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Research Article

Framework of an Implementation Strategy for a Modular Construction Toolkit Design in Construction Companies

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ABSTRACT

This paper presents a production flow-oriented framework for measuring and enhancing productivity in construction projects. Departing from traditional resource-based approaches, the proposed framework integrates value stream mapping with advanced simulation techniques and real-world data acquisition to comprehensively assess process performance. The simulation model employs a Monte Carlo method, incorporating lognormal distributions to generate realistic process durations for key construction activities. This approach effectively captures both central tendencies and variability while preventing the occurrence of unrealistically short process times. Data were collected from an actual construction site in Munich, where piles were constructed using Kelly drilling machines with a diameter of 50 cm and a depth of 12 m, followed by reinforcing and concreting. On-site measurements were obtained via manual recording and automated sensor technologies, including camera-based monitoring and data from construction equipment. The simulated and measured process times were compared using density graphs and statistical indicators. This showed that some of the processes are very similar to the reference processes but that there are also significant differences in variability and durations. These findings highlight the necessity for process-specific productivity benchmarks and underscore the importance of a flexible, production flow-oriented approach that can be adopted to the unique operational requirements of individual companies. The framework provides a robust tool for productivity assessment and offers practical insights for optimizing construction processes and reducing schedule variability.

Keywords: Construction industry, Lean construction, Implementation Strategy, Productivity.

INTRODUCTION

A. Problem identification

The construction industry incurs annual expenditure of over $10 trillion, which accounts for 13% of the world's gross domestic product. (Barbosa et al., 2017) Despite its scale and importance, the sector has consistently faced criticism for lagging behind other industries regarding efficiency and productivity. (Howell et al., 1993) Numerous reports and academic studies have identified a concerning trend in recent decades. While manufacturing sectors have embraced innovation and achieved significant productivity gains, the construction sector has often experienced stagnation or a decline in productivity. (Bogliacino Pianta, 2011; Heshmati, 2003) This situation is exacerbated by high fragmentation, where multiple stakeholders—owners, contractors, subcontractors, and suppliers—frequently operate in isolation rather than in concert, causing inefficiencies and communication barriers that delay progress and inflate costs. (Project Management Institute, 2013)

In stark contrast, industries such as automotive have undergone a profound transformation by adopting Lean principles. (Kumar et al., 2022) Pioneered by the Toyota Production System (Ōno, 2008), Lean methodologies heavily emphasize optimizing workflow, eradicating waste, and fostering a culture of continuous improvement. (Nicholas, 2018) Decades of practice in manufacturing have led to massive gains in both productivity and quality, positioning Lean as a highly sought-after model for managing complex processes efficiently. (Palange y Dhatrak, 2021) Recognizing these advantages, researchers and practitioners alike have sought to transfer Lean concepts into construction. (D. Kim Park, 2006; Nowotarski et al., 2016) Lean Construction principles have emerged, highlighting ways to reduce inefficiencies and improve coordination in building projects. (Kashikar et al., 2016) Despite the promising theoretical underpinnings and demonstrable successes in select case studies (Nikakhtar et al., 2015), Lean-based production methods—particularly those centered on managing and measuring flow—have yet to see widespread or systematic application in construction.

One potential explanation for this gap is the fundamental differences between manufacturing and construction environments. (Riley Clare-Brown, 2001) While manufacturing is typically repetitive, factory-based, and controlled, construction sites are inherently dynamic, open to environmental unpredictability, and shaped by multiple, often competing, stakeholders. (Verein deutscher Ingenieure, 2019) Moreover, traditional productivity metrics in construction have historically focused on resource optimization—assessing the efficient use of materials, labor, and equipment—without adequately capturing the holistic flow of work across the entire project lifecycle (Modig Åhlström, 2012). This resource-centric perspective can obscure inefficiencies within the continuous process, thus hindering the identification of bottlenecks and process delays. Therefore, adopting a flow-oriented approach to measure productivity is crucial to accurately reflect the dynamics of construction operations. (Awad et al., 2021)

Nevertheless, the ongoing calls for greater efficiency, cost savings, and timely project delivery underscore the importance of overcoming these barriers. Significant research on holistic production systems and Lean Construction methodologies exists, but industry adoption remains limited. (Albalkhy Sweis, 2021)

Given the persistent calls for greater efficiency, productivity, and collaboration in construction, a systematic framework for adopting flow-based productivity measurement systems is both timely and critical. It is not enough to assume that Lean principles, originally initially developed for manufacturing, can be transplanted into building projects. Instead, careful analysis is required to identify where and why these principles fail to take root.

The research question guiding this study is therefore:

How can the production flow be used as an indicator to measure productivity on construction sites?

B. Related work

Many models deal with the resource-optimized approach. (Crawford Vogl, 2006; John O'Grady, 2014; Lowe, 1987) These models aim to assess productivity by evaluating the ratio of inputs to outputs, whereby a project is considered productive if it utilizes minimal resources. However, this productivity metric often neglects the significance of maintaining a continuous process flow. Focusing exclusively on resource minimization can result in bottlenecks, delays, and overall production disruptions. (Goldratt, 1990) In contrast, a flow-based production approach prioritizes continuous, synchronized workflows, enhancing system resilience and overall operational efficiency. (Womack Jones, 1997) Geiger et al. (2024) propose a novel production model for labor productivity in construction that shifts the analytical focus from traditional cost control to a flow-oriented approach. (Geiger et al., 2023) Their model is based on a modular construction toolkit design that emphasizes capturing the actual production flow on-site rather than relying solely on resource optimization. Their central approach – shown in Figure 1 - is the concept of standardized modules, which are used to decompose a building into discrete, manageable units. A "construction module" is defined as a distinct spatial and functional building segment produced through a specific, repeatable sequence of processes. These modules are further subdivided into building components, such as a bored pile or a wall section, each produced through a series of standardized process steps.

The production process for each building component is systematically mapped using value stream mapping, a technique that breaks down the overall process into discrete steps, records the throughput times, and allows for a direct comparison with target process durations. The model enables the automatic capture and analysis of production data by standardizing these process steps and associating them with defined productivity parameters. In contexts where production is mainly mechanized, sensors and AI-driven pattern recognition can record real-time process times; in less automated environments, manual recording remains a viable alternative. This detailed tracking of the

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production flow provides managers to gain a better understanding of where delays or inefficiencies occur, thereby offering concrete opportunities for process optimization, and consequently, improving productivity.

