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Construction Work Efficiency Analysis—Application of Probabilistic Approach and Machine Learning for Formworks Assembly

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Abstract: Analyses of efficiency are vital for planning and monitoring the duration and costs of construction works, as well as the entire construction project. This paper introduces a combined quantitative (probabilistic) and qualitative (machine learning-based) approach to the problem. The proposed approach covers probabilistic analysis based on fitting a triangular distribution to empirical data, followed by the application of support vector machines (SVM). Following the theoretical assumptions, the paper also presents an application of the proposed approach for formwork assembly as an exemplary construction work. This is based on real-life data, including conditions, characteristics, and features of formwork assembly work recorded on a construction site. As a result of the study, triangular distributions were fitted to data representing efficiencies of formwork assembly for three different types of structural members made of reinforced concrete. The parameters (a—minimum, m—peak and b—maximum values of efficiency measured as square meters of an assembled formwork per hour) of the fitted distributions for the particular real-life data were as follows: for columns a = 0.100, m = 1.450, b = 1.900, for walls a = 0.700, m = 1.995, b = 3.300 and for slabs a = 0.200, m = 2.125, b = 3.200. The obtained distributions allow us to assess the probability of achieving efficiency not less than a certain assumed critical value. The study also developed two SVM models—the first based on so-called C-classification and the second based on ν-classification—capable of recognising with satisfactory accuracy whether the efficiency of formworks assembly works for certain conditions, characteristics, and features of works are above or below median values computed based on previously fitted distributions. The performance of both developed models in terms of proper classification, either for training or testing, was above 80%.

Keywords: construction works; efficiency; formworks assembly; triangular distribution; machine learning; support vector machines; classification

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1. Introduction

Despite the fact that new technologies, equipment, and machinery are emerging, as well as the implementation of automation and robotics, labour remains an important resource in the construction industry. Actually, labour, as one of the active resources, drives the duration of construction works in terms of single tasks or the whole construction stage of a project. Construction work planning is of key importance and involves, among other things, the definition of work tasks, the choice of technology, and the estimation of the required resources and durations for individual tasks. Actual durations depend on the efficiency, productivity, or performance achieved on a construction site.

The terms mentioned—efficiency, productivity, or performance—are used interchangeably (as seen in the state-of-the-art part of the paper) and refer to the results or output of construction works measured against the use of resources engaged in executing these works. The fact is that even in the case of the most careful planning performed by the main contractor and/or subcontractors, schedules and baselines are verified by the actual progress of works. Deviations from planned durations seem to be inevitable.

The aim of the paper is to present an approach based on both quantitative and qualitative analysis of construction work efficiency. Efficiency is understood herein as a work's output measured in units specific to certain construction work (representing weight, length, surface) or volume per hour. The output of construction work is measured against labour in terms of the number of engaged workers and the number of working hours spent on the execution of construction work. The quantitative approach relies on the analysis of data, including construction work efficiency measures, fitting triangular continuous distribution, and probabilistic analysis of efficiency. On the other hand, the implementation of support vector machines (SVM) as a machine learning tool is proposed for the qualitative approach. As a result, the solution to the classification problem is expected, which allows recognising whether the efficiency of construction work for a given combination of factors is above or below a certain value called critical efficiency.

Another objective is to present the results of the application of the proposed approach to an example of system formwork assembly works for the three types of reinforced concrete structural members—columns, walls, and slabs. The applied analysis was carried out with the use of real-life data obtained from a construction project as recorded on a construction site. The application of a triangular distribution for quantitative work efficiency analysis precedes the application of machine learning methods for qualitative predictions of efficiency.

The paper's content includes a brief discussion of the background and a state-of-the-art review, a presentation of the approach for efficiency analysis, the introduction of the data used in the course of the applied analysis, a case study and research results, a discussion of the advantages and drawbacks of the presented approach, and conclusions.

2. Background and State-Of-The-Art

Issues related to efficiency and productivity in construction are widely discussed and presented from different perspectives and at different levels. They are addressed as problems of the construction industry branch, construction projects, specific technologies, or the use of resources.

In [1], the authors presented a comprehensive study and review of numerous works investigating factors affecting construction productivity. The study of works published over 30 years allowed them to point out a set of factors influencing productivity in the construction industry regardless of differences in various countries. These are: "non-availability of materials, inadequate supervision, skill shortage, lack of proper tools and equipment, and incomplete drawing and specifications." They stated that some factors, namely, "implications of technology, site amenities, process studies, project culture, and impacts of physiological and psychological factors", have not been thoroughly investigated so far.

The further paper [2] contributes to the construction management body of knowledge by providing a comprehensive review of different productivity monitoring techniques. The authors' findings are that the most adopted data acquisition techniques are traditional, computer vision-based, and photogrammetry-based methods. These are being combined with machine learning and BIM for the purposes of automated monitoring of construction productivity.

Another work [3] focused on quantifying time waste in the architecture engineering construction industry as an important factor that counteracts performance and efficiency. The study provides a synthesis of the findings presented in several publications, which showed that an average of 49.6% of the time in construction is wasted. The conclusion is that there is considerable potential for improvement and reduction of wasteful activities.

There are also several studies aiming at the use of different methods and approaches for the purposes of construction productivity, efficiency and performance investigation. These are analytical hierarchy process (AHP) applications for the purpose of analysis and improving productivity [4], descriptive and regression analyses along with a co-relational study for investigation of training and motivation practices effects on teamwork improvement and tasks efficiencies [5], performance metrics analysis and comparison with the use of queuing theory followed by simulation experiments for quantitative analysis of rate-driven and due date–driven residential buildings projects [6], the introduction of lean-based flow optimisation and Industry 4.0 concepts and principles for improving the efficiency of road construction [7].

Literature studies have shown that labour efficiency in construction is a widely discussed topic. The efficiency is being investigated with regard to the conditions and distinct character of regional and national construction markets. Several works have investigated this topic, including cases of European countries [8], specifically Poland [9], the United States of America [10], China [11], Turkey [12], Kuwait [13], Jordan [14], Uganda [15], Egypt [16], and Zimbabwe [17], which have presented broad analyses of factors affecting labour efficiency. From these works, it can be concluded that although some factors are common, there are strong regional influences on the attitude towards the problem.

