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Scheduling Optimization Using an Adapted Genetic Algorithm with Due Regard for Random Project Interruptions

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Abstract: Current socio-economic conditions impose certain requirements on construction and renovation projects that need new methods making evaluations of construction work performance schedules more reliable. Towards this end, the authors propose a consolidated methodology of construction work scheduling based on the interval estimation technique. The boundaries of the interval, as well as determining minimum and maximum construction time, are obtained by minimizing and maximizing the term of construction work performance by introducing random interruptions into successions of critical and subcritical works. Such reasons for interruptions as the failure of key construction machines, unavailability of labor resources, and accidental man-induced or natural impacts are considered. Risk calculations are employed to devise an approach to evaluating the reliability of construction schedules, including minor schedules designated for single-facility projects and major schedules developed for projects that encompass the construction of groups of buildings and structures. Projects on construction of monolithic reinforced concrete frames of buildings were used to verify the efficiency of the proposed approaches to work performance scheduling.

Keywords: optimization; construction time; scheduling; reliability; random term extension factors; project interruptions; evolutionary modelling

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1. Introduction

1.1. Review of the Literature

Construction project scheduling is highly relevant. It is known from the author's experience that the following aspects of schedule modeling are vital for practical construction undertakings: predicting the total time required to construct a facility or perform individual items of construction work; determining the extent of correctness of process control solutions made in terms of the entire project and individual stages of construction; determining the risks of emergency situations that may occur due to the failure to meet work performance deadlines and emergence of various interruptions neglected in the course of modeling.

Currently used deterministic approaches cannot prognosticate work performance duration as they neglect a number of random factors, such as: the failure of construction machinery or equipment due to breakdowns; the idle time of construction machinery and personnel due to the late delivery of material and technical resources, including structures, to the construction site for their subsequent assembly and installation; deviations from the construction schedule due to the absence of key construction workers or engineering personnel from their workplaces; interruptions caused by a change in the project work start and completion dates; force majeure situations caused by climatic conditions or other external factors.

Work [1] addresses the influence of delays, caused by the distribution of resources in the process of scheduling, on the cost of construction. It is emphasized that such delays can substantially increase the cost of work items, including those that are not on the critical path.

An optimization model is developed in furtherance of these research undertakings [2,3]; this model minimizes construction costs with account taken of repetitive work items and the number of interruptions. According to [4], such a variable as construction duration influences the whole scheduling process, and it can greatly change the effect of management. Approaches, based on the probabilistic analysis of scheduling efficiency, evolve in the field of maintenance of a natural gas distribution system, addressed in ref. [5]. The notion of the high risk of undesired events is introduced, and their probability is identified using Bayesian Network (BN). Development of scheduling methods, applied to information modelling technologies, is addressed in [6–9]. Article [6] takes account of scheduling time, resources, and space. However, several random factors are not considered in this article. One of the practice-oriented approaches to scheduling is a model that allows revising the schedule depending on the situation on site [7], in particular, on the actual productivity of machines and teams of construction workers. However, this model may be insufficiently effective since it cannot take onsite safety into full account. Safety is considered in several works, including ref. [7]. There, and also in refs. [9,10], safety is improved by introducing a BIM-based occupational accident risk assessment instrument (4D). A number of works take account of random factors in the process of scheduling. For example, authors of article [9] draw attention to poor labour productivity, inadequate equipment, and poor weather. A dynamic model is used to identify construction duration. This article and works [11,12] take account of these factors to schedule construction work for the case of prefab construction projects. A large number of studies address risk management in the process of scheduling. Hence, authors of article [13] propose an improved construction risk prognostication system, developed on the basis of the Bayesian Network. However, in absence of observation data, the Monte Carlo method is employed in the course of risk analysis. Machine learning is used as an alternative to this approach [14–16]. Some works also focus on scheduling optimization with account taken of projected construction delays [17,18] that occur in the process of implementation of major construction projects. For example, authors of article [19] address the employment of genetic algorithms to optimize the scheduling of repetitive projects using the criterion of investor profit maximization. They have proven that optimal schedule options are problematic to generate using traditional scheduling techniques. A number of studies [20–22] employ meta-heuristic search strategies to optimize project durations with account taken of work interruptions due to the growing complexity of construction projects to be scheduled. In some cases, this process is a complex scientific and practical task. The usefulness of fuzzy logic, applied to such problems, is demonstrated in review article [23]. Some studies, for example refs. [24,25], consider the use of smart management systems in mining and power consumption industries. However, these systems are also applicable to construction projects. Besides scheduling techniques, these systems have risk prognostication components, data on spatial topological characteristics and facility operation. Several works [26–29] address the dynamic nature of construction processes; they entail the use of multi-criterial optimization to solve scheduling problems. Towards this end, such important factors as the presence of risks and uncertainty [30], delayed commencement, completion of works, and repetitiveness of processes in construction projects are considered.