A key advantage of this modular approach is its capacity to reflect the dynamic nature of construction sites, where variability in environmental conditions and process execution often renders cost-focused metrics insufficient. By concentrating on production flow, the model aligns closely with Lean Construction principles, which advocate for eliminating waste and improving processes (Womack Jones, 1997). Moreover, the standardized module toolkit facilitates just-in-time deliveries by ensuring that the duration of each process step is known and predictable, thus reducing idle times and enhancing overall operational efficiency. (Geiger et al., 2023)

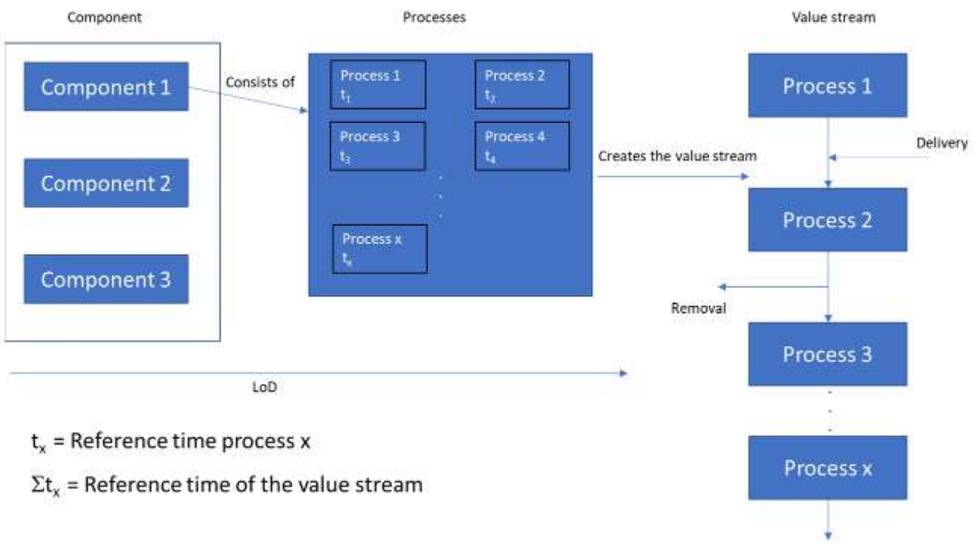

Figure 1: Modul toolkit design according to (Geiger et al., 2023)

C. Objectives

The primary objective of this study is to implement and extend the production model framework presented by Geiger et al. to develop a methodology for measuring productivity in construction. By adopting the modular construction toolkit design, the study aims to break down complex construction processes into discrete, repeatable modules that can be systematically analyzed and compared across different projects (Geiger et al., 2023). This approach is intended to capture the average performance of construction processes and the variability inherent in on-site production processes, thereby providing a more realistic basis for productivity benchmarking. To achieve this, the study sets out several specific objectives. First, objective is to develop a simulation model that mirrors the sequential production flow of construction processes and incorporatinges stochastic elements that reflect the inherent variability observed in practice. This simulation model uses advanced probabilistic methods to generate process durations. Second, the study aims to compare simulation model results with the measured data collected from construction sites, thereby establishing reference process times for production modules. This comparative analysis will highlight discrepancies between idealized simulation outcomes and actual performance, on identifying processes that often exhibit high variability and serve as significant productivity bottlenecks. Furthermore, the research provides a framework for companies to assess and improve their production flow. The proposed approach facilitates benchmarking across sites and projects by quantifying productivity based on the standardized modules of the production process. The model is designed to serve as both a diagnostic tool and a prescriptive framework, enabling practitioners to identify inefficiencies, reduce process variability, and ultimately optimize the production system.

DEVELOPMENT OF DEVELOPMENT OF A METHODOLOGY FOR CONTROLLING AND IMPROVING PRODUCTIVITY IN CONSTRUCTION SITE PRODUCTION

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The methodology for controlling and enhancing productivity in construction site production is built on a flow-based production model and comprises three key components that ensure comprehensive process control.

In the first component involves developing a simulation framework that continuously generate reference processes. This probabilistic simulation runs in parallel with the actual construction activities, dynamically adapting to changing conditions and serving as a predictive baseline for assessing actual process performance.

The component focuses on systematic monitoring of construction processes onsite. A comprehensive sensor network, including cameras and various data acquisition devices, is deployed to collect real-time operational data. The recorded data is analyzed and statistically evaluated using distribution functions to identify process deviations and uncover potential inefficiencies.

In the third component involves managing the production flow by utilizing insights from both the simulation and the monitoring. Discrepancies are identified, the sensitivitiy of relevant parameters is assessed, and overall process productivity is analyzed. This is achieved by comparing the distribution functions derived from the simulation with real-time measurements. This combined approach enables precise process control. Decision-makers can detect which parameters remain stable and where subtle deviations occure, allowing for timely, real-time interventions or strategic adjustments.

This integrated methodology not only enhances the efficiency of construction production but also significantly increases the resilience and adaptability of the construction process.

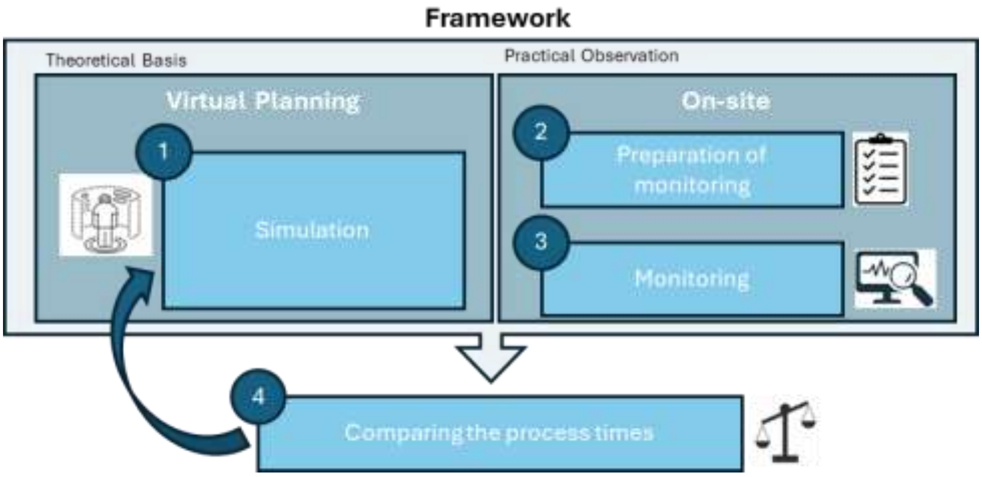

Figure 2: Framework for the implementation strategy

A. Modelling and simulating of the production-flow

Creating a production flow begins with a detailed mapping of each step involved in the construction process. In practice, this is often accomplished through value stream mapping, a technique established in lean production systems that focuses on visually representing the flow of materials and information across all stages of production. By decomposing the construction flow into discrete tasks, practitioners can identify dependencies, handover points, and potential waiting times. This breakdown clarifies the order in which activities occur and shows areas where inefficiencies or disruptions might arise. Once the production flow has been mapped, each process step is associated with a probabilistic duration derived from historical data, empirical measurement, or mathematical estimation, forming a foundational "target state" for subsequent comparison.