There is also a significant amount of attention given in published research to the relationships between different factors and the efficiency of construction works. The focus is on the influence of either certain specific factors or sets of factors on efficiency. However, the research is predominantly carried out at a country level. In [18], the authors investigate the relationship between change orders and labour efficiency. They develop a statistical dependency capable of estimating the actual amount of labour efficiency lost due to change orders. Several papers deal with thermal comfort as a factor, such as research on thermal environment variations and their influence on the loss of workers' productivity, along with statistical models developed for the purpose of loss predictions, presented in [19]. This is followed by similar work from the same authors [20], which proposes productivity-thermal environment relationship models for three different types of construction works. A more specific analysis, presented in [21], reports an investigation of construction rebar workers' productivity against heat stress. The modelled dependency explains how heat stress reduces productivity. Another paper [22] explores the relationships between the work motivation of construction workers and their productivity. The study reveals motivation-related factors influencing productivity. In [23], research on the efficiency of construction workers in the carpentry trade is presented. The authors report the results of a two-year study of workers' efficiency with regard to human issues. One of the publications [24] presents an analysis that aims to reveal how unsatisfactory working conditions negatively affect the efficiency of workers, as well as the image of the construction industry.

An important trend in research is the development of models that can predict labour efficiency, productivity, or performance using various mathematical methods. Fuzzy logic, presented in [25], is believed to aid in the determination of construction workers' productivity. A regression model that explains the dependencies between identified factors and construction workers' labour productivity in Vietnam is presented in [26]. The study focused on 17 factors influencing productivity (including environmental factors) and was ordered into five groups relevant to construction workers, site operation and management, motivation, working time, working tools, working conditions, health and safety, project information, natural environment, and socio-economic conditions. Another study introduces the application of artificial neural networks for formwork labour productivity prediction [27]. Among the investigated types of models, including backpropagation networks, general regression networks, radial basis function networks, and adaptive neuro-fuzzy networks, the first mentioned appears to outperform the others for modelling construction labour productivity. The concept of labour efficiency modelling based on an ensemble approach and combining several neural networks into one predictive model is presented in [28]. The analysis is provided for steel reinforcement works and is based on data records from construction sites. The research resulted in the development of a model based on a generalised ensemble averaging approach capable of predicting efficiency with satisfactory accuracy within an acceptable range of errors. The application of a broad range of machine learning tools for the analysis and prediction of construction masonry works productivity is presented and discussed in [29]. The authors propose using subjective measures referring to the compatibility of the personality of workers, together with other workers' characteristics, external conditions, and site conditions, as efficiency driving factors. In the course of the research, k-nearest neighbours, deep neural networks, logistic regression, support vector machines, and convolutional neural networks were examined to discover the mapping between driving factors, and masonry works efficiency. Artificial neural networks are also a tool used to build a predictive model in another study [30]. The authors focus on the construction works efficiency prediction problem in Iran as a developing country and a specific type of project—namely, commercial-office complex projects. Nineteen factors ordered into five groups, including individual, managerial, economic, technical, and environmental aspects, were used as efficiency drivers. The study resulted in the development of a hybrid model based on artificial neural networks and the grasshopper optimisation algorithm capable of predicting construction work efficiency with satisfactory precision.

The following general conclusions can be drawn from the literature review:

- Although there are some common factors affecting efficiency, productivity, or performance across different regions and types of construction works, these analyses are often dependent on regional specificity and environmental issues,
- Various models for predicting efficiency, productivity, or performance have been investigated and developed, but there is no universal tool that can be applied to all cases.
- The selection of tools for efficiency, productivity, or performance modelling is individual and should be motivated and justified by the availability of data.

3. Methods and Data

Figure 1 shows a conceptual scheme of the proposed approach, which starts with the collection of data on actual construction works.