The research, addressed in ref. [31], identifies ten principal reasons for such delays, including the importance of the construction project location. The authors of articles [32,33] propose solutions to specific construction scheduling tasks, in which the logistics of inventory routing and reliability of suppliers are the important factors that influence successful schedule implementation. This problem may cause work disruptions in the course of the prefab construction of buildings [11,12]. Digital risk management models, solving the problem of poor-quality joints, including welds, were developed. Schedule robustness to changes, triggered by random factors, is another vital aspect of scheduling [34,35]. Two principles must be implemented to improve schedule robustness: continuous resource flows and continuous work performance. Statistical control over labour productivity, coupled with higher levels of construction process automation, is another approach to schedule robustness and reliability assurance [36,37]. Transport schedule optimization procedures may be applied in the course of construction work performance or resource delivery to improve management efficiency [38,39]. Implementation of artificial intelligence methods in project management is a prospective scheduling trend [15,16]; in particular, machine learning algorithms can be applied to generate a consolidated knowledge base that has information about a construction project and its environment (labour and material resources, weather conditions). These systems need a computational tool that uses accurate data on previous construction experience [40,41]. Some authors study the influence of hazardous emissions from urban construction projects on the environmental condition of built-up areas [42]. Other researchers focus on the management of climate risks in the countries that have large seasonal temperature differences [43]. Several teams of scientists study decision making systems based on the video monitoring of work performance and condition of construction machinery [44].

Issues of work scheduling are effectively solved by genetic algorithms applied to new construction and renovation projects. These algorithms are applicable to civil engineering projects [45] and construction of linear infrastructure facilities [46]. Hence, Pareto-frontier sorting is used to obtain a solution based on several optimality criteria [47]. In genetic search, three main criteria are frequently applied, such as the time, cost, and quality of a project [48,49]. Other studies [50,51] address optimization problems and scheduling options for cases of limited resources. To solve multi-criterial optimization problems, combinations of genetic algorithms and individual functions based on the pre-set properties of work schedules are applied. Specific tasks, solved by genetic algorithms, address the allocation of resources. These are labor resources distributed with due regard to multi-site and multi-project development [52], as well as consumers of power and investments [50]. The works [53,54], considering risks and safety aspects of scheduling, are most relevant to the topic of the present article. These risks could be attributed to delays in deliveries [53] and emergency situations [54]. In these and similar studies, random factors are viewed as deterministic values. The distinction between this article and similar works is that interruptions in scheduled projects are presented as random variables and pre-defined discrete sets.

1.2. Purpose, Objective and Summary of the Study Outlined in This Article

Since all random factors cannot be accounted for at the stage of deterministic scheduling of large-scale projects, comprising several facilities and individual buildings, the authors offer alternative optimality criteria for construction schedule modeling.

The purpose of the present study is to develop a method which will allow optimal schedules based on the reliability of the process organization and technologies. This option has minimum and maximum duration. The duration is minimum if few or no random factors emerge during the construction process, and the duration is maximum if random factors are numerous and trigger long delays. At the same time, deviations related to the unavailability or failure of labor resources, construction machines, and poor climate conditions can be taken into account in the course of a single scheduling effort.

To achieve the pre-set objective, one should solve the problem of choosing the option of work schedules that might comprise both various work sequences and random interruptions belonging to each of the three abovementioned types. To solve this problem, a new heuristic search algorithm is applied on the basis of evolutionary modelling. It differs from those currently used by the availability of a function allowing single and multiple work schedules for large-scale construction projects at minimum risk. The problem statement is provided in Section 2.1.1. The formulas for calculating the cost of risks that might emerge in the event of deviations from the schedule (Section 2.1.3) are outlined for interruptions of three types. Then, being aware of the risk values for specific types of work, one can assess the reliability of their performance (Section 2.1.4). The emergence of random factors is interpreted as an interruption that consumes time rather than resources (Section 2.1.5). In Section 2.2, the application of the genetic search procedure, based on the use of parallel evolving populations, is described. This approach differs greatly from other methods applied to scheduling. Gant's diagrams are provided in Section 3 as cases of schedules. Cases of interval estimation of work duration are provided together with the reliability evaluation of construction work sequence and evaluation of risks of deviations from schedules.

The scientific novelty of the authors' approach consists in its ability to take account of random interruptions of various types in the course of a single process based on the mechanism of parallel evolving populations. This approach allows for saving resources, reducing scheduling costs, prognosticating delays, and maximum work performance time.

2. Materials and Methods

2.1. Scheduling Optimization Problem Formulation

2.1.1. General Provisions

To solve the problem of schedule modeling means to make a list of work items to be performed and assign the performance time to each of them. The labor intensity, determined in the standards or a directive, can be applied to find the work performance time. Labor, material, and technical resources should be assigned to each work item. To estimate the reliability of work performance, alternative patterns of their precedence/sequence should be developed in accordance with the approved construction technology. Discrete sets of values denoting interruptions, caused by man-induced and machinery-related reasons, should be made as input data designated for random process modelling. These sets are made on the basis of observations over real construction work in progress. They can be represented as follows:

$$T_{ex}^{(X)} = \{0, t_1, \ldots, t_y\}, \tag{1}$$

where $T_{ex}^{(X)}$ is the set of interruption values; 0, t_1, t_y are durations of onsite work performance interruptions, days; $(X), y$ is the interruption type identifier. Hence, zero means no interruption or delay.

