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UNDERSTANDING LABOUR PRODUCTIVITY IN REINFORCEMENT WORKS THROUGH REAL-LIFE DATA ANALYSIS AND SIMULATION

Michał Juszczyk[a,*]

[a] *Faculty of Civil Engineering, Cracow University of Technology, Warszawska 24, 31-155 Kraków, Poland*

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Abstract

Labour productivity in construction exhibits significant variability, which poses challenges for reliable estimation of task duration. This study proposes a probabilistic framework for modelling labour productivity and execution time in reinforcement works, based on empirical data and Monte Carlo simulation. Labour productivity is modelled using fitted continuous probability distributions, while crew size is represented as a discrete empirical variable. The analysis is conducted separately for different types of structural elements to avoid aggregation bias. The results show that productivity varies not only in magnitude but also in distributional characteristics across element types. The apparent relationship between productivity and crew size is shown to result primarily from data aggregation rather than a direct dependency. Simulation outcomes indicate that execution time distributions are asymmetric, with higher-percentile values significantly exceeding median estimates, reflecting substantial schedule risk. The proposed approach provides a more realistic basis for construction duration estimation under uncertainty and supports improved planning and decision-making by explicitly accounting for variability and heterogeneity in construction processes.

Keywords: labour productivity; reinforcement works; Monte Carlo simulation; construction duration; uncertainty modelling.

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1. Introduction

Accurate estimation of labour input and task duration is a fundamental problem in construction project planning. In practice, these estimates are often based on deterministic assumptions regarding labour productivity and crew size, which do not adequately reflect the variability observed in real construction processes. As a result, such approaches may lead to biased schedules and insufficient consideration of execution risk. Labour productivity in construction has been widely investigated both in reviews addressing productivity-related factors and monitoring approaches [1, 2], and in studies focusing on various contextual and operational determinants [3–6]. These determinants include, among others, the type and scale of structural elements, working conditions, organisational practices, workforce-related aspects, and trade-specific characteristics. At the same time, crew size is typically adjusted depending on the characteristics of the task, making both variables inherently variable and interdependent at the project level. However, many existing models either treat these parameters as fixed values or do not explicitly account for their statistical properties. A key challenge arises from the aggregation of heterogeneous data. When different types of structural elements are analysed jointly, apparent relationships between labour productivity and crew size may emerge, despite the absence of a direct causal link. This may lead to incorrect modelling assumptions and reduced reliability of simulation-based approaches.

*Corresponding author. *E-mail address:* michal.juszczyk@pk.edu.pl (Juszczyk, M.)

This study addresses these limitations by developing a probabilistic framework for modelling reinforcement works, based on empirical data from construction projects. The proposed approach distinguishes between labour productivity and crew size and models them using different statistical representations: labour productivity is described by fitted continuous probability distributions, while crew size is represented using empirical discrete distributions. The model is applied separately to homogeneous categories of structural elements to avoid aggregation bias. The developed framework is implemented using Monte Carlo simulation to estimate execution time as a function of reinforcement quantity, labour productivity, and crew size. The results enable probabilistic assessment of task duration, including the identification of variability and schedule risk. The main contribution of this study lies in the integration of empirical data analysis, distribution fitting, and simulation modelling into a coherent framework that reflects both technological and organisational aspects of construction processes. The proposed approach provides a more realistic basis for planning reinforcement works and supports improved decision-making under uncertainty.

From a theoretical perspective, the study contributes to construction production modelling by demonstrating the importance of disaggregated analysis in avoiding aggregation bias and by proposing a dual representation of key variables, combining continuous modelling of labour productivity with discrete modelling of workforce allocation. This contributes to the development of stochastic modelling approaches in construction, where both technological and organisational aspects of production processes are explicitly represented.