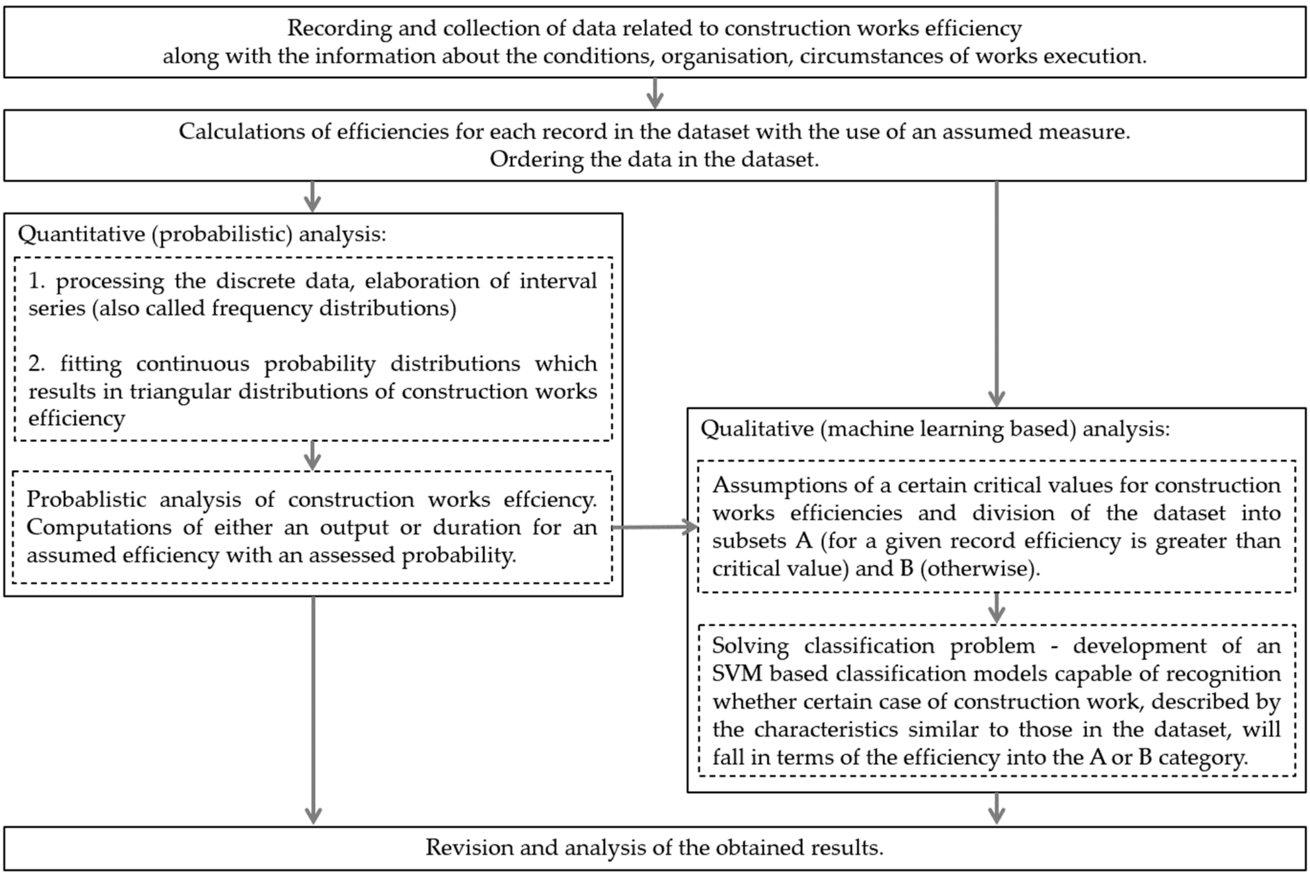

Figure 1. Conceptual scheme of the proposed approach.

The approach presented in the paper involves a series of steps that integrate both quantitative and qualitative analyses of construction work efficiency. To make the analysis of the actual (real-life) construction works efficiency possible, data collection is necessary.

In terms of quantitative analysis, it is sufficient to record data that are directly related to efficiency, such as the work output, number of hours spent, and resources used in executing a particular construction work. Based on these data, efficiency can be computed using various measures, but in this study, it is defined as the work output per unit of time (hour of work). This quantitative approach enables probabilistic analysis of construction work efficiency, leading to computations of either the duration or output of construction works, along with an assessment of the probability for a given case.

To obtain a more comprehensive view and deeper insights, additional information about the conditions, circumstances, organisation, and characteristics of construction works must also be recorded. Such information is particularly crucial for qualitative analysis and the application of machine learning tools. The qualitative approach follows probabilistic analysis and is designed to enable the recognition of whether, under certain circumstances, the construction work efficiency being considered will be above or below a certain critical value.

3.1. Assumptions for Quantitative Analysis and Probabilistic Approach

The collected and processed data are supposed to serve for calculations, resulting in a series of discrete values representing actual efficiencies of construction works. The calculated efficiencies should then be ordered according to the types of work. The discrete empirical data should be processed to obtain an interval series (or so-called frequency distribution) which, in turn, allows for fitting a continuous distribution of probability. The range of empirical data must be divided into intervals, preferably of equal width. The next step is fitting continuous distribution to the interval series. One may consider different types of continuous distribution, such as beta, Kumaraswamy, metalog, quantile-parametrized, trapezoidal, triangular, or others (continuous distributions are widely discussed in statistical literature, e.g., [31–33]).

In this study, the triangular distribution was chosen due to its simplicity and ease of application. Moreover, the triangular distribution is expected to be understandable for practising construction engineers.

To provide examples of how the triangular distribution is used in engineering, some applications are mentioned in this paper: analysing and examining cost estimates for electrical services contracts in government clinics in Hong Kong [34], deriving the occurrence probabilities of major construction project risk factors for proactive scheduling [35], estimating the duration of horizontal directional drilling works [36], assessing the duration of construction works, such as finishing plastering [37], estimating the duration of construction tasks for project evaluation and review techniques (PERT) [38], and analysing construction cost risk for practical application in the bidding process [39].

The triangular distribution is a continuous probability distribution named after its triangle-shaped density function. Some issues with its application are discussed in [40]. This distribution is characterised by three values: the minimum, peak, and maximum (referred to as a, m, and b, respectively), and it is a simple and suitable model for skewed distributions. By defining finite lower and upper limits, unwanted extreme values can be avoided when the distribution is applied. The general form of the density function for the triangular distribution is provided below.

$$f(x) = \begin{cases} 0, \ x < a \\ \frac{2(x-a)}{(b-a)(m-a)}, \ x \in < a;\ m) \\ \frac{b-a}{2}, \ x = m \\ \frac{2(b-x)}{(b-a)(m-a)}, \ x \in (m; b > \\ 0, \ x > b \end{cases} \tag{1}$$

Following this, the expected value $E(X)$, median Me, standard deviation σ, and mode D can be computed, respectively. The equations for these calculations are given below.

$$E(X) = \frac{a+m+b}{3} \tag{2}$$

$$Me = \begin{cases} a + \frac{\sqrt{(b-a)(m-a)}}{\sqrt{2}}, & m \geq \frac{b-a}{2} \\ b - \frac{\sqrt{(b-a)(b-m)}}{\sqrt{2}}, & m \leq \frac{b-a}{2} \end{cases} \tag{3}$$

$$\sigma = \sqrt{\frac{a^2+m^2+b^2-ab-am-mb}{18}} \tag{4}$$

$$D = m \tag{5}$$

On the basis of the fitted distribution, it is possible to assess the probability of obtaining an efficiency that is not less than a certain value, which can be denoted as x_c and referred to as critical. The formal notation for this is given below:

$$P(X > x_c) = \int_{x_c}^{a} f(x)dx \tag{6}$$

Assuming the distribution allows for assessing a certain value of efficiency for which a probability is assumed. Furthermore, it is possible to compute work duration, work output, or gang size with the assumed probability. Examples of applications for formwork assembly works based on real-life data are presented in Section 4 of this paper.

3.2. Assumptions for Qualitative Analysis—Application of Machine Learning

With the use of data that describes the circumstances, characteristics, and features of construction works execution, it is possible to explore the prediction of efficiency. Machine learning provides a wide variety of tools that can be applied in this area. Fundamental knowledge and principles of machine learning can be found in the relevant literature, such as [41–44].

During the initial studies, the option of efficiency predictions based on solving both regression and classification problems was investigated. However, it was found that the developed regression models' performance was not satisfactory when using the collected data. As a result, the decision was made to focus on classification problems. This is also an explanation for why this part of the study was called qualitative analysis.

The main idea was to develop a machine learning-based tool that can differentiate cases describing construction works execution and classify them based on their efficiency, either greater or lower than a certain assumed critical value. The critical value of efficiency can be determined based on previously fitted continuous distributions, and the records in the dataset can be labelled for supervised training. There are several methods that can be applied to this problem, such as neural networks, classification trees, naive Bayes method, k-nearest neighbours, support vector machines (SVM), and others. SVM is a machine learning tool whose theory is based on the principles of statistical learning, which are broadly presented in [45,46].

