues, e.g. queued concrete truck mixers or the pump waiting for the truck mixer to arrive, which expectedly has a negative financial effect [1].

The research subject in this paper is the productivity of concreting during building construction and the development of a model for predicting the productivity. It considers the concreting process, where the concreting technology involves concrete production in a concrete plant, transport to the construction site with truck mixers, transport to the poured place with mobile concrete pump and consolidation with a concrete vibrator. The paper analyzes the productivity of concreting of reinforced slabs. It also presents an approach to predicting the productivity of the concreting process, which involves a quantitative research in order to identify major factors that affect productivity, and proposes a model for productivity prediction and control.

Similar to many other construction processes, concreting, which is the subject of this research, is also a stochastic process. Due to its random nature, this system is impossible to simulate in a deterministic manner, using average data as the input, because the productivity and duration thus obtained would be incorrect, since the effects of random events would be completely disregarded. For instance, the duration of the mixing cycles varies within specified limits depending on a variety of conditions, such as technical adequacy of truck mixers, driver qualifications, weather conditions, road conditions, etc. Duration of truck mixer loading varies depending on the truck mixer drum capacity (it is not always possible to work with truck mixers with the same drum capacity), technical adequacy of the concrete plant, etc. Achievable pump efficiency depends on the type and dimensions of the element to be concreted, technical properties of the pump, operator skills, pump age, etc. Queued truck mixers are to be expected, as it is highly unlikely that the next truck mixer will arrive at the exact moment the previous one departs; if a truck mixer arrives late, the process is delayed and the pump and the workers have to wait. Consequently, the concreting process is a stochastic system whose behaviour cannot be predicted with certainty; however, the probability of change of its state is something that can be determined. On the other hand, concreting can be viewed as a system whose states change discontinuously over time, i.e. in specific moments in time, which makes it a discrete system.

This paper deals with the concreting process as a cyclic construction process, examining actual and current projects in order to obtain real-world data. The data were collected through constant monitoring of construction work and recording of the concreting process (using a work measuring method – photo view), examination of technical and project documentation, and conversation with technical and operating staff directly involved in the process at eight high rise construction sites. The data were then used to develop simulation models for productivity prediction. The core issue when designing a model is to select the most influential parameters and combine them, as well as quantify their influence.

1.1 A Brief Review of the Development and Application of Simulation Techniques and Methods

Computer simulation in construction has been used for over four decades. In addition to its applicability to complex processes, the popularity of simulations also grows due to the development of computer technology. One of the first special-purpose simulation languages was CYCLONE (CYCLic Operations NEtwork), developed by Halpin (1973) [2]. Some ten years later, the MicroCYCLONE version, based on graphic interpretation, was developed and it was much simpler to understand [3]. However, even though the method was well received in the scientific community, it failed to find proper practical application. All subsequently developed simulation techniques for resolving cyclical construction issues were based on the CYCLONE model. In his doctoral dissertation, Martinez [4] introduced STROBOSCOPE, a simulation language for modelling complex processes in various fields. This simulation model utilizes a network representation, similar to an activity network diagram [4]. Martinez and Ioannou [2] elaborated on the STROBOSCOPE simulation platform and developed EZStrobe, based on Discrete Event Simulation, to be used in construction. Combining the advantages of CYCLONE and STROBOSCOPE with genetic algorithm, SimEarth was developed, a simulation platform for specific purposes of modelling earth moving operations. "The developed framework supports time–cost trade-off analysis and can assist users in considering what if scenarios with respect to fleet configurations. A computer-based platform (SimEarth) was developed to assist in selecting near-optimum fleet configurations" [5]. Park et al. [6] use system dynamics as a method for designing a simulation model of ready-mix concrete (RMC) delivery. "The research findings indicate that the model-generated information helps in achieving an economical RMC supply by maintaining the number of queuing truck mixers at the desired level, while satisfying the contractor's need. Ultimately, this dynamic model could potentially be used as an effective automated tool to assist RMC suppliers in supply planning" [6]. Labban et al. [7] deal with discrete event simulation for the asphalting process. Their paper describes the building of an asphalt paving simulator, as an example of the rigor and effort required in developing construction simulation models, and then briefly describes an alternative model building method currently being researched, which may potentially make it easier and faster for stakeholders to quickly build simulation models on construction projects [7]. Zankoul and Khoury [8] designed two models for earthmoving simulation – discrete event simulation and agent-based simulation – using the simulation software AnyLogic 7.1. Both approaches, DES and ABS, are compared and the advantages and drawbacks of each approach when modelling earthmoving operations are evaluated. These two models were then tested on a case study in Marjeyoun, Lebanon. "The results highlighted the efficiency of both modelling types as both yielded the same results" [8]. Agent-based simulation was used to study labour efficiency. Related research also shows that congestion on construction sites often leads to lowered efficiency. Using these findings as a point of departure, the agent-based modelling method is used to represent the construction site as a system of complex interactions and explore whether labour efficiency can be treated as an emergent property resulting from individual and crew interactions in space. "This allows us to use a 'bottom-up' approach to analysing labour efficiency, which supplements existing 'top-down' approaches to modelling the impacts of space congestion on labour efficiency. A pilot implementation of the agent-based model and preliminary results illustrating the relationships between congestion and labour efficiency are presented" [9]. The research about labour productivity during scheduled overtime using Monte Carlo simulation model was presented by Woo [10]. Borshchev [11] describes modelling in the AnyLogic software. He presents three methods of simulation modelling: system dynamics, discrete event modelling, and agent-based simulation. He indicated a possibility of combining the three methods using multi-method modelling [11]. Data from concreting processes at construction sites in Dubai were collected and then statistically analysed, after which a simulation model was created using the discrete event method. The goal was to identify a bottleneck in the concreting process, which in this instance was the concrete pump [12]. Nojedehi and Nasirzadeh [13] present an integrated fuzzy System Dynamics (SD) approach for modelling and improving of labour productivity. Han et al. [14] developed an analysis methodology in order to compare and evaluate the predicted productivity and cost of the construction process, steel staircase system method, and of the reinforced concrete staircase method, using as a basis CYCLONE simulation technique.