Building on this value stream representation, the next stage is to simulate the production flow. A common approach is to use a Monte Carlo simulation. The reason Monte Carlo methods are favored is that they can handle stochastic input variables in a straightforward manner: each process step is sampled repeatedly from an underlying probability distribution, and the results are aggregated to estimate the total production time distribution. By executing a sufficiently large number of such iterations, the simulation provides a robust statistical portrait of likely outcomes, including worst-case and best-case scenarios. This randomness allows the model to capture inherent variability and

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uncertainty—an integral aspect of construction, where even the most standardized processes can be subject to influences such as weather, soil conditions, and logistical constraints.

In many real-world applications, the distribution of process times is neither purely symmetric nor bounded by zero in a manner that a normal distribution would suggest. Instead, empirical evidence often shows that the durations are right-skewed and strictly positive—factors that make the lognormal distribution particularly suitable. If X follows a normal distribution with parameters μ and σ, then the random variable [$T = e^X$]follows a lognormal distribution. Its probability density function (PDF) is given by

$$[f_T(t) = \frac{1}{t\,\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln t - \mu)^2}{2\sigma^2}\right), \quad t > 0.]$$

This PDF ensures that all simulated durations are strictly greater than zero while accommodating the observed asymmetry (a longer right tail). The expected value E[T] and variance Var(T) of a lognormal random variable can therefore be computed as:

$$[E[T] = \exp\left(\mu + \frac{1}{2}\sigma^2\right)]$$

$$[\mathrm{Var}(T) = \exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)]$$

These closed-form expressions are particularly convenient for construction process simulations as they connect empirical estimates of μ and σ to well-known moments of the distribution. Moreover, a lognormal distribution can be further "truncated" to exclude unreasonably small (or, in some cases, tremendous) values that rarely occur. Truncated lognormal models are appealing because they ensure no sampled duration dips below a certain threshold (for instance, 80% of an empirically observed minimum), thus preventing artificially short process times.

From the process times distribution, one can derive the mean or median total time, confidence intervals, quantiles (e.g., 90th percentile for worst-case planning), and an overall risk profile for potential schedule overruns. This simulation-based representation is then used to benchmark actual measurements obtained on-site. If the empirical times ,deviate substantially from the simulated reference distribution—mainly if they fall in the higher quantiles—project managers can investigate the causes of these discrepancies and refine logistical processes, workforce allocation, or site coordination.

B. Construction site monitoring

1). Preparation for construction site monitoring

Establishing robust and accurate methods for measuring process times on construction sites is the primary focus of this part. Accurate on-site data collection is essential for validating simulation models and benchmarking production performance, yet the inherent complexity of construction activities demands a multifaceted approach. Traditionally, manual data collection has been widely employed, where trained observers record the durations of specific tasks using stopwatches or digital tablets. Although manual time studies can provide detailed insights into individual process steps, they are labor-intensive and vulnerable to human error and subjectivity. Michael Ott (2007) demonstrated that manual observations, when executed under controlled conditions, can yield helpful valuable data (Ott, 2007); however, their scalability is limited due to the high cost of time recording and the reliability of such measurements often suffers due to observer bias and inconsistencies in measurement practices.

In response to these challenges, recent advancements have introduced automated data collection techniques that significantly enhance the precision and the volume of data captured. Camera-based monitoring serves as a valuable tool. Modern digital cameras, combined with computer vision and deep learning algorithms, can continuously record construction activities and automatically extract time-related information. (Hjelseth et al., 2023) Such systems offer the advantage of capturing real-time data over extended periods, making them particularly valuable for large-scale projects where manual data collection would be prohibitive.

In addition to camera systems, construction equipment is increasingly equipped with telematics devices that record operational data automatically. This method also enhances objectivity by reducing reliance on manual input and providing continuous monitoring that can be integrated into a broader digital framework for process analysis. (Fischer et al., 2021)

Furthermore, wearable technologies such as smart helmets (Aliyev et al., 09102020) offer a novel approach to data collection by monitoring the activities of workers directly. These devices can track various parameters, including movement, heart rate, and even spatial location, offering detailed insights into the human element of construction processes. Kim et al. (2019) have shown that wearable sensors can capture real-time work patterns effectively, enabling a more granular understanding of on-site productivity and safety. Such systems complement manual observations and machine-based data by delivering contextual information critical for a holistic analysis of process performance. (S. Kim et al., 2019)

Overall, this phase aims to establish a comprehensive data acquisition strategy by integrating manual observations, automated camera monitoring, equipment telematics, and wearable sensor data. Each method contributes unique strengths: manual recordings offer high granularity in controlled settings; camera systems and telematics provide continuous and objective data streams; and wearables capture the nuanced human factors influencing process times. Together, these approaches form a robust basis for benchmarking and improving production flow on construction sites.

2). On site process monitoring

In the third phase, the focus shifts to analyzing the data collected directly from the construction site to derive accurate process time distributions. The next step is to characterize the underlying statistical distribution of the process times. Kernel density estimation (KDE) constitutes an effective method for deriving the relevant statistical distribution functions from empirical data. Given a dataset $\{t_1,t_2,\dots,t_i\}$ representing process durations, the KDE is defined as

$$[\hat{f}(t) = \frac{1}{n\,h}\sum_{i=1}^{n} K\left(\frac{t-t_i}{h}\right),]$$

where K is typically a Gaussian kernel, and h is the bandwidth parameter controlling the smoothness of the density estimate. This method also highlights the central tendency of data and reveals the spread and skewness, which are critical for understanding the variability in construction processes.