SVM has the capability of learning from experience hidden in the data and knowledge generalisation. The fundamentals, description, and methodology of the tools are discussed in many works, e.g., [47–49]. Due to the advantages of SVM, it was decided to apply this particular method in the study.

In particular, SVM is a supervised training algorithm that has been shown to have good generalisation performance and is applicable to many problems. SVM is known to perform well with limited datasets. Another important advantage to mention is the low number of free parameters in the learning machine, so the model architecture does not need to be found by experimentation.

- Let's assume that:
- x_i is an n-dimensional vector of independent variables,
- y_i takes values 1 or -1 denoting the class to which the i-th point belongs, respectively,
- w is the weight vector,
- b is the bias.
- During the SVM training process, the weight vector and bias are computed. To allow solving problems which are not linearly separable:
- slack variables ξ_i, which aim is to measure the degree of misclassification, are introduced,
- the use of a kernel function φ (which may be polynomial, Gaussian radial basis or sigmoid) allows nonlinear mapping of the nonlinear input space to the high-dimensional feature linear space.
- SVM classification can be performed using two variants—C-classification or ν-classification [50]. In the case of C-classification (later referred to as classification type 1), optimisation of the following objective function takes place:

$$\frac{1}{2}w^T w + C\sum_i \xi_i \to min \tag{7}$$

subject to following constraints:

$$\begin{cases} y_i\left(w^T\varphi(x_i) + b\right) \geq 1 - \xi_i \\ \xi_i > 0, \quad i = 1, \ldots, n \end{cases} \tag{8}$$

where C is a constant called capacity—a parameter that determines the trade-off between the margin size and the amount of error in training. The parameter $C > 0$, which means it may take any positive value.

For ν-classification (later referred to as classification type 2) objective function is given:

$$\frac{1}{2}w^T w - \nu\rho + \frac{1}{n}\sum_i \xi_i \to min \tag{9}$$

subject to:

$$\begin{cases} y_i\left(w^T\varphi(x_i) + b\right) \geq \rho - \xi_i \\ \xi_i > 0, \quad i = 1, \ldots, n \\ \rho \geq 0 \end{cases} \tag{10}$$

where $\nu \in [0, 1]$ is a parameter which represents an upper bound on the fraction of margin errors and a lower bound of the fraction of support vectors relative to the total number of training examples. An additional variable to be optimised is ρ. (Hyperparameters of kernel-based classification are discussed, e.g., in [51]).

By using SVM-based classification, the study aimed to develop a machine learning tool that could distinguish cases describing construction works execution and classify the cases based on their efficiency, either greater or lower than a certain assumed value of efficiency. This tool would allow for the assessment of whether certain circumstances of work execution, as described by the features and parameters, are likely to result in efficiency lower or higher than the assumed value.

In Section 4 of the paper, the author presents examples of the applications of this tool for formwork assembly works based on real-life data. These examples demonstrate how the SVM-based classification method can be used to identify the key factors that influence the efficiency of construction work execution and to predict the likely efficiency of future construction works based on these factors.

3.3. Data

Formworks are critical components in the construction of reinforced concrete structures, and the selection of the appropriate formwork system is essential for achieving the desired results. Various types of formwork systems have been developed over the years, and their advantages and limitations have been extensively studied. In [52], one may find an introduction and overview of the various forming systems used for reinforced concrete structures. A comprehensive overview of formwork systems, including their raw materials, flexibility, fabrication methods, applications in concrete structures, and environmental impacts, is provided in [53]. This review compares and discusses the advantages and limitations of various formwork systems, including traditional timber and plywood formwork, aluminium formwork, and modular formwork systems. In [54], the concept of adaptive design of formworks is introduced, with a case study for building renovation. The authors investigate the use of building information modelling (BIM) environment for the adaptive design of formwork elements in the context of sustainability. The selection of the appropriate formwork system is a complex process that involves various criteria. In [55], the focus is put on the criteria for selecting a certain formwork system. Following that, a structural equation is developed and presented in [56]. The analysis reveals the quantitative interrelationships among criteria for formwork system selection.

The approach proposed in the previous subsections was applied to analyse the efficiency of construction works based on real-life data recorded on a construction site in Kraków, Poland. (Details about site location, name of the project and name of the contractor have been restricted by the party that shared the data for research purposes.) The project included the erection of several mid-rise residential buildings.

The data included information related to a specific type of construction work—the assembly of formworks for structural members of a building superstructure, such as columns, walls, beams, and slabs, as part of the construction of several residential buildings. The data were collected by site engineers responsible for the supervision of formworks assembly in collaboration with foremen. They recorded information about the completed quantities of work, actual activity duration in working hours, number of workers assigned, gang experience and skills, and weather conditions.

The data for beams were excluded from further analysis due to the relatively low cardinality of records in the dataset and the different measure of work quantity (i.e., meters of length) compared to the other elements. For walls, columns, and slabs, the quantity of work was measured in units of assembled formwork surface (square meters).

Finally, the dataset contained 152 records. Table 1 presents basic information about the dataset in terms of the number of records with regard to the type of structural member and their shares.

- The dataset included several types of information related to the features of formwork assembly works, including details on the organisation, time, circumstances of works execution, and performance. It's important to note that the data were recorded during the autumn period. The obtained dataset consisted of nine features recorded on a construction site, with an additional two features requiring simple calculations. The features are mentioned and explained concisely below:
- type of structural member—called "Element"(which took one of the values: COLUMN or WALL or SLAB);
- building storey—called "Level" (the values varied from 0 to 2);
- size of a gang assigned to a certain task—called "Number of workers" (the values varied from 2 to 5);
- Gang experience and skills (which took the values: MS for moderately skilled and experienced gang or AS for the averagely skilled and experienced gang, or HS for highly skilled and experienced gang);
- duration of work within one working day in hours—called "Duration" (which varied from 2 to 10 h);

- "Total labour"—calculated as follows:

$$\text{Total labour} = \text{Number or workers} \times \text{Duration}, \quad (11)$$

- (standing for a number of hours spent by a certain number of workers to complete work);
- The temperature in °C for a certain working day—called "Temperature" (the values varied from −2 °C to 14 °C);
- information about the occurrence of falls on a certain working day—called "Falls" (which took one of the values: YES or NO);
- information whether the work took place at the beginning, middle or end of a week—later called "Day of the week" (which took values M—for Monday, TWT—for Tuesday or Wednesday or Thursday, FS—for Friday or Saturday);
- the output of work—called "Total quantity" given in m^2 of assembled formwork's surface in a certain day (values varied from 3.60 m^2 to 133.5 m^2);
- "Efficiency"—calculated as follows:

$$\text{Efficiency} = \text{Total quantity}/\text{Total labour} \quad (12)$$

Table 1. Number of observations according to the type of element.