2.1.2. Formulation of Goal Optimization Criteria

An optimal schedule has integral relative risk $\overline{R}(p)$ that slightly differs from some admissible value $[R]$, ensuring safe and timely work performance. A set X in Formula (1) can be represented as

$$X = \{w,\ m,\ c\} \tag{2}$$

Notably, in the general case, work can be performed for N facilities using M concurrent work performance patterns, each of which can include L work items with zero slacks or critical path work items. Relative risks are associated with failures caused by various factors, and the main ones are w—workforce, m—construction machines and mechanisms, c—climate conditions and other external force majeure events.

Another optimality criterion is minimization of construction time T_{constr}, with regard for its interval estimation in the case of the minimum difference between its maximum $T_{\max}$ and minimum $T_{\min}$ time values. The final optimality criterion is minimization of any interruptions in the process of construction.

Thus, to implement construction projects, including large-scale ones, a general system of criteria for optimal computer-aided scheduling in the probabilistic formulation is developed:

$$\begin{cases} (T_{constr} = [T_{\min}, T_{\max}] \to \min) \wedge ((\overline{R}(T_{\max}) - \overline{R}(T_{\min})) \to \min), \\ T_{\max} = \max\limits_{L}\left(\sum t_q + \max\limits_{q}(T^{(w)}_{ex,q}, T^{(m)}_{ex,q}, T^{(c)}_{ex,q})\right); \\ T_{\min} = \min\limits_{L}\left(\sum t_q + \min\limits_{q}(T^{(w)}_{ex,q}, T^{(m)}_{ex,q}, T^{(c)}_{ex,q})\right); \\ \sum\limits_{i=1}^{N}\sum\limits_{j=1}^{M}\sum\limits_{k=1}^{L}\left(T^{(w)}_{ex,ijk} + T^{(m)}_{ex,ijk} + T^{(c)}_{ex,ijk}\right) \to \min; \\ \overline{R}(T) = \sum\limits_{i=1}^{N}\sum\limits_{j=1}^{M}\sum\limits_{k=1}^{L}\left(\begin{array}{l} p^{(w)}_{ijk}U^{(w)}_{ijk}/C^{(w)}_{ijk} + p^{(m)}_{ijk}U^{(m)}_{ijk}/C^{(m)}_{ijk} + \\ +\chi(C)p^{(c)}_{ijk}U^{(c)}_{ijk}/C^{(c)}_{ijk} \end{array}\right) \to [R]. \end{cases} \quad (3)$$

Here, $p^{(w)}_{ijk}$ is the probability of consequences of workforce unavailability (factor w) for work k, which is part of the critical path of a model that has technology j implemented at facility i; $U^{(w)}_{ijk}$ is the cost of damage caused by workforce unavailability; $C^{(w)}_{ijk}$ is the total cost of material resources used and workforce involved for the purpose of complete work performance; $\chi(C)$ is the Heaviside function for value $C = \{0;1\}$, showing the need to consider factor c; q is the number of the critical path.

As a result of analysis of Formula (3) and minimization of all interruptions to zero, $T_{constr} = T_{\min} = T_{\max} = const$ is obtained. Hence, the scheduling model becomes deterministic. In this case, one can solve a simpler task of assessing the reliability of engineering solutions for each of options j by solving task $\overline{R}(T) \to [R]$ for one or several (all) factors X. A solution to this problem is considered further in the article.

The general solution to the optimization problem is shown in Figure 1. It is based on system of the Equation (3). N, M values, shown here, are the numbers of possible optimal schedules, having identical or similar durations. These numbers are not the input data; they are not adjustable in the optimization algorithm. They depend on the results, generated by genetic operators, the number of possible interruptions, and the number of values in sets made for these interruptions.