Furthermore, key statistical metrics such as mean, median, standard deviation, and variance are computed to summarize the performance. For instance, if T denotes the set of total process times, the sample meaning is given by

$$[\bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i\,,]$$

and the sample variance is calculated as

$$[s_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}(t_i - \bar{t})^2\,.]$$

The range of outcomes, mainly the frequency of extreme values that may signal process disruptions or delays, can be predicted based on quantile analysis. By comparing the statistical distributions derived from the measured data with those predicted by simulation models, practitioners can assess discrepancies and identify potential inefficiencies. This comparison is instrumental in calibrating simulation models and providing actionable insights for process optimization. Integrating advanced analytical techniques, including machine learning and computer vision, into the data analysis workflow enhances the accuracy and reliability of productivity assessments, thereby supporting more effective decision-making in construction management.

C. Steering the production flow

In this part, the primary objective is to compare the distributions obtained from the simulation with those derived from field measurements to assess the productivity of the construction process. Based on these comparisons, active control measures can be applied to further improve the production flow. Notably, all three phases of the

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implementation model—simulation, monitoring, and controlling—operate concurrently and continuously throughout the construction process. Initially, simulated data are aggregated and preprocessed to yield a probability distribution for each process step and the overall production time. In parallel, field data are collected—manually or via automated methods such as camera-based monitoring, sensor readings from construction equipment, or wearable devices—and similarly processed to obtain a representative set of process durations. Non-parametric techniques, such as Kernel Density Estimation (KDE), are then applied to both the simulated and measured datasets to derive smooth density curves. These curves visually represent the underlying probability distributions, highlighting differences in central tendency, spread, and skewness. By overlaying the density plots of simulated and measured data, discrepancies between the idealized model and actual performance become evident. Importantly, this comparison is performed not only for the total production time but also for each process step. Such a detailed analysis facilitates identifying specific processes that conform to the simulated benchmarks versus those exhibiting significant deviations. A critical aspect of this phase is defining what constitutes "productive" performance. The criteria for productivity may vary between organizations—some may define productivity in terms of median process times, while others might rely on specific quantiles as benchmarks. By continuously comparing simulation and monitoring data, this analysis provides a quantitative basis for evaluating the performance of each process, identifying potential bottlenecks, and informing both immediate corrective actions and long-term strategic adjustments.

EVALUATION

A practical use case was implemented to assess the given framework. For this, a civil engineering project was selected, in which a bored pile wall was created using a Kelly drilling rig. Each pile was designed with a diameter of 50 cm and a target depth of 12 m. The construction process was divided into three sequential stages: drilling, reinforcing, and concreting. During the drilling phase, the Kelly drilling machine bore through the subsoil, establishing the initial cavity for the pile. Following drilling, each pile was reinforced with steel to ensure structural integrity, and finally, the piles were concreted to complete the foundation system. This site provides an ideal setting for data collection, as detailed measurements were recorded for each of the individual process steps. The data from this project facilitated the analysis of process times and the validation of the simulation model developed within the framework. By comparing the measured durations against the simulated outputs, it is possible to assess the effectiveness of the production flow-oriented approach and identify specific process steps that contributed to delays or exhibited high variability. In essence, this case also demonstrates the practical applicability of the framework and offers valuable insights into the factors influencing productivity in a real actual construction setting.

A. Simulation of the production flow

The first step in applying the production flow framework was to simulate the primary construction processes: drilling, reinforcing, and concreting. The overarching goal was to generate a probabilistic model that could capture the average performance and the variability of these tasks under realistic conditions. By creating a simulation that closely mimicked real-world constraints, it became possible to benchmark to each process's expected productivity and identify where external influences or operational inefficiencies might lead to significant deviations in actual performance.

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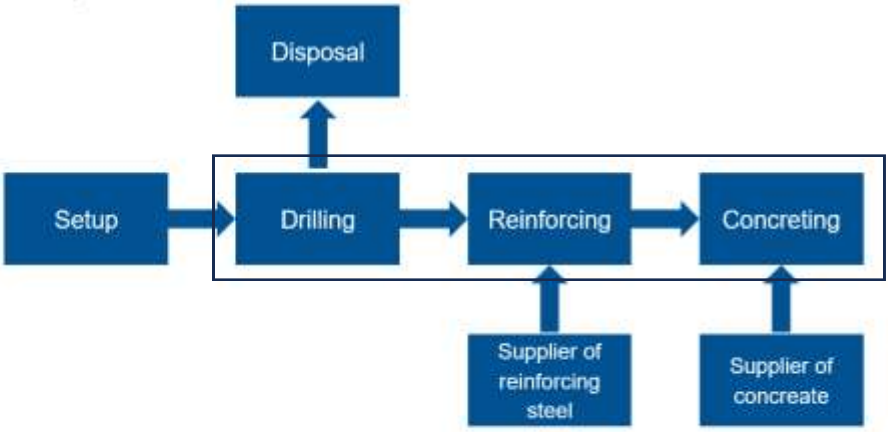

Figure 3: Value stream mapping of Kelly-drilling

The process times used/applied for the simulation are based here on literature data or assumptions and are broken down in Table 1.

Table 1: Input-Parameters of the Simulation

	Vale	Source
Drilling rate	0,12 m^3/min	(Andreas Fritz Köninger, 2021)
Concreting rate	0,36 m^3/min	(Maximilian Geber)
Reinforcing rate	1,26 m/min	(Maximilian Geber)
Variance factor	0,5	(Wang et al., 2003)
Influence of driver	lognormal with $\sigma = 1$	Assumption
Influence of ground conditions	lognormal with $\sigma = 1$	Assumption
Influence of weather	lognormal with $\sigma = 1$	Assumption

Drilling was modeled using a stochastic approach designed to reflect the complex factors affecting the Kelly drilling machine's operational speed, such as subsoil conditions, equipment characteristics, and weather-related delays. Rather than adopting a single deterministic time estimate, a distribution-based model was employed. For instance, a lognormal distribution was used to ensure that no unrealistically short drilling times were generated, while still capturing the longer tail associated with challenging ground conditions. This approach allowed the simulation to produce a wide range of drilling durations, reflecting typical performance and the possibility of considerable variability due to unexpected obstructions or mechanical issues. In a similar manner, reinforcing was also modeled probabilistically. The reinforcing process depends on the availability of steel cages, the speed of crane or hoist operations, and the skill level of the construction crew. Each of these influences was represented in the simulation through random variables that captured their individual effects on the overall reinforcing time. By integrating these variables into a single stochastic framework, the simulation could estimate a distribution of reinforcing durations rather than a single static value. This approach offered a more nuanced understanding of potential bottlenecks—such as crane downtime or crew coordination issues—that can cause delays in practice. Concreting, the third core process, was simulated with a focus on the concrete supply and the time required to pour and place the material in the drilled and reinforced pile shaft. Variations in supply logistics, concrete quality, and site coordination were accounted for using random variables influencing the placement rate and waiting times. As with drilling and reinforcing, a lognormal or a similar distribution was typically employed. This choice also allowed the model to incorporate the heavier tails that arise when external delays—such as traffic congestion affecting delivery trucks—exert an outsized influence on total placement time.