Element	Formwork Type	Number of Observations	Observations Shares in the Dataset
COLUMN	system formwork	37	24.34%
WALL	system formwork	51	33.55%
SLAB	system formwork	64	42.11%

standing for output of work per one hour with respect to the number of workers assigned to a certain scope of work.

Altogether, the dataset includes 11 types of features for each record. Table 2 presents a random sample of dataset records, including the discussed 11 features and their corresponding values.

Table 2. Random data sample including all types of collected information.

Element	Level	Number of Workers	Gang Experience and Skills	Duration [Hours/Day]	Total Labour [Hours]	Temperature [°C]	Falls	Day of the Week	Total Quantity [m^2]	Efficiency [m^2/Hour]
WALL	0	5	AS	9	45	9	YES	FS	80.60	1.79
SLAB	2	3	HS	7.5	22.5	8	YES	FS	46.00	2.04
COLUMN	2	4	AS	7.5	30	0	NO	FS	40.10	1.34
WALL	0	3	AS	7	21	6	YES	TWT	43.00	2.05
COLUMN	1	3	AS	4.5	13.5	3	NO	TWT	19.00	1.41
SLAB	2	2	MS	7	14	−2	NO	FS	4.50	0.32
WALL	0	3	MS	9	27	5	NO	TWT	43.40	1.61
COLUMN	2	3	MS	8	24	0	NO	FS	30.50	1.27
COLUMN	1	3	MS	4	12	3	NO	TWT	17.50	1.46
SLAB	1	3	HS	7	21	3	NO	FS	48.00	2.29
COLUMN	0	4	MS	10	40	1	YES	TWT	21.90	0.55
WALL	0	3	AS	7	21	6	YES	TWT	45.20	2.15
SLAB	1	3	AS	8	24	11	YES	M	50.00	2.08
WALL	1	4	AS	8	32	11	YES	TWT	59.50	1.86
COLUMN	0	3	AS	4	12	6	NO	TWT	17.00	1.42
WALL	0	5	MS	9	45	9	YES	FS	80.60	1.79

In the case of the three features presented in Table 2, some additional comments seem necessary. "Gang experience and skills" were assessed, taking into account the individual abilities of workers belonging to a certain gang. The contractor's site engineers simply put an average score expressed by one of the three possible values into the dataset. Concerning "Temperature", the values represented the temperature measured in the middle of a particular working day. The ranges of the temperatures are adequate for the autumn period when the data were collected and recorded. Finally, "Falls" values are elementary information about the occurrence of any kind of falls.

Although the way the data were recorded is disputable (some subjective judgements and inaccuracies are inevitably present), it was decided to use it for this study as is. The issue is addressed in the discussion section of the paper.

The dataset discussed above was used for the application of the approach presented in Sections 3.1 and 3.2. Firstly, a probabilistic analysis of work efficiency was carried out. From that point of view, it was necessary to present descriptive statistics computed for empirical data. This was performed with regard to the type of element. This division is important from a technical point of view since the formworks assembly works for columns, walls, and slabs (as reinforced concrete structural members) differ.

Table 3 presents descriptive statistics for the efficiency of formworks assembly with regard to the type of element.

Table 3. Descriptive statistics for observed values of efficiency [1].

Element	Min	Mean	Max	Median	Standard Deviation
COLUMN	0.19	1.250	1.81	1.360	0.402
WALL	0.80	1.869	3.18	1.880	0.615
SLAB	0.28	1.728	3.14	1.901	0.721

[1] All values for descriptive statistics are given as [m^2/hour].

The second step involved using the dataset for quantitative analysis by utilising SVM as a machine learning tool.

The results of the applied analysis are presented in Section 4 and discussed in Section 5.

4. Results

Following the assumptions given in Section 3.1, the observed efficiencies were ordered into interval series with respect to the type of element. The results of this operation are presented in the following Tables 4–6. It is noteworthy that the number of intervals k for each type of element was assessed using the following equation:

$$k = 1 + 3.3 \log m \tag{13}$$

where m stands for the number of observations presented in Table 1. The ranges of the intervals resulted from an even division of efficiency value ranges by k (with the lower and upper ends rounded down and up, respectively).

Table 4. Interval series based on observed efficiencies for column formworks assembly works.

Intervals' Ranges [m^2/Hour]	Middle of the Interval [m^2/Hour]	Number of Observations	Accumulated Number of Observations	Share [%]	Accumulated Share [%]
0.10 ÷ 0.40	0.25	2	2	5.405	5.405
0.40 ÷ 0.70	0.55	2	4	5.406	10.811
0.70 ÷ 1.00	0.85	5	9	13.513	24.324
1.00 ÷ 1.30	1.15	6	15	16.216	40.540
1.30 ÷ 0.60	1.45	16	31	43.243	83.783
1.60 ÷ 1.90	1.75	6	37	16.217	100.000

Table 4 shows that for column formworks, the observed values were grouped into six intervals, with a range of 0.3 for each interval.

In the case of wall formwork assembly efficiencies, the observed values were grouped into seven intervals, as shown in Table 5. The range of each interval was 0.37.

Table 6 shows the results for slab formworks, where the observed assembly efficiencies were also grouped into seven intervals. The range of intervals was 0.43.

Table 5. Interval series based on observed efficiencies for wall formworks assembly works.

Intervals' Ranges [m^2/Hour]	Middle of the Interval [m^2/Hour]	Number of Observations	Accumulated Number of Observations	Share [%]	Accumulated Share [%]
0.70 ÷ 1.07	0.885	8	8	15.686	15.686
1.07 ÷ 1.44	1.255	3	11	5.882	21.568
1.44 ÷ 1.81	1.625	10	21	19.608	41.176
1.81 ÷ 2.18	1.995	17	38	33.333	74.509
2.18 ÷ 2.55	2.365	8	46	15.686	90.197
2.55 ÷ 2.93	2.740	0	46	0.000	90.197
2.93 ÷ 3.30	3.115	5	51	9.803	100.00

Table 6. Interval series based on observed efficiencies for slab formworks assembly works.