In the opinion of experts in the field, systems that are predominantly analytical and theoretical have low practical applicability. Therefore, simulation systems should be presented as figures or schematics, with highlighted input and output parameters. As far as the share of machine operations in the process is bigger, the simulation will yield better results, because such operations are easier to model than those that prevalently require manual execution. A discrete event simulation works best in the case of complex construction processes and operations, whereas it is meaningless to use simulations to analyse relatively simple processes [15].

2 GENERAL NOTES ON THE MODELLING AND SIMULATION

Modelling is one of the ways to resolve real-world issues; it is in fact a translation of an actual system into a model. Modelling offers the opportunity to observe rules or patterns, to interpret meaning, to assess and predict, to manage processes and objects, etc.

Designing a comprehensive, all-encompassing, model is not the point of modelling; it is much more useful to design the simplest model, which contains the essential elements of a real-world system to be modelled. Accordingly, modelling involves identifying and extracting the elements that are relevant to a given research and including them in the model, whereas other elements may be disregarded. Thus, a model does not contain only objects and attributes of a real system but also specific assumptions about the conditions of its validity.

Simulation modelling is one of the leading contemporary methods of computer-aided modelling. This method allows the description, understanding, and quantitative analysis of complex dynamic systems in various fields: production, transport, economy, mass service, computing, etc.

Simulation models are models that are associated with dynamic systems, i.e. systems that change over time. Typical examples of these systems are queues, production processes, storage, transport, etc. Nowadays, simulation is widely used across many fields, e.g. in the management of organization and business systems, engineering, military industry, medicine, computer sciences, biology, education, and increasingly in social sciences [16].

It is convenient to model stochastic dynamic systems using simulation methods and techniques. Simulation experiments are most often conducted in order to collect specific information, the acquisition of which through experimenting on a real-world system would be impractical, unfeasible, or too costly. That information is later used to make decisions that are important for real-world system management. The goal of a simulation is to study the behaviour of a system that is the object of simulation and also to analyse how the same system would behave if it were affected by another set of variable circumstances (input quantities and parameters).

Discrete event simulation is a simulation modelling method where discrete changes of state in a system occur discontinuously over time. The model is executed in steps, whereby the next state of the system depends on the current state and current impact from the environment. It is usually used for analysing dynamic systems with stochastic properties.

In recent years, the agent-based simulation has been for system modelling in discontinuous time. Agents are individual objects that can mutually interact in a suitable surrounding. This method allows the use of agents to obtain models that better reflect the behaviour of real-world systems as compared to discrete event modelling. Object interdependency is presented in more detail, which ultimately yields more precise results. Agent-based modelling tools can also be used to optimize a model or to test its stability.

For more precise and more comprehensive models, the possibility of combining these techniques (multi-method modelling) by designing the so-called hybrid models should be considered. Discrete event models already contain individual entities, which facilitates the inclusion and application of agent-based models. The set of rules defined in block diagrams in the discrete event method can be represented by agent state diagrams in the agent-based method.