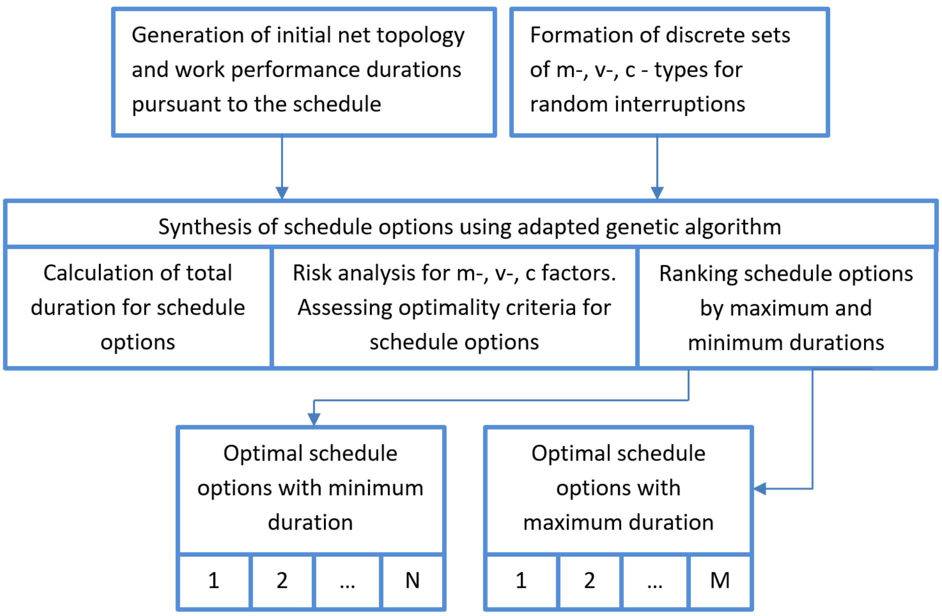
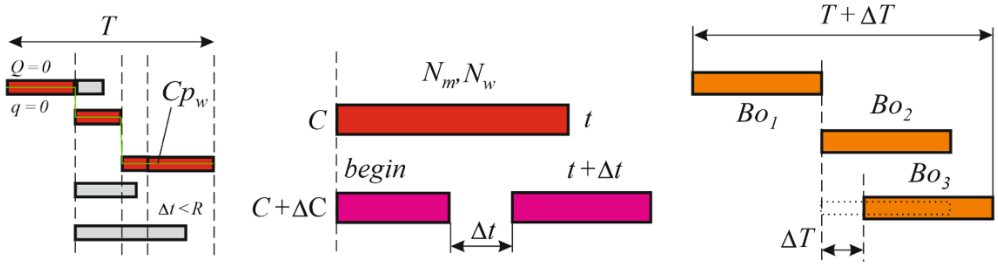


Figure 1. The block diagram describing the search for solutions applicable to a construction schedule with account taken of random factors.

2.1.3. The Estimated Cost of Risks, Associated with Failure to Meet Scheduled Deadlines

The failure to meet the scheduled deadlines is assumed for critical path Cp_w (Figure 2a). This failure may occur in the process of work performance at a construction facility (Figure 2b), and in the course of construction of several facilities that represent a consolidated construction project (Figure 2c).



(**a**) (**b**) (**c**)

Figure 2. Construction work scheduling options: (**a**) a single schedule; Cp_w is the critical path for a schedule model that has no interruptions; T is the time of this critical path; Q, q_0 are general and specific slacks in the course of work performance; (**b**) simulation of interruptions in the process of work performance, included in the critical path; (**c**) construction of several facilities; $Bo_1 - Bo_3$ are durations of facility construction, ΔT is simulation of process interruptions.

If there is virtual interruption Δt, the value of the absolute risk of failure to perform the work can be calculated as a virtual penalty:

$$R = p\Delta C(t + \Delta t), \quad (4)$$

where p is the probability of unavailability of a resource or an emergency situation; ΔC is a virtual penalty per unit of time, for example, per work shift, and t is the basic scheduled time of work performance.

If emergencies, related to factor c, are considered improbable, then the probability of failure $p(w, m)$ is calculated by assuming that the availability of resources in the course of work performance is subject to the normal law of distribution. In this case, dependencies for its identification can be written as follows:

$$p(w, m) = 0.5 - \Phi(\beta);\ \beta = \frac{(N_m + N_w)\Delta t}{t\sqrt{S^2(N_m) + S^2(N_w)}}, \quad (5)$$

where $\Phi(\cdot)$ is the value of the Laplace integral; $S(\cdot)$ is standard deviation; N_m is the number of machines and mechanisms used; N_w is the number of construction workers involved in the work performance. The value of the standard is determined using general formulas of mathematical statistics and workforce performance.

As for the emergency situation, the probability of failure can be based on government reports. If these data are not provided, it can be assumed that $p(c) = 0.5$. Then the total probability of failure and the risk of material damage can be calculated as follows:

$$p = p(m, w) \cdot p(c), R = p(C_{bo} + \Delta T \Delta C), \quad (6)$$

where C_{bo} is the cost of a construction facility lost as a result of an emergency situation and ΔT is the interruption caused by delays in the liquidation of consequences of an emergency situation.

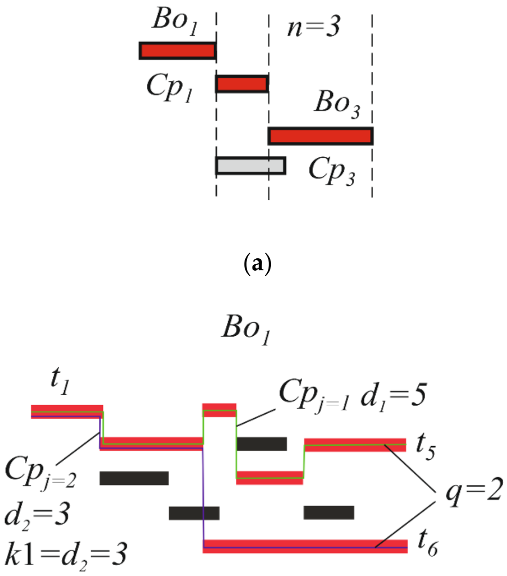
2.1.4. Evaluation of Reliability of Organizational and Technological Solutions