Intervals' Ranges [m^2/Hour]	Middle of the Interval [m^2/Hour]	Number of Observations	Accumulated Number of Observations	Share [%]	Accumulated Share [%]
0.20 ÷ 0.63	0.415	4	4	6.250	6.250
0.63 ÷ 1.06	0.845	10	14	15.625	21.875
1.06 ÷ 1.49	1.275	7	21	10.938	32.813
1.49 ÷ 1.91	1.700	11	32	17.187	50.000
1.91 ÷ 2.34	2.125	20	52	31.250	81.250
2.34 ÷ 2.77	2.555	8	60	12.500	93.750
2.77 ÷ 3.20	2.985	4	64	6.250	100.000

In the next step, triangular distributions were fitted to the observed efficiencies. Table 7 presents the minimum value a, the peak value m and the maximum peak b values. Moreover, based on Equations (2)–(4), the expected value $E(X)$, median Me and standard deviation σ were computed for the fitted distributions and presented in the table as well.

Table 7. Characteristic values for fitted triangular distributions [1].

Element	a	m	b	$E(X)$	Me	σ
COLUMN	0.100	1.450	1.900	1.150	1.202	0.382
WALL	0.700	1.995	3.300	1.998	1.997	0.531
SLAB	0.200	2.125	3.200	1.842	1.899	0.621

[1] All values given as [m^2/hour].

The fitted distributions are visually depicted in Figures 2–4, where the horizontal axes represent the efficiency of column, wall, and slab formwork assembly, respectively, given in [m^2/hour] (compare with Equation (12) and Tables 4–7). The vertical axes indicate the values of the probability density function $f(x)$, computed using Equation (1) and the parameters a, m, and b from Table 7.

For the efficiencies of column formwork assembly $f(x = m) = 1.11$. From Figure 2 it is evident that the distribution is left-skewed.

In the case of the distribution fitted for wall formwork assembly efficiencies, $f(x = m) = 0.769$. Figure 3 shows that the distribution is almost symmetric.

For slab formwork assembly efficiencies, the value of the fitted distribution function $f(x = m) = 0.667$. Figure 4 shows that the distribution is slightly left-skewed.

Fitting the distributions to the data allowed for further considerations. Based on Equations (1) and (6) and the parameters a, m and b presented in Table 7, the probability of the chance that the efficiency of formwork assembly works would be no less than an assumed critical value x_c was assessed. In Table 8, three hypothetical values of x_c for each of the elements are presented, along with computed probabilities. (It is noteworthy that probability may be computed for any assumed value of x_c that falls into the range $<a; b>$).

With the knowledge of the probabilities, it was also possible to assess the duration of work or total quantity (output). This was performed on the basis of Equations (11) and (12) or their simple transformations. The results of these exemplary calculations are also presented in Table 8.

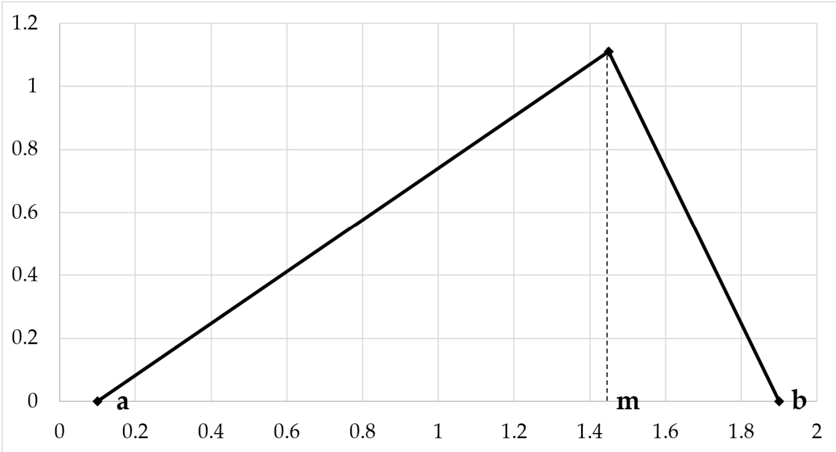

Figure 2. Triangular distribution fitted for column formwork assembly efficiency.

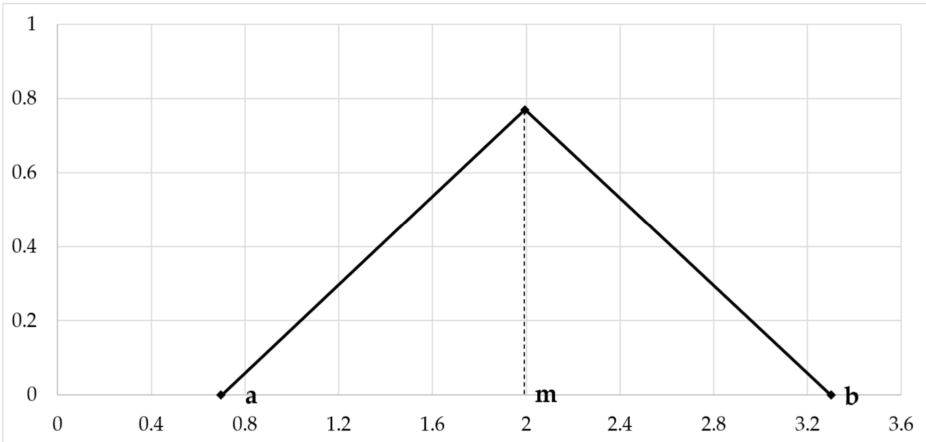

Figure 3. Triangular distribution fitted for wall formwork assembly efficiency.

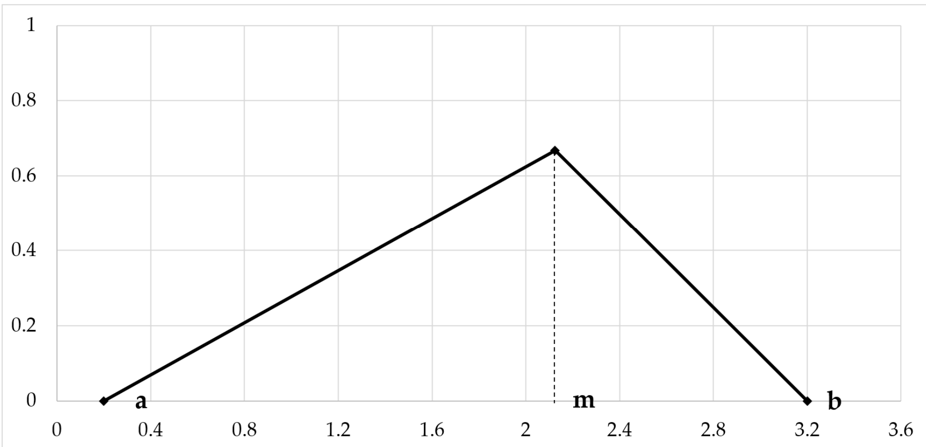

Figure 4. Triangular distribution fitted for slab formwork assembly efficiency.