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This simulation-based approach was selected because it captures the intrinsic uncertainties and operational complexities of each major process step, rather than relying on a deterministic estimate. By generating a probability distribution for drilling, reinforcing, and concreting, the model provides a robust statistical foundation for subsequent comparisons with measured data. It also allows for sensitivity analyses, in which parameters such as ground conditions or delivery schedules can be varied to assess their impact on productivity. Ultimately, this method ensures that the simulation output aligns more closely with the real-world variability observed on construction sites, thus enhancing the value of the production flow framework as a diagnostic and planning tool.

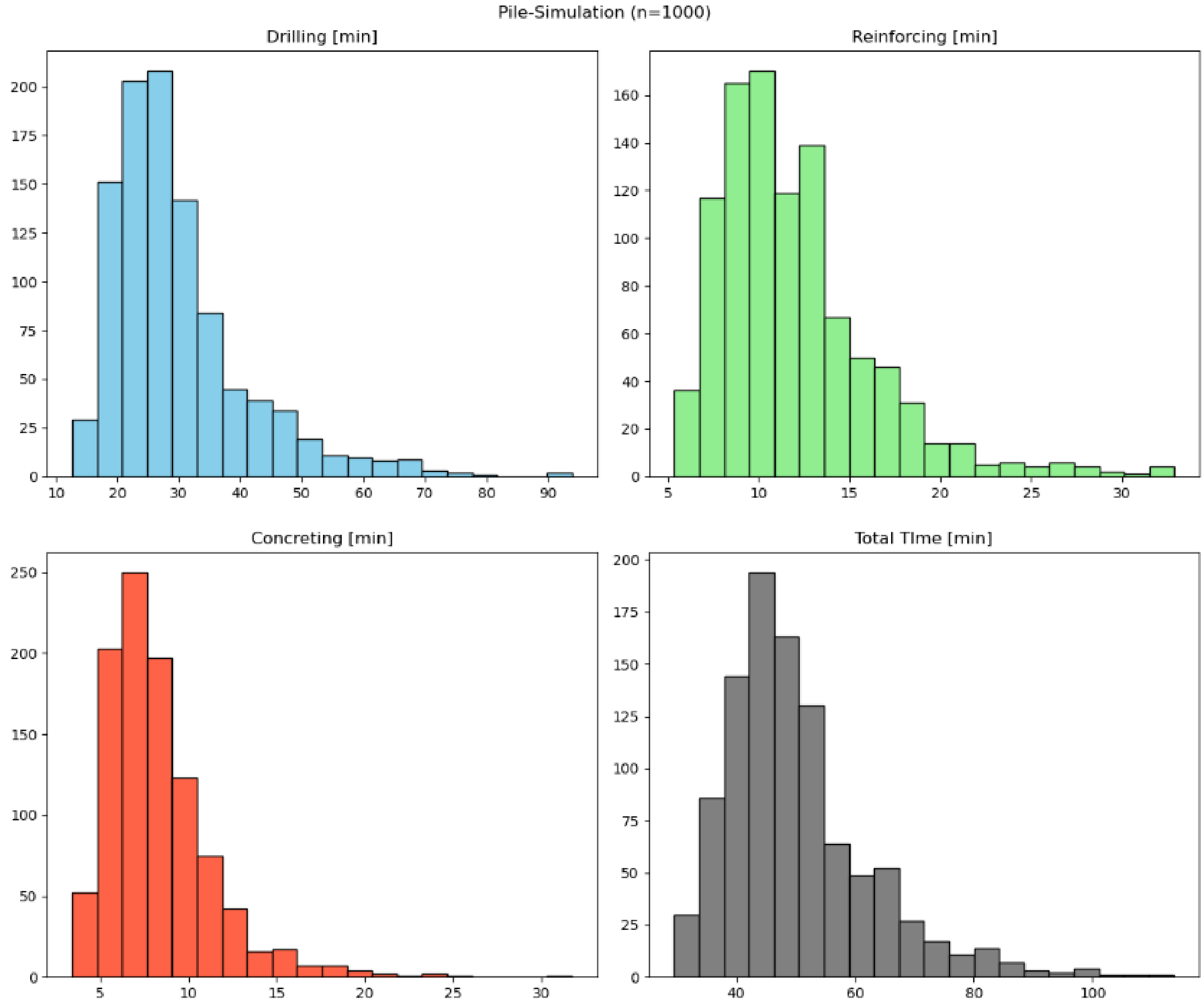

Figure 4: Simulation of Process-Times

Table 2: Statistical Parameters of the Simulation

	Concreating	Reinforcing	Drilling	***Total time***
Mean value	7 min	10 min	26 min	***43* min**
Median	7 min	9 min	23 min	***42* min**
Standard deviation	3 min	5 min	11 min	***13* min**

B. Preparation for construction site monitoring

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Installing and calibrating the sensors to record key parameters during the construction process is a critical step. These sensors are selected based on their ability to provide detailed, real-time information about drilling operations and machine performance. For example, a depth sensor is employed to continuously monitor the progress of the bore, while crowd-force sensors record the thrust exerted on the drilling tool. Pressure pumps are also instrumented with sensors capable of measuring hydraulic pressures in multiple lines, and inclinometers track the angle of the processes to ensure vertical alignment. Finally, torque sensors are attached to the Kelly bar or rotary drive to measure the rotational force required to penetrate the ground.

This sensor-based approach is deemed indispensable for accurately capturing the variability and complexity of on-site operations. By integrating data from depth, crowd-force, pressure, inclination, and torque sensors, it becomes possible to establish a comprehensive picture of the drilling process and to correlate specific machine states or ground conditions with deviations in drilling speed or efficiency. These readings are then aggregated and timestamped, creating a synchronized dataset that can later be merged with other process information, such as reinforcing and concreting times.

C. Monitoring of the processes on the construction site

During the monitoring phase, two distinct approaches were employed to transform raw machine data into a coherent record of process times. Initially, a manual method was adopted, in which the data streams collected from sensors were carefully examined to identify the start and end points of each construction process step—such as drilling, reinforcing, and concreting. In practice, this involved aligning time stamps with changes in parameters like depth, torque, or pressure pump readings and then assigning these segments to the appropriate phase of the workflow. This labor-intensive procedure yielded a reliable reference dataset, providing clear demarcations of when a particular process began and concluded.