Let's analyze a schedule model developed for one construction facility i, $i = 1 \ldots n$. This model can have several critical paths Cp represented by discrete sets of work, having performance time t. Let's assume that each of these types of work is subject to virtual interruption $\Delta t = 1$ s. Then, each type of work will get a virtual penalty calculated using Formula (4). The minimal total penalty, imposed on critical path works, will indicate the most reliable sequence of works. If the project has several schedule models, summation should be carried out according to the "critical" sequence of facilities construction. In terms of mathematics, this problem can be written as follows:

$$\begin{gathered}\left(\sum_{k1} R(Cp)_1 + \sum_{k2} R(Cp)_2 +, \ldots, + \sum_{kn} R(Cp)_n\right) \rightarrow \min, \\ R(Cp)_1 = \{R(t_1), \ldots, R(t_{k1})\} = \min\left\{\sum_{dj} R(Cp)_j\right\}, Cp_j = \left\{t_1, \ldots, t_{dj}\right\},\end{gathered} \tag{7}$$

where n is the number of schedule models (the number of construction facilities); $k1 - kn$ is the number of work items within the critical path that has minimum risk for this schedule model; q is the number of critical paths in the schedule model; $j = 1 \ldots q$, dj is the number of work items within critical path j.

An individual case of dependencies used to calculate the risk disregarding factor c is shown in Figure 3c as an explanation of Formula (7).



$$R(Cp)_1 = \min\left\{\sum_5 R(Cp)_{j=1}; \sum_3 R(Cp)_{j=2}\right\}$$

$$= \sum_3 R(Cp)_{j=2}; (Cp)_{j=1} = \left\{t_1, t_2, t_3, t_4, t_5\right\};$$

$$(Cp)_{j=2} = \left\{t_1, t_2, t_6\right\}; \sum_3 R(Cp)_{j=2} = R(t_1)$$

$$+R(t_2) + R(t_6); R(t_1) = p_1 \Delta C \cdot (t_1 + \Delta t);$$

$$p_1 = p(w, m) = 0.5 - \Phi(\beta_1);$$

$$\beta_1 = \frac{\left(N_{m1} + N_{w1}\right)\Delta t}{t\sqrt{S^2(N_{m1}) + S^2(N_{w1})}};$$

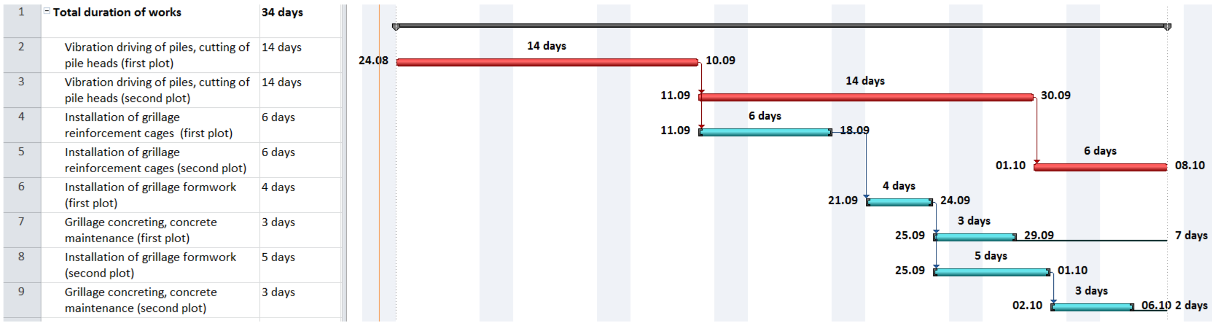
$$\sum_{k1} R(Cp)_1 = \sum_3 R(Cp)_{j=2}$$

(c)

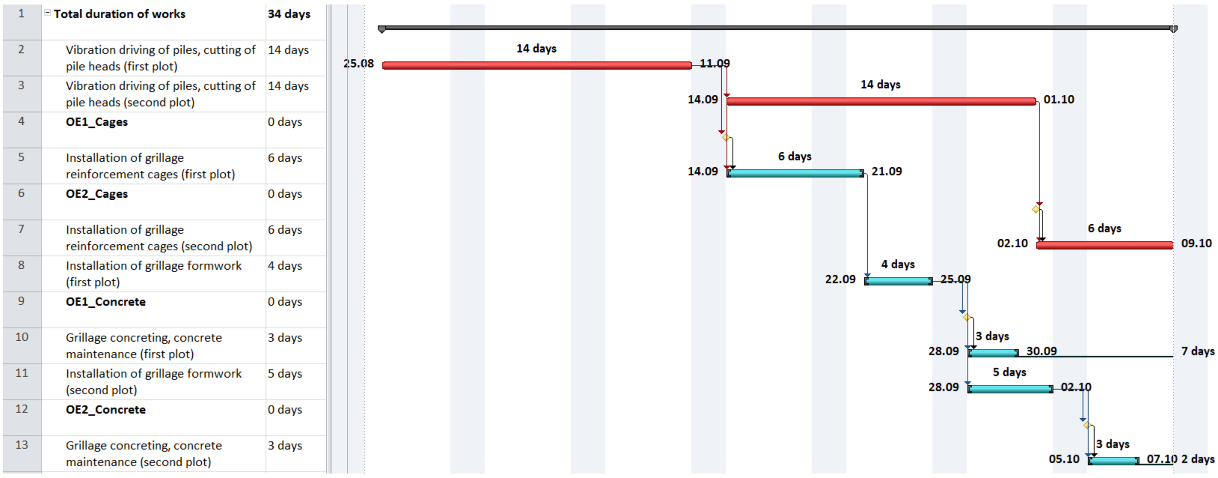
Figure 3. A case of variables taken from Equation (6) used to simulate three facilities (**a**), if the schedule of the first facility has two critical paths (**b**), results of using Formula (7) for the schedule in (**c**).