3 DESIGN OF THE SIMULATION MODEL OF REINFORCED SLAB CONCRETING

Based on construction site experience with concreting and the collected data about this process, we designed models of the concreting process using the AnyLogic simulation software. The data gathered by recording of the concreting process at construction sites, processed and presented through proper probability distributions, serve as the input data for model design. The simulation model was designed using the modelling software AnyLogic 7.2.0, which operates in JAVA object-oriented interface. The advantage of this software is the possibility to design a model by combining three different methods: discrete event simulation, system dynamics, and agent-based simulation. A multi-method (discrete event combined with agent-based simulation) was used for system modelling.

3.1 Preparation of Input Data

The quality of the simulation process depends on the quality of the created model and the quality of input data. The preparation of input data involves the following steps:

- input data collection,
- formulation of a hypothesis on input data probability distribution,
- assessment of parameter values for a selected distribution,
- testing whether the selected distributions match the input data.

In the period of 20 months, there were 81 recordings of foundation slabs, floor slabs, and beams concreting. The total amount of placed concrete is 11 951 m^3 and the total consumed time is 503 work hours. For the purpose of creating a simulation model, the data collected from the construction sites were statistically processed using the XLSTAT 2014 statistical software for MS Excel. After testing the samples for the presence of outliers using the Grubbs' test for outliers, a statistical analysis is performed and constructed probability distributions. All the constructed probability distributions are presented as values of the corresponding parameters in the model that were used individually or to create functions, or the distribution parameters were used directly to represent the duration of specified processes and operations.

Based on the collected data, the following influential variables were proposed with probability distribution functions or with expressions that define them:

- truck mixer motion speed, represented by probability distribution function for Beta (4-parameter) distribution,
- time required to position the truck mixer within the construction site, represented by probability distribution function for Weibull (3-parameter),
- time required to position the truck mixer on the street, represented by probability distribution function Lognormal,
- regression analysis was also performed for the time required to unload the truck mixer when concreting slabs and the following Eq. (1) was obtained:

$$\begin{aligned} Un(SB)_{pred} &= 1.81013 + 1.295st + 0.01986H + \\ &+ 0.00889E_{t,p} + 0.07231PA - 0.07121PR - \\ &- 0.54425ST.F \end{aligned} \tag{1}$$

where:

$Un(SB)_{pred}$ – predicted time of truck mixer unloading (min/m^3),
st – slab thickness (m),
H – concrete placement height (m),
$E_{t,p}$ – theoretical pump efficiency (m^3/h),
PA – pump age (year),
PR – pump reach (m),
$ST.F$ – slab type (full reinforced concrete (RC) slab).

- concreting delay time, represented by probability distribution function for Gamma (2-parameter),
- time required to reposition the pump, represented by probability distribution function for Beta (4-parameter),
- time required to wash the truck mixer funnel with water, represented by probability distribution function for Weibull (3-parameter),

- time required to clean the truck mixer funnel with a shovel, represented by probability distribution function for Weibull (3-parameter).

3.2 Development of the Simulation Model using the AnyLogicSoftware Package

The simulation model of the concreting process was created using blocks to represent specific concreting processes and operations. The model in its development stage (writing functions using JAVA methods, defining parameters and variables, determining the ways to present output data, etc.) is shown in Fig. 1.

AnyLogic is a software simulation tool developed by a group of scientists and developers who do not deal with modelling, which is why no approach specific to model design was used. The intention was to create a tool to be used for the modelling of complex real problems [17]. Since AnyLogic is an object-oriented tool, it can easily create reliable models in a visual environment, but the developers also left the option to use JAVA to define and implement specific structures.