Table 8. Results of probabilistic analysis for hypothetical critical values of formwork assembly works efficiencies.

Element	x_c	$P(X > x_c)$	Number of Workers	Duration [1] [Hours /Day]	Total Quantity [1] [m^2]
COLUMN	0.8	0.798	2	8 h	12.8 m^2
	1.0	0.667	2	8 h	16 m^2
	1.2	0.502	2	8 h	19.2 m^2
WALL	1.6	0.759	3	8.33 h	40 m^2
	1.8	0.641	3	7.41 h	40 m^2
	2.0	0.498	3	6.67 h	40 m^2
SLAB	1.2	0.827	5	7.5 h	45 m^2
	1.4	0.751	4	9 h	50.4 m^2
	1.6	0.661	3	6.5 h	31.2 m^2

[1] Some of the values were assumed and some computed; the latter are underlined.

The computations, which results are presented in Table 8, were performed based on hypothetical critical efficiencies, x_c, and a given number of workers. Either duration or total quantity had to be assumed in order to compute the other. Similar computations can be carried out for any reasonable and justifiable assumptions about the combination of values describing the number of workers, planned quantity of work, or duration of the task. The assessed probability is an added value for operational planning and day-to-day scheduling purposes.

For the purpose of applying SVM-based classification to a real-life dataset describing formwork assembly works, this study assumed a critical value of $x_c = Me$. Note that *Me* was taken separately for each element type (column, wall, or slab) according to the fitted triangular distributions. It is also important to note that for *Me*, it can be assessed that the probability of achieving an efficiency greater than *Me* is 0.5, and the same probability would be for achieving an efficiency lower than *Me*. Based on these assumptions, all cases in the dataset were labelled as follows:

- A (above the median value) for efficiency > *Me*,
- B (below the median value) for efficiency < *Me*.

Thus, for the purpose of supervised training, two classes, A or B, were defined to represent y_i. It is important to mention that the vector x_i consisted of eight variables, namely "Element", "Level", "Number of workers", "Gang experience and skills", "Duration", "Temperature", "Falls", and "Day of the week", as presented in Table 2. SVM models for classification problem type 1 (Equations (7) and (8)), as well as type 2 (Equations (9) and (10)), were trained using the TIBCO® Statistica™ 13.3 software suite (developed by TIBCO Software Inc. 3307 Hillview Avenue, Palo Alto, CA 94304, USA, distributed by StatSoft Polska Sp. z o.o., 30-110 Cracow, Kraszewskiego 36, Poland).

Before initiating the training, the dataset was randomly divided into training and testing subsets in the ratio of 70% to 30%, respectively. All variable values were automatically scaled for the purpose of SVM training.

The models' parameters were determined using the grid method and 10-fold cross-validation, with a maximum of 2000 epochs for the training process. For the purposes of cross-validation, the dataset was randomly divided into 10 equal-sized subsets. In each fold, a single subset was retained as the validating data, and the remaining 9 subsets were used for training. The cross-validation process was repeated ten times for each point on the grid, which was defined by the lower and upper boundary of parameter values and the step size. The goal was to find the optimal value of the C parameter for the type 1 and ν parameter for the type 2 SVM-based classification. The considered range of parameters, including lower and upper boundary values and the step size, is presented in Table 9.

The considered kernel functions φ included: polynomial, Gaussian radial basis and sigmoid. The best results and performance, however, were obtained in the case of the Gaussian radial basis kernel function implementation.

Table 9. Parameters range considered for SVM-based classification problem.

SVM Based Type of Classification [1]	Parameter	Lower Boundary	Step	Upper Boundary
type 1	C	1	1	10
type 2	ν	0.1	0.1	0.5

[1] With regard to Equations (7)–(8) and (9)–(10).

As a result of the supervised training, two SVM-based models were obtained—one for each of the classification problem types. The models are later referred to as SVMct1 (developed as a result of solving type 1 problem) and SVMct2 (developed as a result of solving type 2 problem). The characteristics of the two models are presented in Table 10.

Table 10. Characteristics of SVM-based classification models.

Model	Parameters	Support Vectors	Bounded Support Vectors	Cross Validation Relevance
SVMct1	$C = 5.0$, $b = 0.9057$	69 (A: 34, B: 35)	52	73.58%
SVMct2	$\nu = 0.3$, $b = 0.2319$	57 (A: 26, B: 31)	16	72.61%

General performance of the obtained SVM-based models in terms of proper classification—either class A or class B is given below:

- model SVMct1: 80.19% for the training subset and 84.78% for a testing subset,
- model SVMct2: 91.51% for the training subset and 84.78% for the testing subset.

Results are also presented in Table 11 in a more detailed way. The table depicts the confusion matrix. Underlined values stand for properly classified cases.

Table 11. Confusion matrix.

Model		Training		Testing	
		A:	B:	A:	B:
SVMct1	A:	<u>42</u>	11	<u>22</u>	3
	B:	10	<u>43</u>	4	<u>17</u>
SVMct2	A:	<u>43</u>	5	<u>26</u>	4
	B:	4	<u>54</u>	3	<u>13</u>

Further classification performance measures were computed based on the confusion matrix and are presented in Table 12. The measures include accuracy of classification for classes A and B, sensitivity for class A, and specificity for class B. The measures are presented separately for the training and testing processes.

Table 12. Performance of classification.

Model		Training		Testing	
	Class	A	B	A	B
SVMct1	accuracy	79.25%	81.13%	88.00%	80.95%
	sensitivity/specificity	80.77%	79.63%	84.62%	85.00%
SVMct2	accuracy	89.58%	93.10%	86.67%	81.25%
	sensitivity/specificity	91.49%	91.53%	89.66%	76.47%

The results of classification are satisfactory. Especially the accuracy of classification in the case of testing, which verifies the performance and ability of knowledge generalisation by the models, was above 80%. This suggests that the models have the ability to generalise and make satisfactory predictions for new cases. (Nonetheless, it is important to note that the models were trained on a specific dataset and may not perform as well on datasets with different characteristics).