2.1.5. Modeling the Introduction of Random Interruptions into the Schedule

Each interruption, represented by the set of values $t_1, \ldots, t_y$ (1), is simulated in a work schedule as work that needs no resources. Figure 4a shows the basic part of a schedule where interruptions can be introduced. The number of such interruptions is predicted on the basis of past experience. The point of introduction of interruptions is associated with factors of resource supply to the construction site, unavailability of a workforce capable of performing complex items of work, relocation of construction machines, etc. The introduction of interruptions OE1_, OE2_ is shown in Figure 4b. The absence of interruptions is simulated as work that takes no time. If values of interruptions are set randomly, both changes in the total time of work in Figure 4c, and the composition of critical path works can be obtained. Therefore, reliability evaluation of organizational and technological solutions, considered in Section 2.1.4, is performed if critical path works remain unchanged.



(**a**)



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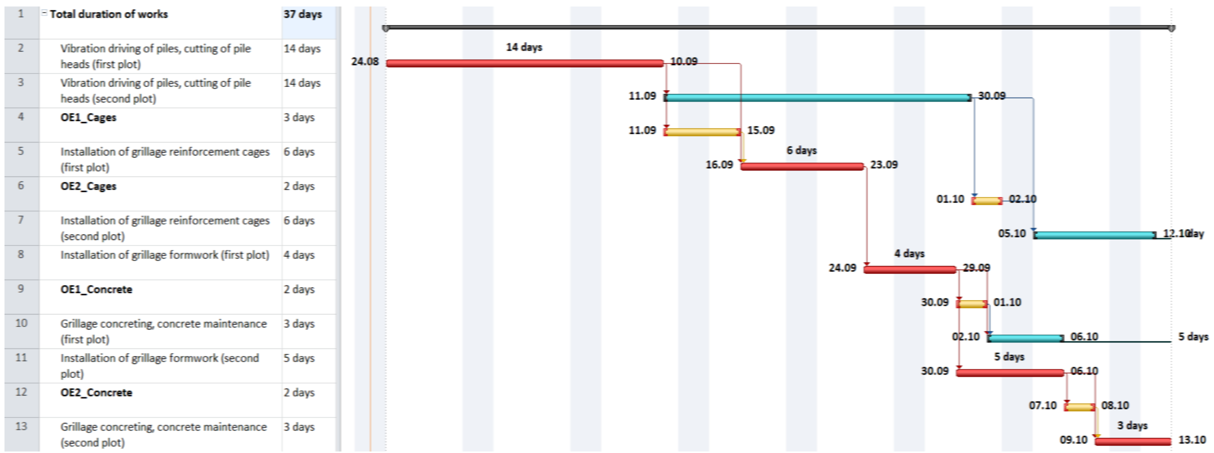

(**c**)

Figure 4. Options of a schedule model that has interruptions: critical path work is in red, normal work that has slacks is in blue, and interruptions are in yellow; schedule without interruptions (**a**), introducing into schedule the fictitious interruptions with zero durations (**b**), schedule variant with non-zero durations of interruptions (**c**).

The schedule model is a matrix. The first matrix has numbers, names, and work performance time. The second matrix has precedence/sequence identifiers; the third matrix has types and identifiers of resources linked to work items. If one work item is performed in several locations, each part of the work item and its location is represented as a separate work item in the schedule.

2.2. The Optimal Schedule Option: The Search Algorithm

For projects comprising several facilities, performance of hundreds and even thousands of work items can be scheduled. Experience has shown that dozens of various random factors can emerge in the process of construction. Therefore, consideration of all factors in the classical deterministic setting is viewed as a very labor-consuming process, because it requires the analysis of a large number of work schedules (millions of options). Hence, no enumeration of schedule options can be used to choose the optimal one that would minimize the work time and ensure maximum reliability. The solution is to apply metaheuristic search methods based on the particle swarm method and genetic algorithms.