2. Literature review

Construction labour productivity has been widely studied as a key determinant of project performance, cost efficiency, and schedule reliability. Systematic reviews indicate that productivity is influenced by a wide range of factors, including environmental conditions, management practices, workforce skills, and technological constraints [1, 2]. Empirical studies further identify specific determinants such as organisational and managerial practices [3], workforce training and motivation [4], environmental conditions [5], and trade-specific characteristics [6]. In the context of reinforcement works, productivity is strongly affected by buildability and structural configuration [7, 8], as well as environmental conditions such as temperature [9]. Despite extensive research on influencing factors, labour productivity in construction remains inherently variable and difficult to predict. Early studies demonstrated that productivity exhibits complex, non-linear variability even under comparable conditions [10]. This variability poses a fundamental challenge for reliable estimation of construction task duration and highlights the limitations of deterministic approaches based on average productivity values.

To address this issue, various data-driven and predictive approaches have been proposed. These include machine learning methods for estimating labour productivity [11] and clustering techniques such as self-organising maps [12, 13]. While these approaches improve predictive accuracy, they typically focus on point estimates and do not explicitly capture the stochastic nature of productivity or its impact on execution time. Simulation-based methods provide a natural framework for modelling uncertainty in construction processes. Monte Carlo simulation and discrete-event simulation (DES) have been widely applied to analyse productivity, resource allocation, and project performance under uncertainty [14–17]. In this context, DES research has also emphasised the importance of flexible modelling structures capable of representing complex construction operations, resource interactions, and decision mechanisms [18]. More advanced approaches incorporate real-time data inputs, dynamic process interactions, and simulation-based optimisation to improve decision-making during project execution [19–23]. Recent research emphasises that the reliability of simulation models depends critically on the accurate representation of input probability distributions, which should be derived from empirical data rather than assumed a priori [24, 25].

In parallel, emerging studies explore the integration of real-time data acquisition, machine learning, and simulation within digital twin frameworks. These approaches enable automated activity recognition and continuous updating of probability distributions for activity durations, thereby enhancing the responsiveness and accuracy of construction planning [25]. However, such methods are often data-intensive and require advanced sensing technologies and computational infrastructure, which may limit their practical applicability in typical construction environments. Another important research direction concerns the relationship between productivity, safety, and ergonomics. Previous studies have shown that productivity is closely linked to human factors and may be influenced by both physical and organisational conditions. Simulation-based frameworks have been proposed to analyse the interaction between labour efficiency and safety performance, demonstrating that these aspects can be interdependent and, in some cases, conflicting [26]. This highlights the complexity of construction processes and the need for modelling approaches that capture both technological and organisational dimensions of production. In the context of construction planning, traditional methods for estimating task duration, such as unit-rate-based approaches and PERT, rely on deterministic productivity assumptions and simplified representations of variability [27, 28]. While these methods remain widely used in practice, they do not adequately reflect the stochastic nature of construction processes or the interaction between key variables such as labour productivity and crew size.

A critical limitation of many existing studies is the treatment of labour productivity as a single aggregated variable. In practice, productivity is influenced by both technological factors (related to the nature of the task) and organisational factors (related to workforce allocation). Aggregating these effects may lead to misleading conclusions, particularly when heterogeneous types of construction elements are analysed jointly. This study addresses these limitations by proposing a probabilistic modelling framework for reinforcement works that explicitly separates labour productivity and crew size and represents them using different types of probability distributions. Labour productivity is modelled as a continuous random variable using fitted theoretical distributions, while crew size is represented as a discrete empirical distribution derived from observed data. The model is applied separately to homogeneous categories of structural elements to avoid aggregation bias and better capture the statistical structure of construction processes.

3. Data and methodological framework

3.1. Data

The study is based on a dataset collected from real-life construction projects (completed in city of Kraków, Małopolska voivodship, Poland within the last five years) involving reinforcement works executed in reinforced concrete structures. The dataset reflects a specific regional and organisational context, as it was collected from construction projects executed under comparable technological and management conditions. While this ensures internal consistency of the observations, it may limit the direct generalisability of the results to other construction environments characterised by different labour markets, climatic conditions, or organisational practices. However, the proposed modelling framework is not context-specific and may be applied to datasets from other regions, provided that appropriate empirical distributions are derived. Detailed information regarding the sites location, projects name, completion dates, and contractors has been withheld at the request of the data provider due to confidentiality requirements.