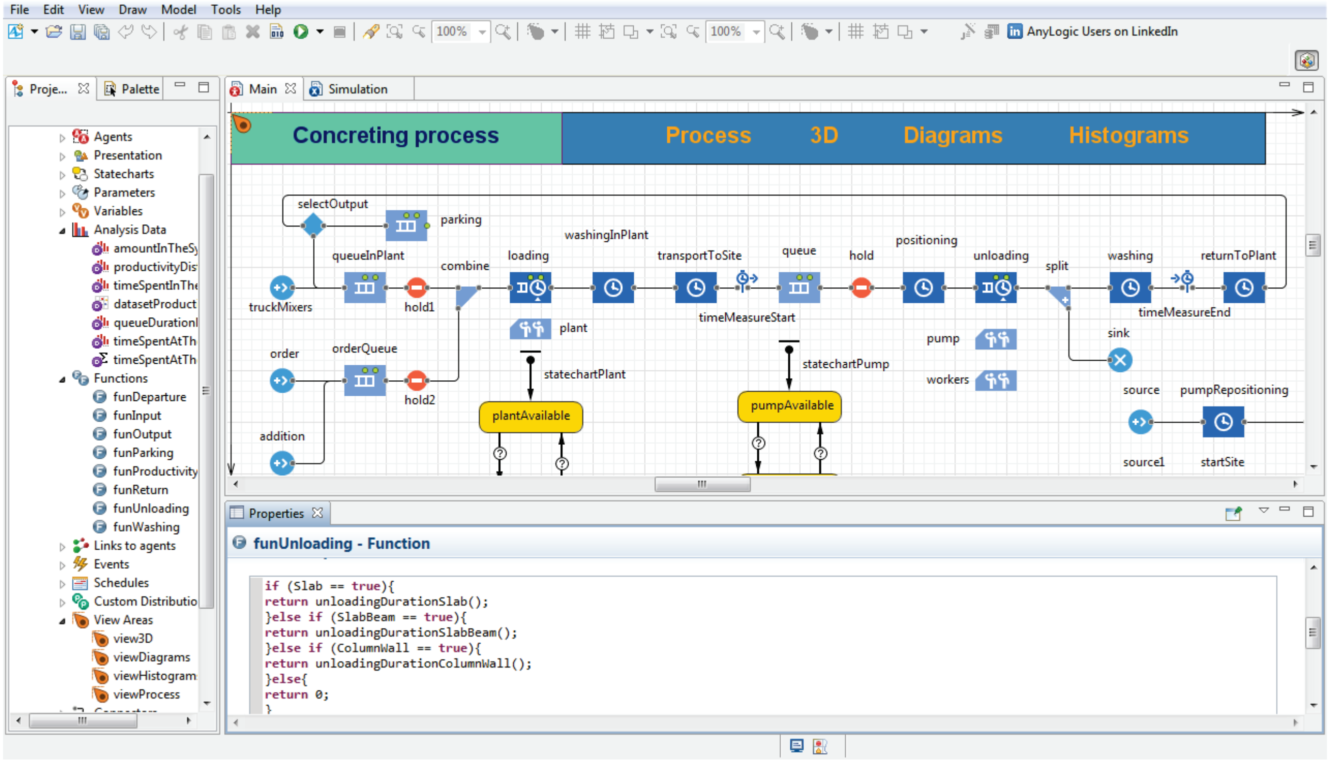

Figure 1 Model of the concreting process – process diagram with function definitions

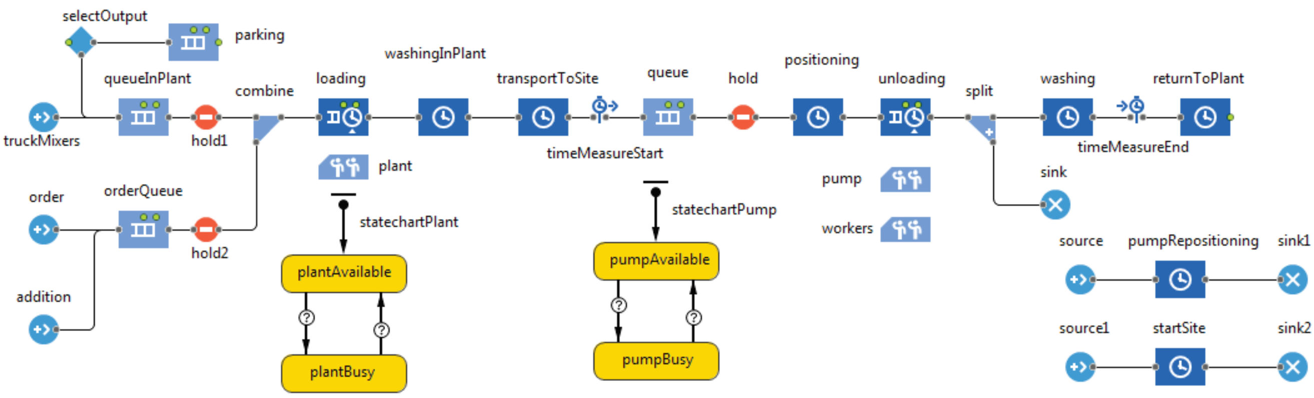

Figure 2 Model of the concreting process – process diagram and state charts

Model design in AnyLogic using the discrete event method utilizes blocks that describe a specific state in the process. There are numerous different blocks in the software's library, as well as several specialized libraries for solving specific problems, such as problems of pedestrians (Pedestrian Library), rail traffic (Rail Library), or fluids (Fluid Library). The blocks are interconnected by connectors. Each block, depending on the type, contains defined properties, such as: name; type; delay time; capacity; maximum capacity; agent location; action: on enter, on exit, on remove; agent type, etc.