The problem is decomposed (3), and construction time is minimized and maximized.

$$\begin{aligned} T_{\max} &= \max_L \left(\sum t_q + \left\{ T^{(w)}_{ex,q} \right\} + \left\{ T^{(m)}_{ex,q} \right\} + \left\{ T^{(m)}_{ex,q} \right\} \right) \to \max, \\ T_{\min} &= \min_L \left(\sum t_q + \left\{ T^{(w)}_{ex,q} \right\} + \left\{ T^{(m)}_{ex,q} \right\} + \left\{ T^{(m)}_{ex,q} \right\} \right) \to \min. \end{aligned} \tag{8}$$

A set of schedule options is employed to solve this problem using evolutionary modeling. Let's consider the basic concepts in the context of the pre-set objectives. For example, let's take variable A_i that will denote the work schedules shown in Figure 3b or Figure 3c. The finite set of work schedule options $\mathit{\Pi} = \{A_1, \ldots A_{Ng}\}$ is considered during each iteration of the genetic algorithm; Ng is the number of options. The population isolation algorithm is used [55] to solve the problem in question (7), and 2 sets of work schedules (2 populations each) are employed to implement problem minimization and maximization. Then, the mathematical description of discrete sets used to solve the minimization problem is considered. These sets will be the same when the minimization problem is solved. Let's introduce the following data structures:

$$\begin{gathered} \mathit{\Pi}_A = \begin{cases} A_1 = \{t_{11}, \ldots, t_{1n}\} + \left\{ T^{(X)}_{ex,q1} \right\} \\ \ldots \\ A_{Ng} = \{t_{Ng1}, \ldots, t_{Ngn}\} + \left\{ T^{(X)}_{ex,qNg} \right\} \end{cases} ; \\ \mathit{\Pi}_B = \begin{cases} \widetilde{A}_1 = \{\widetilde{t}\}_1 + \left\{ \widetilde{T}^{(X)}_{ex,q1} \right\} \\ \ldots \\ \widetilde{A}_{Ng} = \{\widetilde{t}\}_{Ng} + \left\{ \widetilde{T}^{(X)}_{ex,qNg} \right\} \end{cases} , \end{gathered} \tag{9}$$

where $\mathit{\Pi}_A$ is the current set of solutions, in which genetic operators are implemented and schedule options are randomly generated; $\mathit{\Pi}_B$ is the elite set containing the best options of work schedules.

A search for solutions, launched for each group of populations, demonstrating parallel evolution, has the following basic steps:

1. The basic (deterministic) topology of (i) a schedule model and (ii) a set of interruption values related to a set of emergence factors X, is developed.
2. During the first iteration, a set of schedules $\mathit{\Pi}_A$ is made randomly by selecting values of interruptions from the sets $\left\{ \widetilde{T}^{(X)}_{ex,q} \right\}$ and assigning them to the work items where they can emerge. The set of best schedule options is not completed yet: $\mathit{\Pi}_B = \varnothing$.
3. Timing is computed for each schedule.
4. Then the iterative process is launched in which the current extreme value of time T_0 is found for each schedule option. After that conditions are verified:

$$\begin{gathered} \varphi(A_i) = (T_0 - T(A_i)) \geq 0,\ T_0 \to \min;\ i = 1 \ldots Ng; \\ \varphi(A_i) = (T_0 - T(A_i)) \leq 0,\ T_0 \to \max \end{gathered} \tag{10}$$

5. If condition (7) is not met, schedule option A_i is replaced by a new one:

$$\begin{cases} \Pi_B = \varnothing, \rightarrow A_i = \{t_{i1}, \ldots, t_{in}\} + \left\{rnd\left(T^{(X)}_{ex,qi}\right)\right\}; \\ \Pi_B \neg \varnothing, \rightarrow A_i = \widetilde{A}_{rnd(i)} \in \Pi_B, \end{cases} \quad (11)$$

where $rnd(\,)$ is a random choice operator.

6. Set Π_B is edited to save the best solution that meets the optimality criterion. For this purpose, the elitism strategy is used, which can be formulated as follows:

$$\begin{cases} (\forall A_i \in \Pi_A) \exists A_i \notin \Pi_B \\ T(\forall A_i \in \Pi_A) \leq T(\forall \widetilde{A}_i \in \Pi_B) \end{cases} \Rightarrow \widetilde{A}_i \in \Pi_B = A_i \in \Pi_A. \quad (12)$$

7. Genetic operators of adjustable multipoint mutation [56] are applied to set Π_A.
8. The computation stopping criterion is verified. The criterion, empirically derived from a solution to a number of optimization problems related to genetic algorithms, is used. Iterations stop after number N_{opt} if there are no changes in set Π_B. This number can be identified as follows:

$$N_{opt} = round\left(\sqrt[n_{GA}/3]{m_{GA} n_{GA}!}\right) \quad (13)$$

where n_{GA} is the number of variable parameters, taken as being equal to the number of interruptions introduced into the schedule model; m_{GA} is the average number of values of variable parameters, $round\,(\,)$ is the operator used to ensure rounding to the whole number.

If the stopping criterion is not met, the iteration process continues and steps 3–8 are executed once again. When implementing the genetic algorithm, work schedules having the same duration $T_{\max}$, $T_{\min}$, but a different set of critical path works may emerge, and in this case, selection of the optimal work schedule should be made using Equations (3) and (4) of system (2) or according to Section 2.1.4 depending on the required level of reliability and safety of construction work.