The dataset comprises 165 daily observations recorded at the level of individual structural elements. The data were collected using a purposive sampling approach, focusing on completed reinforcement works at the level of individual structural elements. Observations were recorded based on site documentation and direct reporting of work progress, including quantities of installed reinforcement, labour input, and crew size. Each record corresponds to a completed work unit, ensuring consistency in the measurement of productivity. The observations are categorised into three groups: slabs – 62 cases, columns – 53 cases, walls – 50 cases. For each element, the following information was collected:

- Quantity of installed reinforcement expressed in kilograms of steel [kg], later denoted as QIR;
- Total labour input expressed in man-hours [mh], later denoted as TLI;
- Number of workers assigned to the element (crew size), later denoted as NW.

Based on the collected data, additional variables were derived for the purpose of analysis. Labour productivity, denoted as LP, was defined as the ratio of installed reinforcement quantity to total labour input [kg/mh]:

$$LP = \frac{QIR}{TLI} \tag{1}$$

In addition, a duration-related measure was obtained by dividing total man-hours by the number of workers assigned to the element, representing the effective working time, EWT associated with the daily execution of a reinforcement [mh]:

$$EWT = \frac{TLI}{NW} \tag{2}$$

The dataset was analysed as a whole and also with regard to categories according to the type of structural element, allowing for separate analysis of slabs, walls and columns. This distinction reflects differences in execution conditions, work organisation and technological characteristics, which may influence both productivity and labour allocation.

3.2. Modelling framework

The methodological approach adopted in the study consists of three main stages: (i) exploratory analysis of the empirical data, (ii) probabilistic modelling, and (iii) Monte Carlo simulation of working time necessary to complete certain quantity of work.

In the first stage, the statistical characteristics of dataset are analysed. Particular attention is given to the identification of variability patterns and potential relationships between variables, which inform subsequent modelling decisions. The analysis is conducted for a whole dataset first and then separately for each of three element categories regarding types of structural elements, in order to account for differences in execution conditions and avoid aggregation bias.

In the second stage, probability distributions are fitted to the key variables. The selection of distributions is based on empirical data characteristics and goodness-of-fit considerations. The modelling approach assumes that the variability observed in the dataset is representative of real construction conditions.

The key variables result from the modelling framework which is based on a probabilistic representation of reinforcement works, in which task duration is treated as a stochastic variable resulting from the combined effects of labour productivity and workforce allocation. The fundamental relationship between quantity of installed reinforcement (QIR), labour productivity (LP), crew size (NW) and efficient working time (EWT) is derived from relationships presented in Section 3.1 and expressed as:

$$EWT = \frac{QIR}{LP \cdot NW} \tag{3}$$

The model assumes that variability in execution time arises from two sources: variability in labour productivity and variability in crew size. These variables are modelled probabilistically based on empirical data.

LP is treated as a continuous random variable. For each category of structural elements (slabs, walls, columns), probability distributions are fitted to empirical data using standard statistical procedures. Candidate distributions include normal, lognormal, gamma, beta, triangular, and Pearson type III distributions. The selection of the final distribution is based on: the observed shape of the empirical distribution, compatibility with the support of the variable, goodness-of-fit assessment using the Kolmogorov–Smirnov test ($\alpha = 0.05$), and model parsimony.

This approach ensures that the selected distributions adequately capture the variability and skewness characteristics observed in the data.

Crew size (*NW*) is treated as a discrete random variable and modelled using empirical probability mass functions derived directly from observed data. The empirical distribution is defined as:

$$P(NW = k) = \frac{n_k}{N} \tag{4}$$

where k is a specific value representing specific crew size (number of workers), n_k is number of observations where crew size equals k and N is a total number of observations in the dataset.

This non-parametric approach reflects the discrete nature of crew size, its limited range, and the absence of a clear theoretical distribution governing its behaviour. It also allows accurate representation of multimodal patterns resulting from different organisational practices. The statistical procedures applied in the study, including computations of descriptive statistics, distribution fitting and goodness-of-fit assessment, follow standard approaches commonly adopted in engineering statistics and probabilistic modelling [29–31].