The model presented in this paper was created using a combination of discrete event simulation and agent-based simulation. State charts were also used to represent the behaviour of specific parts of the system. The concreting process of reinforced concrete slabs is shown as a process diagram in Fig. 2.

The process during simulation is shown in Fig. 3.

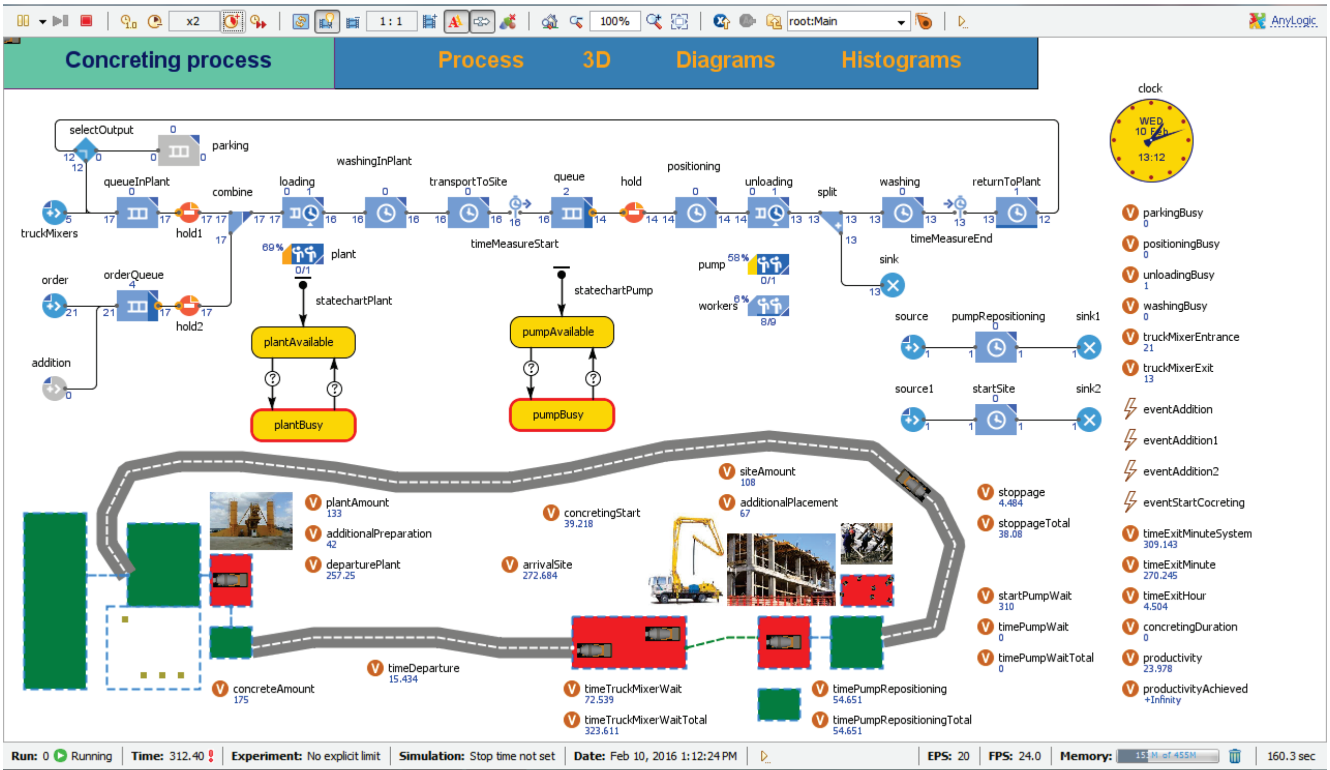

Figure 3 Process diagram and 2D representation during simulation

4 ANALYSIS OF THE SIMULATION EXPERIMENT OUTPUT DATA

In order to obtain output data of the simulation experiment and to verify the designed model, experiments were conducted for all cases collected at the construction site. Considering that random variables are involved, it is necessary to conduct a large number of experiments with different arrays of random numbers and to perform a statistical analysis of the output variables. Based on the simulation results during trial-run experiments, smaller corrections of the model were made on several occasions so that the model would depict the actual state more realistically and so that the results would be more valid. Depending on the dispersion of results, the required number of simulations was calculated and 14 simulations were derived for every reinforced slab concreting – a total of 1,092 simulation experiments.