Building on the insights from this manual assignment, a more automated technique was later introduced, leveraging a Long Short-Term Memory (LSTM) network. LSTM models are particularly well suited to time-series data, as they can learn to recognize patterns over extended sequences while mitigating issues of vanishing or exploding gradients. In this context, the model was trained to detect transitions between process steps based on torque sensor readings changes—such as crowd-force or rotary torque fluctuations. By presenting the LSTM with labeled examples from the initial manual assignment, the model was able to identify when drilling concluded and reinforcing began, or when reinforcing ended and concreting started – almost in real-time.

Once the LSTM-based classification was sufficiently accurate, the resulting assignments of sensor data to discrete process segments enabled an automated derivation of process times. This allowed the creation of distributions for each phase—drilling, reinforcing, and concreting—without manual intervention. The distributions, in turn, were analyzed using standard statistical techniques (e.g., Kernel Density Estimation) to capture each process's variability and central tendencies. By comparing these automatically generated distributions to those derived from manual assignments, it was possible to validate the model's performance and confirm that the distributions aligned with the reference data.

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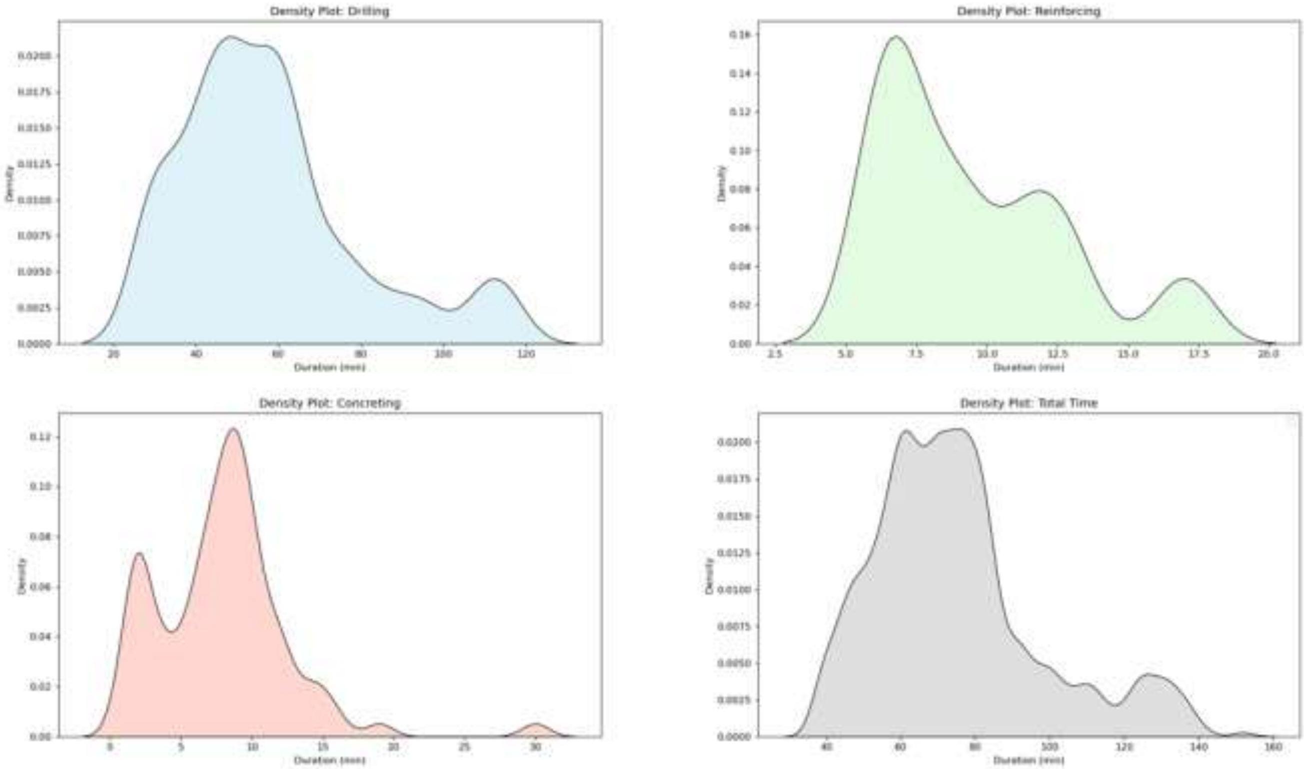

Figure 5: Density Plot of Measured Times of Drilling/Reinforcing/Concreating/Total Time

Table 3: Statistic Parameters of the Measurement

	Concreting	Reinforcing	Drilling	***Total time***
Mean value	8 min	9 min	57 min	***75* min**
Median	8 min	9 min	53 min	***71* min**
Standard deviation	5 min	3 min	22 min	***23* min**

D. Comparison of process times

Overall, a process can be state productive, when 75% of the measured data is inside the 90th quantile of the simulated distribution. This threshold must be reviewed for each individual project based on the project-specific circumstances. The density plot, overlaid with both simulated and measured distributions, provides an immediate visual contrast between the idealized model and the actual process durations. In this specific scenario, the simulated data, generated using a lognormal distribution, displays a peak distribution between approximately 5 and 7 minutes, whereas the measured data reveals a slightly broader distribution extending further towards higher values.

A more quantitative assessment is presented in the accompanying statistical table, which includes key metrics such as the mean, median, standard deviation, and variance for both datasets. The results indicate that the simulated distribution has a mean and median of 7 minutes, with a standard deviation of 3 minutes. By contrast, the measured distribution exhibits a mean and median of 8 minutes, accompanied by a higher standard deviation of 5 minutes. This discrepancy in the spread is further highlighted by the variance values of 9 (simulated) versus 21 (measured).