Based on the results of the exploratory data analysis, labour productivity and crew size are treated as independent variables within each category of structural elements. Although a strong correlation between *LP* and *NW* is observed in the aggregated dataset, this relationship is shown to be a consequence of aggregation bias and disappears when data are analysed within homogeneous element groups. This assumption is also justified from a conceptual perspective. Labour productivity is defined at the level of individual workers and reflects the efficiency of task execution, whereas crew size is primarily determined by organisational and planning decisions related to task scale and scheduling. These variables are therefore governed by different mechanisms. When the analysis is performed at the level of homogeneous structural elements, the apparent dependency observed in aggregated data disappears, which supports their independent treatment in the probabilistic model. The independence assumption ensures that the model reflects the actual statistical structure of the data and avoids introducing spurious dependencies into the simulation.

The probabilistic model is implemented using Monte Carlo simulation. For each structural element type, input variables are sampled from their respective distributions: *LP* from fitted continuous distributions, *NW* from empirical discrete distributions.

For a given reinforcement quantity (*QIR*), execution time (*EWT*) is calculated for each simulation run using the governing equation. Multiple iterations are performed to obtain a distribution of possible outcomes. The simulation outputs are analysed using summary statistics and selected percentiles (e.g., P50, P90), allowing for probabilistic assessment of expected execution time and associated variability. The simulation framework adopted in this study is grounded in established principles of Monte Carlo simulation and construction process modelling [14, 16, 17]. Its application follows approaches commonly used in modelling labour productivity and uncertainty in construction operations [21, 22].

4. Results

4.1. Exploratory data analysis

Table 1 presents descriptive statistics for the variables quantity of installed reinforcement (QIR), total labour input (TLI), crew size (NW), labor productivity (LP), and efficient working time (EWT), computed for the entire dataset comprising 165 observations. For each variable, the minimum, mean, and maximum values are reported, together with the standard deviation, median, and the first and third quartiles (Q1 and Q3, respectively).

Table 1. Descriptive statistics computed for the whole dataset

Variable	Descriptive statistics						
	Min.	Mean	Max.	St. Dev.	Q1	Med.	Q3
QIR [kg]	94.00	2322.18	6997.00	2312.89	600.00	880.00	4633.00
TLI [mh]	4.00	50.95	133.00	32.47	27.00	36.00	74.00
NW	1	5.84	15	3.46	3	5	8
LP [kg/mh]	12.73	36.38	93.24	19.43	20.65	27.5	54.44
EWT [mh]	2.00	8.63	14.63	1.89	7.75	9.00	9.25

The results indicate substantial variability across all analysed variables. The QIR and TLI exhibit wide ranges and high standard deviations, reflecting significant differences in the scale of analysed elements. LP also shows considerable dispersion, with values ranging from 12.73 to 93.24 kg/mh, confirming the influence of varying execution conditions. In contrast, effective working time EWT demonstrates relatively low variability, suggesting a more stable duration pattern once labour input is normalised by NW.

To investigate the relationship between labour productivity and workforce allocation, the correlation between LP and NW was analysed. For the entire dataset, a positive correlation was observed (Pearson's $r = 0.758$). However, this relationship should not be interpreted as causal. From a theoretical perspective, LP is defined at the level of individual workers and should not increase solely as a function of NW. The observed correlation is therefore likely to result from confounding factors, particularly the type of structural elements. Both LP and NW are influenced by the characteristics of structural elements, including their geometry, scale and execution conditions of reinforcement placement works.

To address this issue, further analysis was conducted separately for slabs, walls, and columns. Table 2 presents descriptive statistics for each category. The results reveal clear differences between element types. Slabs are characterised by larger quantities of reinforcement, higher labour input, and larger crews, as well as the highest average productivity. Walls represent smaller-scale elements, executed by smaller crews and associated with lower and more concentrated productivity values. Columns exhibit intermediate characteristics but with greater dispersion, reflecting variability in execution conditions. Despite these differences, EWT remains relatively stable across element types, indicating that variations in labour input are largely offset by adjustments in crew size.