During the collection of results from simulation experiments, it was observed that the predicted productivity was considerably different from the actual productivity in cases when the concrete plant serviced third parties as well (there were longer waiting periods for concrete delivery at the observed construction site). This is an expected occurrence, since this piece of data was not considered during the simulation model design because detailed recording of the process was made only at construction sites. In order to make the set more homogeneous, only those cases when the concrete plant was in operation exclusively for the purpose of the observed construction site were considered. As a result, out of the 78 originally analyzed instances of slab concreting, 61 instances were analyzed for the simulation experiment.

After the experiments were conducted, the results were statistically analyzed, sorted according to specified criteria, and represented using histograms and diagrams, which is discussed in the following section.

5 DISCUSSION OF THE PROPOSED MODEL

Evaluation for the simulation model was performed using the Mean Absolute Percentage Error (MAPE) between actual and predicted values. The obtained mean absolute error was MAPE=16.28% for the entire sample (78 instances of concreting), and MAPE=7.29% for the reduced sample (61 instances of concreting). Fig. 4 shows a comparison of actual productivities (blue) and predicted productivities (orange) for the sample with the lower mean absolute errors, i.e. the sample with 61 instances of concreting.

The results were sorted based on the Absolute Percentage Error (APE) and the classification of concreting according to actual productivity. The recorded concreting processes were divided into six groups according to actual productivity, as follows: processes with actual productivity up to 15; 15–20; 20–25; 25–30; 30–35; and over 35 m^3/h. Absolute errors were divided into four groups: up to 10; 10–25; 25–50; and over 50%.

The results overview, shown in Fig. 5, reveals that 74% of the results contain an absolute error lower than 10% for productivity prediction using the simulation, i.e. 95% of all results were predicted with an error up to 25%. Higher deviations occurred only in 5% of the results, with an error up to 50%. Errors between actual and predicted values that were over 50% did not occur. It is noticeable based on these data that the model has the best predicting power for productivities ranging from 25 to 30 m^3/h, because within this range the APE usually does not exceed 10%. In case of productivities higher than 30 m3/h, the results were mostly even with the absolute errors up to 10% and from 10% to 25%. In case of productivities lower than

25 m^3/h, most results had an error up to 10%, but there were also results with an error of over 25%. These data are shown in the histogram below (Fig. 6).