Several interpretations arise from these findings. First, the elevated mean and median in the measured data suggest that, on average, concreting on-site took longer than the model predicted. This difference may stem from practical factors such as logistical delays, operator coordination, or variations in the concrete supply chain that were not fully captured by the simulation. Second, the notably higher variance in the measured data implies that real-world conditions introduce more variability—perhaps due to equipment availability, scheduling conflicts, or inconsistent

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batching of concrete—than the simulation's lognormal distribution was configured to represent. The two peaks could be the data generation over more than one day and, therefore, the work of two concreting crews. Nevertheless, with 84% under the simulated data, a very productive process

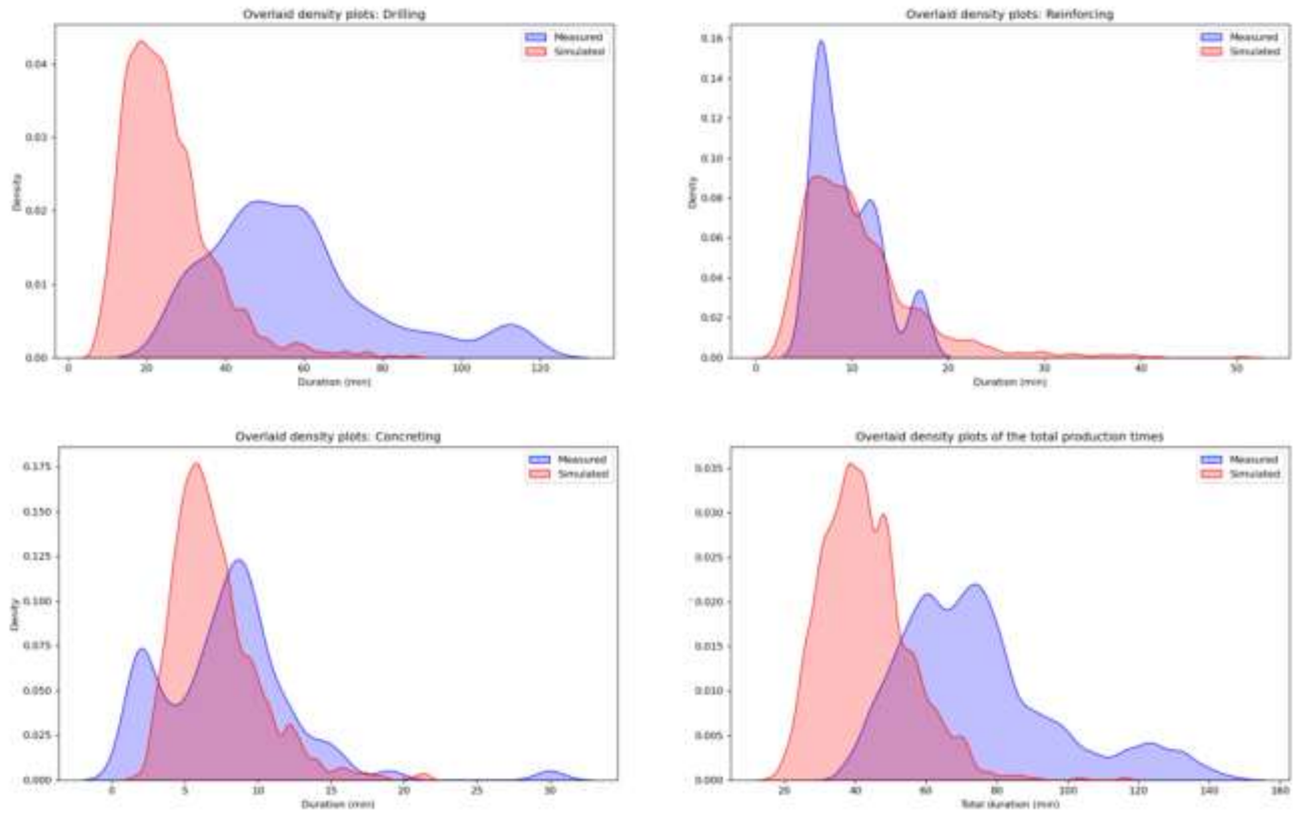

Figure 6: Overlapping density plots Drilling/Reinforcing/Concreating/Total Time measured and simulated

Table 3: Comparison of Statistic Parameters

	C. Simulated	**C. Measured**	**R. Simulated**	**R. Measured**	**D. Simulated**	**D. Measured**	***TT. Simulated***	***TT. Measured***
Mean value	7 min	8 min	10 min	9 min	26 min	57 min	***43 min***	***75 min***
Median	7 min	8 min	9 min	9 min	23 min	53 min	***42 min***	***71 min***
Standard deviation	3 min	5 min	5 min	3 min	11 min	22 min	***13 min***	***23 min***
Variance	9 min²	21 min²	21 min²	11 min²	128 min²	486 min²	***163 min²***	***529 min²***
Overlap-ping	-	84%	-	91%	-	14%	-	***30,4%***

For reinforcement (R.), the comparison between simulated and measured process times offers valuable insights into the model's ability to capture real-world variability. In the overlaid density plot, the simulated distribution exhibits a broader spread and peaks around 9–10 minutes, whereas the measured data cluster more tightly around a peak of approximately 8–9 minutes. While the mean values are similar (10 minutes simulated vs. 9 minutes measured) and the medians align at 9 minutes, the standard deviations differ more substantially: 5 minutes for the simulation versus 3 minutes in the measured data. Consequently, the variance in the simulated dataset (21) exceeds that of the measured dataset (11), suggesting that the model projects more variability than was observed in practice.

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From a productivity standpoint, this finding has twofold implication. First, the close alignment in mean and median indicates that the reinforcing process on-site was performed near the level predicted by the simulation's central tendencies. This alignment suggests that the objective actual process is generally efficient and meets the simulated benchmarks for average performance. Second, the standard deviation and variance discrepancy highlights that the process is more stable and productive than in simulation. In practice, the narrower spread of the measured data implies more consistency in how the reinforcing crew operates, possibly due to stable crew skill levels, well-organized material supply, or reliable equipment availability. The process is even more productive, with more than 91% under the 90^{th} quantile of the simulation.

The comparison of drilling (D.) times reveals the most pronounced divergence between simulation and real-world performance among the three core processes. The density plot shows that the simulated distribution peaks around the 20–30-minute range, whereas the measured data exhibit a substantially higher mean and a right-skewed tail extending well beyond 50 minutes. This contrast is further underscored by the statistical metrics: while the simulation predicts a mean of 26 minutes and a median of 23 minutes, the measured data shows a mean of 57 minutes and a median of 53 minutes. Moreover, the measured standard deviation (22) and variance (486) significantly exceed those in the simulation (11 and 128, respectively), indicating not only a longer average duration but also much greater variability in actual drilling operations.

From a productivity standpoint, this discrepancy implies that the drilling step is performing well below the simulated benchmarks. Field observations might point to causes such as unanticipated ground conditions, more frequent downtime for maintenance or tool changes, or logistical disruptions that impede a continuous drilling flow. The right tail of the measured distribution suggests that extreme delays—such as equipment malfunctions or unexpected geological obstacles—occur with greater frequency than the model initially accounted for.