The results of the correlation analysis differ significantly when performed for individual element types (Table 3). While a strong correlation between LP and NW is observed in the aggregated dataset, this relationship effectively disappears within homogeneous groups. The correlation coefficients are close to zero for slabs and walls, and remain weak for columns. In contrast, a significant correlation persists between QIR and NW across all element types.

Table 2. Descriptive statistics computed separately for the three categories of structural elements

Element type	Variable	Descriptive statistics						
		Min.	Mean	Max.	St. Dev.	Q1	Med.	Q3
Columns	QIR [kg]	94.00	2322.18	6997.00	2312.89	600.00	880.00	4633.00
	TLI [mh]	4.00	50.95	133.00	32.47	27.00	36.00	74.00
	NW	1	5.84	15	3.46	3	5	8
	LP [kg/wh]	12.73	36.38	93.24	19.43	20.65	27.5	54.44
	EWT [wh]	2.00	8.63	14.63	1.89	7.75	9.00	9.25
Slabs	QIR [kg]	1800.00	5071.77	6997.00	1396.90	4125.00	5350.00	6300.00
	TLI [mh]	36.00	86.69	133.00	23.82	72.00	90.00	102.00
	NW	4	9.55	15	2.75	7	10	12
	LP [kg/wh]	31.40	59.15	93.20	11.27	53.00	56.80	65.68
	EWT [wh]	5.54	9.20	14.63	1.46	9.00	9.00	9.75
Walls	QIR [kg]	94.00	530.87	1088.00	244.35	286.50	580.00	695.00
	TLI [mh]	4.00	27.51	70.00	13.03	16.25	27.00	36.00
	NW	1	3.74	8	1.43	3	4	5
	LP [kg/wh]	12.70	19.63	27.60	3.83	17.10	19.75	23.03
	EWT [wh]	2.00	7.42	14.00	2.11	6.21	7.78	8.73

Table 3. Pearson's correlation coefficients

Dataset	Pearson's correlation coefficient between variables	
	LP and NW	QIR and NW
Entire dataset	0.758	0.927
Data subset for element type: Columns	0.158	0.707
Data subset for element type: Slabs	−0.002	0.793
Data subset for element type: Walls	−0.127	0.786

These findings indicate that crew size is primarily driven by the scale of the element rather than by productivity. The apparent correlation between LP and NW observed in the aggregated dataset is therefore a consequence of aggregation bias. Larger elements tend to be executed by larger crews and simultaneously exhibit higher productivity due to more favourable working conditions. When data are not disaggregated, this leads to a misleading interpretation of a direct dependency between productivity and workforce size.

The results confirm the importance of disaggregated analysis in construction data modelling and provide a basis for treating labour productivity and crew size as independent variables within each category of structural elements.

4.2. Distribution fitting

Based on the results of the exploratory data analysis, probabilistic modelling was carried out separately for each category of structural elements. Two variables were considered: labour productivity (LP) and crew size (NW). LP was modelled using theoretical probability distributions, while NW was represented using empirical distributions derived directly from observed data.

To account for different possible shapes of empirical LP distributions, several candidate probability models were considered, including normal, lognormal, gamma, beta, triangular and Pearson type III distributions. The selection of the final distribution for each element type was based on the observed shape of the data, compatibility with the support of the variable, and goodness-of-fit assessment using the Kolmogorov–Smirnov (KS) test at a significance level of $\alpha = 0.05$. Table 4 presents the results of the KS tests together with p-values for LP.