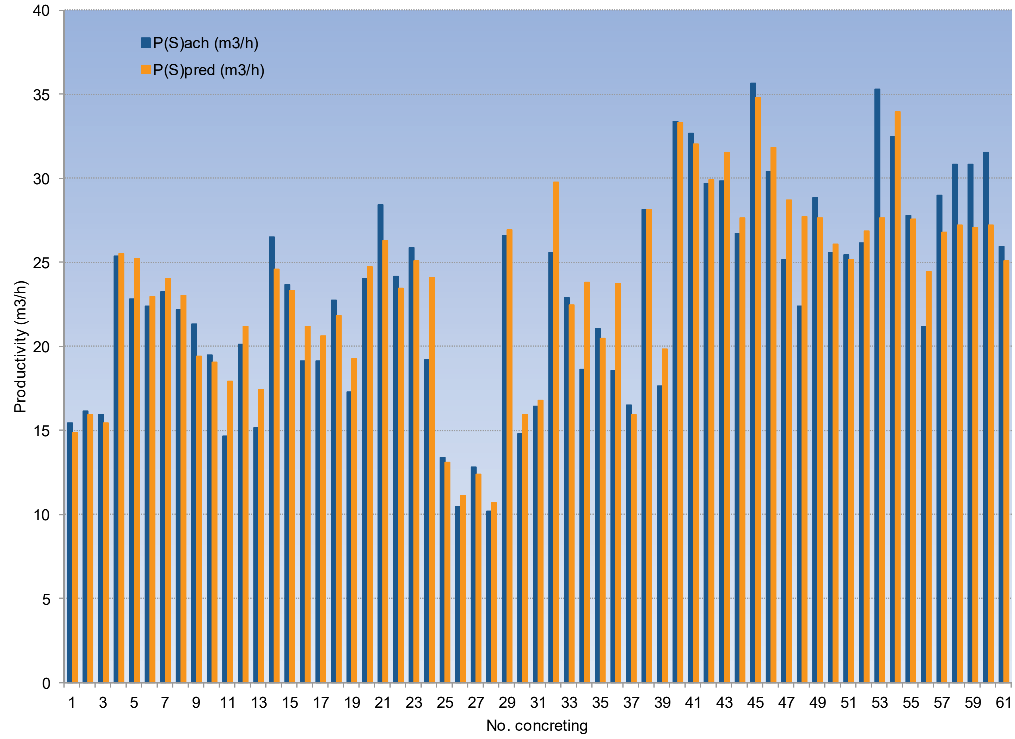

Figure 4 Achieved P(S)ach and predicted P(S)pred productivity

P_{ach} (m3/h)	to15	15-20	20-25	25-30	30-35	over 35	sum
APE ≤ 10%	5	7	12	16	4	1	45
10% ≤ APE ≤ 25%	1	5	1	2	3	1	13
25% ≤ APE ≤ 50%	0	2	1	0	0	0	3
APE>50%	0	0	0	0	0	0	0
sum	6	14	14	18	7	2	61
APE ≤ 10%	8%	11%	20%	26%	7%	2%	74%
10% ≤ APE ≤ 25%	2%	8%	2%	3%	5%	2%	21%
25% ≤ APE ≤ 50%	0%	3%	2%	0%	0%	0%	5%
APE>50%	0%	0%	0%	0%	0%	0%	0%
sum	10%	23%	23%	30%	11%	3%	100%

Figure 5 Achieved productivity according to APE

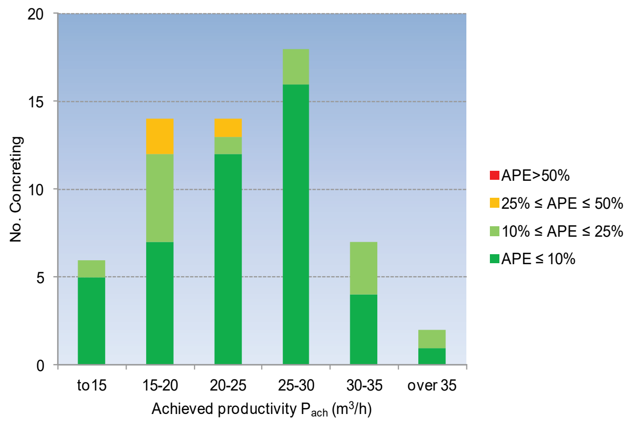

Figure 6 Histogram of achieved productivity according to APE

The second part of result analysis involved the analysis of model quality in relation to the amount of concrete. For the purpose of a simpler analysis of the amount of concrete for which the productivity was over- or undervalued, the Percentage Error (PE) was calculated. Fig. 7 shows the percent deviation of actual productivities and those predicted by the simulation, sorted in ascending order according to the amount of concrete.

The cases which exhibited a higher deviation of actual in relation to predicted productivity (marked yellow in the diagram) mostly involved halts and interruptions, which were not considered when the model was designed. Concreting was slower in the first two cases shown on the graph in Fig. 7 due to uncompleted formwork and reinforcement; very cold weather with frequent rain interruptions was responsible for slower concreting in the case where PE=−23%, while inaccessible space for slab concreting above the sixth floor slowed down the process in the case where PE=−25%.

Fig. 8 shows the compared values of actual and predicted productivity in terms of the amount of concrete. It is noticeable that predicted productivities usually deviate only slightly from the actual ones for all amounts of concrete used for slab concreting.