The developed SVM models were used to assess work efficiencies for six new cases, which were neither used in the training nor testing processes. The results are presented in Table 13.

Table 13. Application of the for new cases of formworks assembly works.

Element	Level	Number of Workers	Gang Experience and Skills	Duration [Hours /Day]	Temperature [°C]	Falls	Day of the Week	Class Identified by SVM	Expected Total Quantity [m^2]
COLUMN	2	4	AS	9.0	−2	NO	FS	A	Not less than 43.3
COLUMN	1	4	MS	2.5	8	YES	TWT	B	No more than 13.6
WALL	0	3	HS	9	14	NO	M	A	Not less than 47.0
WALL	1	2	MS	10	6	NO	FS	B	No more than 28.0
SLAB	1	3	AS	9	11	NO	M	A	Not less than 51.3
SLAB	2	4	AS	10	−1	YES	TWT	B	No more than 76.0

Table 13 presents the classification for the new cases. It must be pointed out that some values were planned (specifically: Element, Level, Number of workers, Gang experience and skills, Duration, and Day of the week), and some had to be forecasted as there is no influence on their actual values (namely: Temperature and Falls). For the new cases as presented in the table, either class A or B was recognised by the developed models. (It is noteworthy that classification results were consistent between the two models, that is, SVMct1 and SVMct2, for the new case.) Classes identified by SVM models for each new case are presented in the relevant column. The classification was followed by a qualitative assessment of the daily output of formworks assembly. The results of this step of analysis are given in the column "Expected total quantity" in m2 of assembled formworks.

Based on the results presented in Table 13, the developed SVM models were able to accurately classify the new cases and allowed for the assessment of work duration or output. Overall, the SVM models demonstrated their usefulness for predicting the efficiency of formworks assembly based on various input factors.

5. Discussion

The possibility of practical application of the proposed approach for the purposes of construction works efficiency analyses depends on the available data. Data collection remains on the contractor's side as the most interested party, which, in turn, usually means an additional effort and, inevitably, cost. However, the effort put in may be counterbalanced by benefits in terms of better insight and understanding of construction works efficiency and knowledge of the issue.

The study presented herein did not have an influence on the data collection process. There was no chance to decide what kind of data were collected, in what way and how relevant information was recorded. The data were used as is. The problem of collecting and recording efficiency-related data and information, however, is interesting in itself, particularly given the development of tools and technologies capable of automatically recording information on a construction site. Although this is not the main focus of this particular research, some works and their results are worth mentioning. For example, there is the use of the Global Positioning System (GPS) for the spatiotemporal recording of construction equipment location and timestamps [57], combining several tools, such as external cloud computing servers, access points, monitoring bands, smartphones, beacons, and radio-frequency identification devices into a system for monitoring construction workers on a site [58], the application of Bluetooth Low Energy (BLE) technology for tracking and collecting data for production control in construction projects [59], and a review and comprehensive discussion of the best practices in unoccupied airborne systems (UAS) aerial imagery collection and processing for construction research, including tasks, such as preconstruction planning, material tracking, project progress tracking, safety, as-built documentation, and building/structure inspection [60].

When it comes to efficiency modelling, the relevant literature review revealed that in studies reported from different countries, some of the factors that play a role as efficiency drivers are common; however, some of them result from regional conditions. Moreover, the scope of data, specifically the types of considered efficiency drivers, is also influenced by the type of construction work or the type of construction project.

For the purpose of the quantitative-probabilistic approach, the triangular distribution appears to be a reasonable choice. While the beta distribution was originally proposed for a similar problem, i.e., the probabilistic analysis of construction work durations in the case of the PERT method, the triangular distribution is simpler and easier to apply for the specific problem of formwork assembly works. However, a limitation of the study is that the results of the applied probabilistic analysis are dependent on the data, and the fitted distributions presented in this paper are specific to the analysed cases of formwork assembly works and the project.

For the qualitative approach and classification problem, SVM is proposed as a machine learning tool. When compared to previously published research, most of which focused on solving regression problems, ANN seemed to be the most frequent choice. However, the selection of SVM for this study is justified by its capabilities, number of training data, and applicability for classification problems. The limitations of the application results are, again, a consequence of the use of particular data. It is worth noting that the study focused on recognising only two classes of efficiency, which is a limitation. In the future, if a large enough dataset including real-life efficiency-related information is available, it is planned to investigate the possibility of recognising at least three classes covering low, moderate, and high efficiencies. Additionally, the use of other machine-learning tools will also be explored.

The proposed approach has limitations, and its results are data-dependent. However, if applied to similar types of construction works with efficiency-related data, it can be useful for operational analysis and day-to-day planning of formworks assembly. It can also be used for short-term control of construction progress. Moreover, if data from a specific construction company are processed, this approach can serve as a basis for setting efficiency standards within the company.

6. Summary and Conclusions

The paper presents an approach for analysing the efficiency of construction works. The approach involves using triangular distribution for quantitative probabilistic analysis, followed by qualitative analysis using a support vector machine (SVM) as a machine learning tool to classify cases of construction works execution based on their assumed critical efficiency.

This is followed by an application of this approach to real-life data analysis, namely formworks assembly works recorded on a construction site. The outcome of this analysis was the fitting of triangular distributions for column formworks assembly, wall formworks assembly, and slab formworks assembly. Considering each of these element types separately, specific distribution parameters were computed. This makes it possible to conduct probabilistic analyses of construction works efficiencies, planned daily durations, and planned daily output of works.

The research also aimed to explore the application of the SVM method as a tool for processing efficiency-related data. The study addressed the classification problem in terms of recognising whether certain circumstances, features, and characteristics of formworks assembly works allow for achieving efficiency greater than or lower than median values. The accuracy of classification was found to be satisfactory, with over 80% accuracy for both developed models based on C-classification (type 1) and ν-classification (type 2).

The results of the analysis were obtained using data that were collected for a specific construction project, a particular type of construction work, and recorded in certain circumstances. Despite these limitations, the results of the study were satisfactory, and it can be concluded that the proposed approach has positive applicative potential. Furthermore, the results suggest that more advanced analyses could be conducted if more extensive and informative data were available.

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