Table 4. KS statistics and p-values for LP distribution

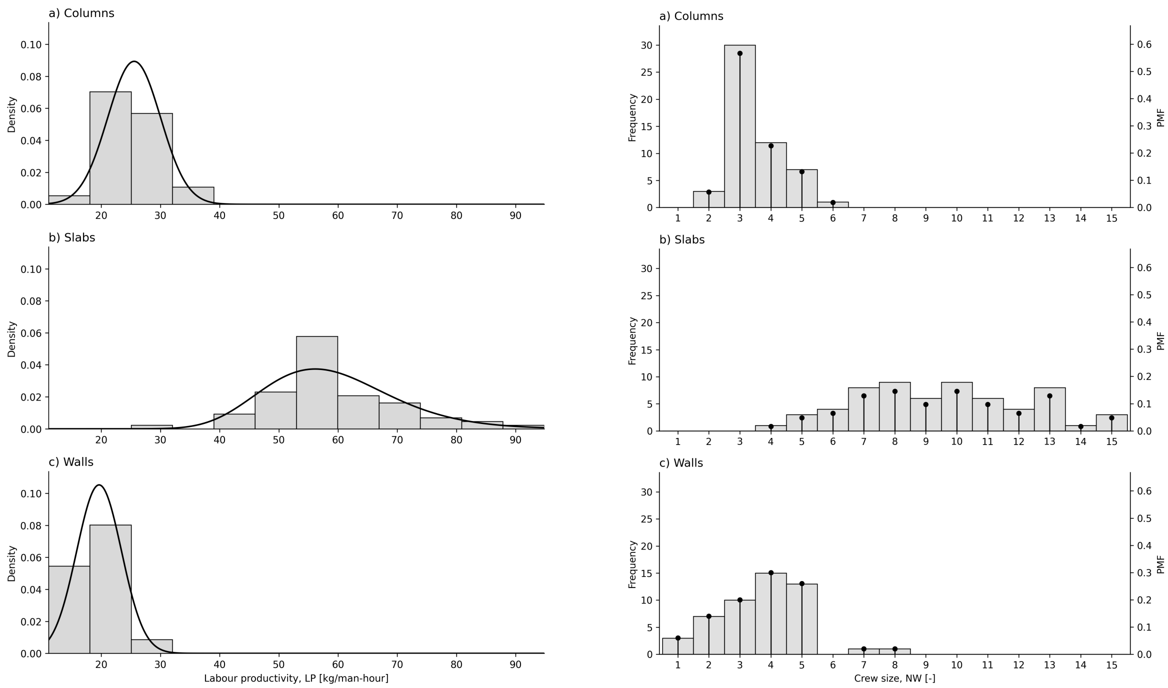
Distribution	Columns		Slabs		Walls	
	KS	p-value	KS	p-value	KS	p-value
Normal	0.102	0.598	0.131	0.217	0.087	0.810
Lognormal	0.124	0.360	0.130	0.224	0.088	0.807
Gamma	0.118	0.424	0.123	0.280	0.087	0.808
Beta	0.102	0.599	0.136	0.183	0.100	0.662
Triangular	0.110	0.512	0.151	0.107	0.105	0.603
Pearson type III	0.107	0.547	0.112	0.388	0.088	0.802

The results indicate that multiple distributions provide statistically acceptable fits for all element types, as confirmed by relatively low KS statistics and high p-values. However, the differences in goodness-of-fit between candidate models are limited, which suggests that distribution selection should be guided primarily by parsimony and interpretability rather than marginal statistical differences. For slabs, the empirical distribution of labour productivity exhibits positive skewness. Although Pearson type III provides the best statistical fit, lognormal and gamma distributions show comparable performance. Given its simplicity and common use in modelling right-skewed production data, the lognormal distribution was selected. For columns and walls, the empirical distributions are more symmetric. In these cases, the normal distribution provides a sufficiently accurate and parsimonious representation, despite alternative distributions yielding comparable goodness-of-fit. The final fitted distribution parameters are as follows: normal distribution for columns ($\mu = 25.553$, $\sigma = 4.465$), lognormal distribution for slabs ($\mu_{\ln} = 4.063$; $\sigma_{\ln} = 0.187$), and normal distribution for walls ($\mu = 19.630$, $\sigma = 3.790$).

In the case of NW, no parametric distribution was imposed. Instead, crew size was modelled using empirical discrete distributions derived from observed frequencies. The probability mass function (PMF) is defined as given in Eq. (4). This approach reflects the discrete nature of the variable, its limited range, and the absence of a clear theoretical distribution governing its behaviour. In contrast to parametric models, empirical distributions allow accurate representation of multimodality and clustering associated with different organisational regimes.