Considering the substantial gap between simulated and measured data, a first step toward improving productivity may involve stabilizing the drilling process to have a more stable time. Concurrently, on-site measures aimed at stabilizing the drilling process might include enhanced equipment maintenance schedules, improved crew coordination, or real-time monitoring systems that can promptly detect and address issues.

By identifying how much longer drilling consistently takes in practice, decision-makers can prioritize process improvements, resource allocation, and contingency planning. Bridging the gap between simulated and measured drilling durations thus stands out as a key target for boosting overall productivity and reducing variability in the construction workflow. With only 14% under the 90^{th} quantile and the extremely high variance, the process is not productive.

When evaluating overall productivity, it is essential to examine the total production time, which aggregates drilling, reinforcing, and concreting durations into a single metric. The density plot comparing the simulated and measured total production times reveals a pronounced shift toward higher values in the real-world data. According to the statistical results, the simulation predicts a mean of 43 minutes and a median of 42 minutes, while the measured total times exhibit a mean of 75 minutes and a median of 71 minutes. Moreover, the standard deviation (13 for the simulation vs. 23 for the measured data) and variance (163 vs. 529) highlight a substantially wider spread in actual operations.

Several factors contribute to this discrepancy. First, the cumulative effect of deviations in drilling, reinforcing, and concreting times can amplify any inefficiencies or delays. As shown in the process-specific analyses, the drilling phase, in particular, deviated significantly from the model's assumptions, potentially due to unanticipated ground conditions or logistical hurdles. Second, the higher variability in the measured total times suggests that sporadic or extreme events—such as equipment breakdowns or major scheduling conflicts—occur with greater frequency in reality than the simulation had accounted for, and therefore, need to be eliminated.

In conclusion, it can be stated that although two of the three processes demonstrated productivity, the overall processing times are primarily inefficient due to the exceptionally high variance. Consequently, future efforts should focus on optimizing the drilling process and mitigating the pronounced variability. Addressing these issues would result in a substantial enhancement of overall productivity.

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DISCUSSION

The results presented in this study highlight both the potential and the challenges of using a production-oriented flow-oriented framework in the construction industry. Several key observations have emerged by applying a simulation model that generates probabilistic distributions for drilling, reinforcing, and concreting, and by comparing these outcomes to actual data gathered on-site.

First, the alignment between simulated and measured times varies considerably across processes. Reinforcing showed relatively close agreement in mean and median values, indicating that the simulation can adequately capture the central tendency of this step. By contrast, drilling displayed the greatest excellent, most significant deviation, with real-world times exceeding simulation outputs by a substantial margin. These differences underscore the importance of validating each process step individually rather than relying solely on total production times to gauge model accuracy.

A second major theme is the role of variability. Processes like concreting showed a moderate spread in measured data, whereas variances. Significantly larger variances characterized drilling times. This pattern implies that certain operations are inherently more susceptible to external disturbances or site-specific conditions. The higher variance observed in the measured total production times further confirms that real construction projects tend to accumulate uncertainties across multiple steps, amplifying the overall risk of schedule overruns.

The definition of productivity is another critical dimension. Each organization may adopt different criteria for assessing whether a process or total production time is deemed productive—some might focus on the median, others might rely on specific quantiles such as the 75th or 90th percentile. The findings suggest that reinforcing and concreting align well with simulation-based expectations, implying that current practices in this step are relatively efficient. However, drilling shows substantial gaps, indicating the need for deeper investigation into ground conditions, machine maintenance strategies, or crew coordination. Ultimately, the ability to tailor productivity thresholds to organizational goals ensures that the framework remains flexible and applicable to diverse project contexts.

Several limitations should be noted. First, the simulation relies on lognormal distributions and Monte Carlo methods that, while robust, may not capture every source of variability. Second, the empirical data, though substantial, stem from a specific construction site in Munich with unique ground conditions and logistical frameworks. Generalizing these findings may require additional use cases or replication in different environments. Third, the definition of productivity remains subjective; organizations with different priorities may interpret the same data in varying ways, underscoring the importance of context in setting benchmarks and thresholds.

Finally, the implications for future research extend in multiple directions. Integrating more advanced machine learning algorithms into the simulation—particularly for variability and highly variable processes—could yield more realistic predictive models. Ongoing data collection from multiple projects would allow for cross-site comparisons, improving the generalizability of the framework. Moreover, analyzing the interplay between process steps in a dynamic, near real-time environment could further enhance the predictive accuracy of total production times. This approach would be especially valuable for large-scale or complex construction endeavors, where marginal gains in accuracy can translate to substantial cost and schedule benefits.

CONCLUSION

In conclusion, this study demonstrates the viability and potential of a flow-oriented framework for measuring and enhancing productivity in construction projects. By integrating value stream mapping with advanced simulation techniques—specifically, Monte Carlo simulations employing lognormal distributions—this research has established a robust benchmark against which real-world process times can be compared. The simulation model provided a detailed probabilistic representation of the key processes, such as drilling, reinforcing, and concreting, enabling the derivation of individual and aggregate production time distributions.

The comparison between simulated and measured data revealed critical insights. While the reinforcing and concreting processes showed relatively close alignment between simulation and reality, the drilling process exhibited

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significantly higher variability and longer durations than anticipated. This discrepancy underscores the importance of reducing the variability of the processes to get a more productive process. Moreover, the analysis of total production time indicated that cumulative variances in individual processes could lead to substantial schedule deviations, reinforcing the notion that productivity must be evaluated holistically rather than in isolation.

Furthermore, the study emphasizes that defining productivity remains a context-specific decision. Organizations must tailor their performance benchmarks based on medians, quantiles, or other statistical indicators to align with their operational objectives and risk tolerances. The framework presented herein offers a flexible foundation for such evaluations, supporting identifying inefficiencies and formulating targeted process improvements.

Looking ahead, integrating real-time data acquisition methods, such as sensor networks, computer vision, and machine learning algorithms, holds promise for further enhancing the accuracy and responsiveness of the production flow model. As the construction industry continues to evolve towards digitalization and lean methodologies, the ongoing refinement of simulation models and systematic on-site data collection will be crucial for achieving sustained productivity improvements. Ultimately, this research lays the groundwork for a more data-driven and process-oriented approach to construction management, providing both a diagnostic tool and a roadmap for future innovations.

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