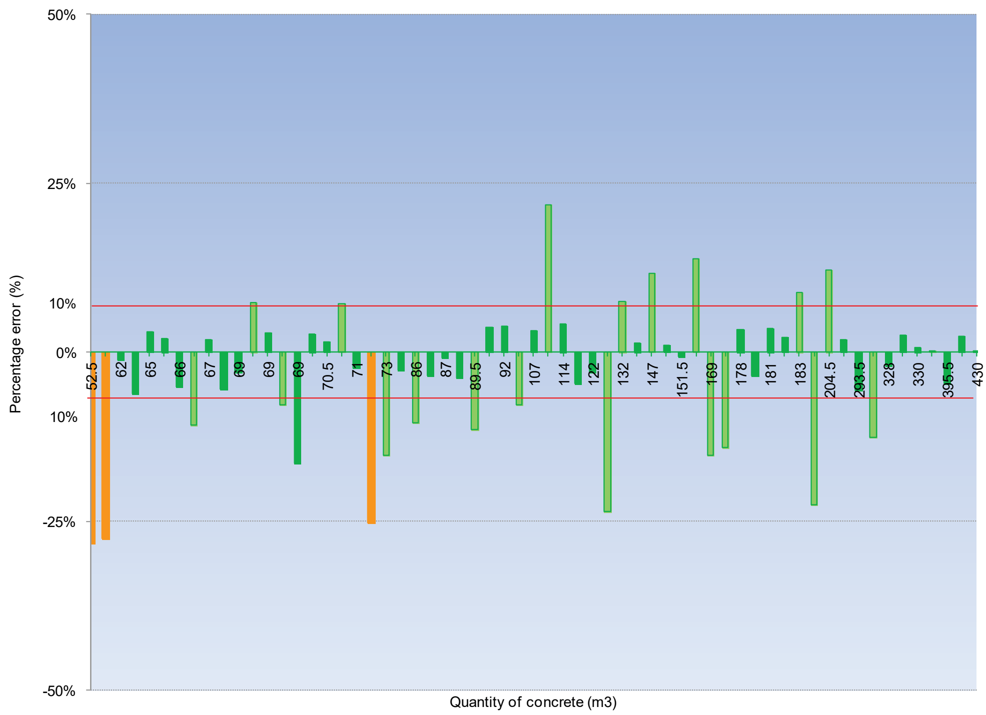

Figure 7 Percentage error

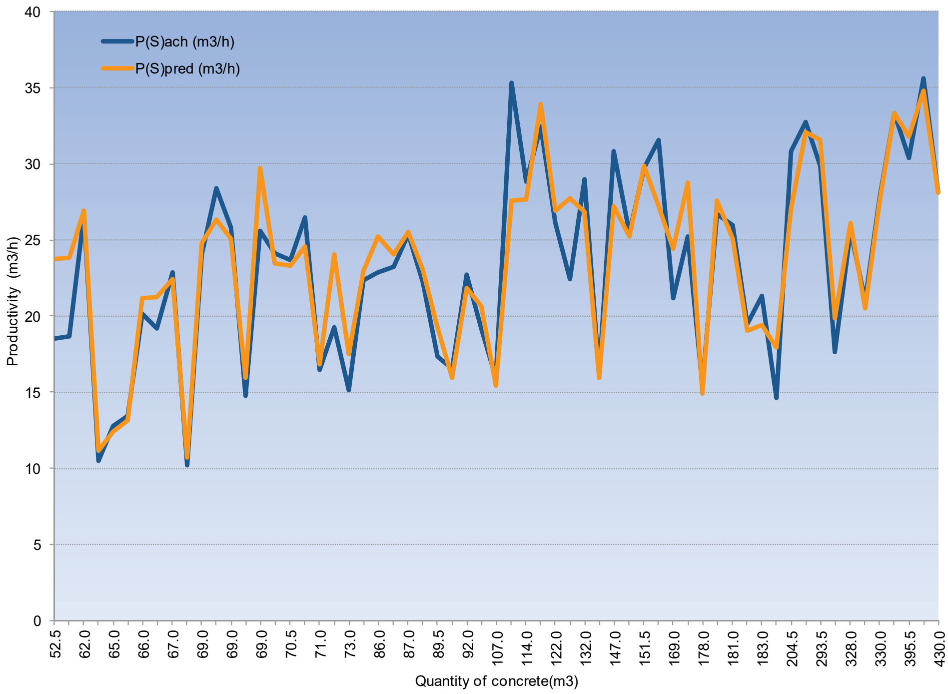

Figure 8 Achieved $P(S)_{ach}$ and predicted $P(S)_{pred}$ productivity in relation to the quantity of concrete

6 CONCLUSION

In this paper an original simulation model for predicting the productivity of concreting of construction elements such as reinforced concrete slabs, is presented. The simulation models were designed in AnyLogic 7.2.0 modelling software, which operates in object-oriented JAVA environment. The process was modelled using a multi-method comprising Discrete Event Simulation (DES) combined with Agent-Based Modelling (ABM). The data collected by recording the process at construction sites, which were processed and represented by their probability distributions, were used as the input data for the model design.

The process was represented in great detail, from production of concrete at the concrete plant, through its transport and placement at the construction site, to the return of the truck mixers to the plant. Specific parameters and functions in the model are represented using their probability distributions. Based on the simulation experiments, it was shown that the model can be used with sufficient accuracy to predict the productivity of reinforced concrete slab concreting. In cases of complete availability of the concrete plant (when it services only the observed construction site), the model yielded highly satisfactory results (74% of errors ranged up to 10%).

The proposed model can be useful in the planning stage and allow for more precise prediction of concreting activities' duration, thus benefiting the decision making and work flow prediction and improving the concreting process management in order to increase productivity, shorten the delays, and reduce costs.

The research, the analyses, and the developed model presented in this paper by no means resolve a broad and important issue of construction work organization such as productivity. Further research should primarily be focused on expanding the database by recording concreting processes in more construction sites and by including concrete plant operations in the recording. Such comprehensive recording and monitoring would enable a more realistic consideration of the entire process and collection of better input data.

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