The resulting distributions adopted for simulations are presented in Fig. 1.

Given the weak correlation between labour productivity and crew size identified in Section 4.1, both variables were modelled independently within each category of structural elements. This ensures consistency with the statistical properties of the dataset and avoids introducing spurious dependencies into the simulation model.



(a) Fitting of theoretical probability distributions to empirical labour productivity (LP) data

(b) Empirical distributions of crew size (NW)

Figure 1. Distributions adopted for simulations

4.3. Simulations

The purpose of the simulation is to assess the variability of labour input and execution time resulting from the stochastic nature of labour productivity and workforce allocation. The simulation framework translates the empirical distributions identified in Section 4.2 into probabilistic estimates of task duration.

Labour productivity (LP) is modelled as a random variable described by the fitted theoretical distributions, while crew size (NW) is represented using empirical discrete distributions. Both variables are sampled independently within each category of structural elements, in accordance with the results of the correlation analysis. For assumed fixed value of QIR Monte-Carlo simulation allowed for calculation of EWT_i in each i-th run:

$$EWT_i = \frac{QIR}{LP_i \cdot NW_i} \tag{4}$$

where QIR is assumed quantity of installed reinforcement, LP_i is labour productivity sampled in iteration i, NW_i is number of workers sampled in iteration i.

The simulation was performed separately for slabs, walls, and columns. For each element type, three representative scenarios of reinforcement quantity were considered, corresponding to the first quartile (Q1), median, and third quartile (Q3) values obtained from the empirical data. For each scenario, a Monte Carlo simulation with 10,000 iterations was conducted. In each iteration, values of LP and NW were sampled, and the corresponding execution time (EWT) was calculated. The simulation results are summarised in Table 5 in terms of mean values, medians (P50), and upper percentiles (P90), providing a probabilistic description of expected execution times.

Table 5. Simulation results for labour input and execution time

Element type	Scenario	QIR [kg]	EWT [h] Mean	EWT [h] P50	EWT [h] P90
Columns	Q1	551	6.78	6.55	9.44
	Med	770	9.44	9.14	12.98
	Q3	990	12.20	11.74	16.90
Slabs	Q1	4125	8.27	7.64	12.42
	Med	5350	10.71	9.85	16.12
	Q3	6300	12.64	11.64	18.97
Walls	Q1	287	5.02	4.00	8.39
	Med	580	10.14	8.07	16.80
	Q3	695	12.13	9.59	20.15

The results confirm that execution time is subject to substantial variability, even for a fixed quantity of reinforcement. For all element types, increasing QIR leads to longer execution times; however, the magnitude and dispersion of results differ between elements. Slabs, despite higher productivity levels, exhibit relatively long execution times due to their larger scale. Columns show intermediate behaviour, while walls are characterised by the highest relative variability.

A key observation concerns the asymmetry of the simulated distributions. In all cases, the P90 values significantly exceed the median, indicating the presence of unfavourable but plausible scenarios that may substantially extend execution time. This effect is particularly pronounced for walls, where variability is highest. The difference between P50 and P90 values can be interpreted as a measure of schedule risk associated with labour variability. These findings have important practical implications. Deterministic estimates based on average productivity correspond approximately to median values and therefore do not account for the risk of adverse outcomes. In contrast, the probabilistic approach enables explicit consideration of such risks, supporting more robust planning and decision-making.

5. Discussions

The results of the study confirm that labour productivity in reinforcement works is inherently variable and cannot be adequately represented by single deterministic values. The empirical analysis and distribution fitting demonstrate that productivity differs not only in magnitude but also in statistical characteristics across element types. In particular, slabs exhibit right-skewed behaviour, while columns and walls are more symmetrically distributed. This justifies the use of different probability distributions for each category and supports the assumption that productivity should be modelled at a disaggregated level.

In addition to structural element type, labour productivity in construction is influenced by a range of external factors, including environmental conditions, workforce experience, site constraints, and organisational practices. These factors are not explicitly modelled in the present study; however, their effects are implicitly captured in the empirical distributions derived from observed data. As the dataset reflects real construction conditions, the variability associated with these factors is embedded in the statistical representation of productivity.

A key methodological implication of the study is the need to separate labour productivity and crew size in modelling construction processes. The exploratory analysis indicated an apparent correlation between these variables; however, this relationship was shown to result primarily from aggregation across heterogeneous element types rather than from a direct causal dependency. By modelling productivity as a continuous random variable and crew size as a discrete empirical distribution, the proposed approach avoids this bias and provides a more realistic representation of site conditions. The simulation results further highlight the importance of accounting for variability in productivity when estimating task duration. The obtained distributions of execution time are asymmetric, with higher percentiles (e.g. P90) significantly exceeding median values. This indicates the presence of unfavourable but plausible scenarios that may substantially extend execution time. The difference between P50 and P90 values can therefore be interpreted as a measure of schedule risk associated with labour variability. From a practical perspective, this suggests that planning based solely on average productivity values may lead to systematic underestimation of execution time. The proposed modelling framework contributes to existing research by extending stochastic approaches to construction production modelling through explicit separation of productivity and workforce allocation, and by demonstrating the role of disaggregated analysis in capturing the statistical structure of construction processes. In contrast to approaches relying on deterministic productivity rates or aggregated data, the presented method captures both variability and heterogeneity across task types. This is particularly relevant in reinforcement works, where differences in geometry, accessibility, and work organisation significantly affect productivity.

From a theoretical perspective, the findings contribute to construction production modelling by showing that labour productivity and workforce allocation should not be treated as a single aggregated productivity mechanism. Instead, the results support a dual representation of reinforcement work processes, in which labour productivity reflects technological work efficiency, while crew size reflects organisational resource allocation. This distinction helps explain why apparent dependencies may arise in aggregated datasets and demonstrates the importance of disaggregated modelling for capturing the statistical structure of construction production processes.

From a practical standpoint, the model may support more reliable planning and decision-making by enabling the estimation of execution time under uncertainty. It can be used to assess the impact of different crew configurations, quantify schedule risk, and support scenario analysis in construction management. The approach is also compatible with more advanced simulation environments and may be extended by incorporating additional variables, such as work interruptions, learning effects, or resource constraints. The proposed framework can be integrated into existing scheduling tools by replacing deterministic activity durations with probabilistic estimates derived from simulation. In practice, this may involve assigning probability distributions to activity durations or using percentile-based estimates (e.g., P50 or P90) within standard scheduling environments. This enables planners to account for variability and assess schedule risk without deep altering existing planning workflows.

Despite its advantages, the study has several limitations. The analysis is based on data from a specific project context, which may limit the generalisability of the results. In addition, the model assumes independence between productivity and crew size within each element category, which, although justified by the analysis, may not fully capture all operational interactions. Future research should focus on expanding the dataset, testing the approach across different project types, and integrating additional factors influencing productivity. Moreover the simulation model adopts a simplified representation of construction processes and does not explicitly account for dynamic interactions between tasks, resource constraints, or time-dependent effects. These aspects could be incorporated in future extensions of the model.

6. Conclusions

This study proposed a probabilistic framework for modelling labour productivity and execution time in reinforcement works, based on empirical data and Monte Carlo simulation. Labour productivity was modelled using fitted continuous probability distributions, while crew size was represented as a discrete empirical distribution. The approach was applied separately to different types of structural elements to avoid aggregation bias.

The results demonstrate that labour productivity exhibits significant variability and differs in its statistical characteristics depending on the element type. The analysis also showed that the apparent relationship between productivity and crew size is largely an artefact of data aggregation, which justifies modelling these variables independently. Simulation results indicate that execution time distributions are asymmetric, and that higher-percentile values (e.g., P90) may significantly exceed median estimates, reflecting substantial schedule risk.

The proposed approach provides a more realistic basis for estimating construction task duration under uncertainty compared to deterministic methods. It enables improved planning by accounting for variability, supporting scenario analysis, and quantifying schedule risk. Future research should focus on expanding the dataset, validating the model across different project types, and incorporating additional factors affecting productivity.

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