3. Results

3.1. Characteristic Case of Interval Estimation of Construction Time

The topology of the schedule, shown in Figure 4a, is addressed to illustrate the effectiveness of the proposed methodology. Sets of interruption values are used as input data, days:

$$\begin{aligned} OE1\_Cages = OE2\_Cages = \{0,\ 1,\ 2,\ 3,\ 4,\ 5,\ 6\}; \\ OE1\_Concrete = OE2\_Concrete = \{0,\ 1,\ 2,\ 3,\ 4,\ 5,\ 6\}. \end{aligned} \quad (14)$$

when sets Π_A, Π_B were made, each genetic algorithm considered 20 interruptions. The iteration process had 150 iterations, with no changes in database Π_B during 42 iterations. As a result, several options of the work schedule, that was $T_{\min} = 34$ days long (one of these options is shown in Figure 5 and one option that was $T_{\max} = 44$ days long (Figure 6), were obtained. Results of the optimal selection of interruptions are presented in Table 1.

The analysis of resulting schedules allows for an interval estimation of construction time; in this case $T = [34; 44]$ days with a potential emergence of interruptions caused by the late delivery of concrete and reinforcement bars.

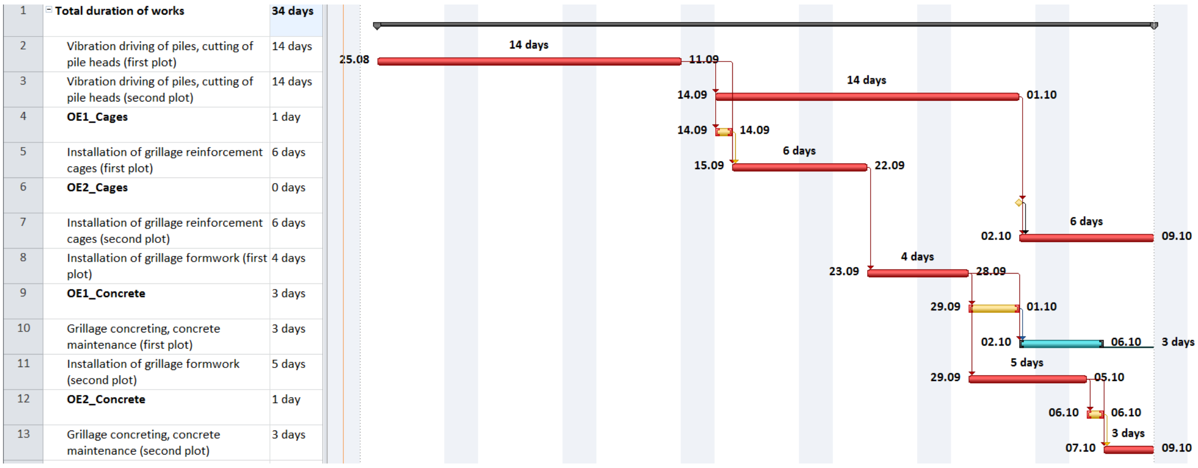

Figure 5. The work schedule option that is 34 days long.

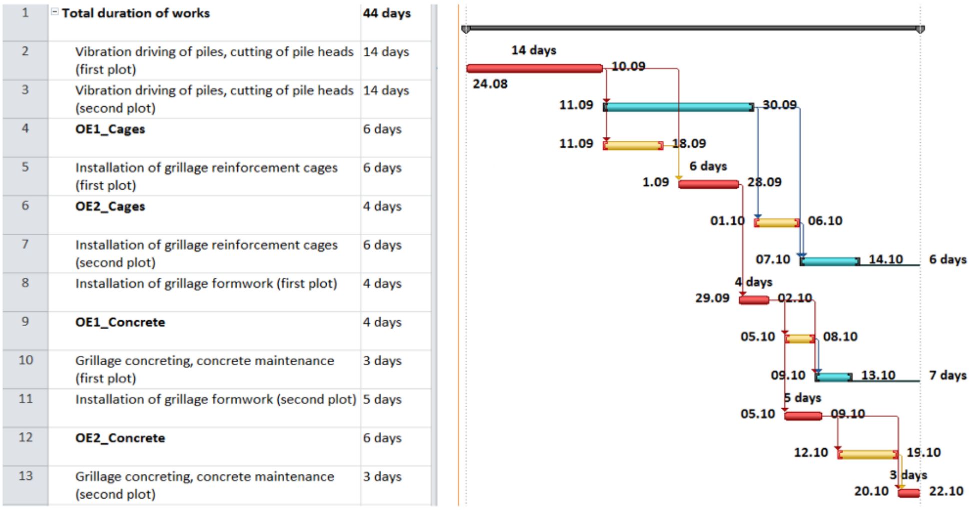

Figure 6. A 44-days' schedule option.

Table 1. Optimal schedules.

Schedules	Interruptions, Days			
Criterion	*OE1_Cages*	*OE2_Cages*	*OE1_Concrete*	*OE2_Concrete*
No. 1. $T \rightarrow \min$	0	0	0, 1, 2, 3, 4, 5, 6 *	2
No. 2. $T \rightarrow \min$	1	0	0, 1, 2, 3, 4, 5, 6	1 **
No. 3. $T \rightarrow \min$	2	0	0, 1, 2, 3, 4, 5, 6	2
No. 4. $T \rightarrow \max$	6	0, 1, 2, 3, 4, 5, 6	0, 1, 2, 3, 4, 5, 6	6

* Neither value of this interruption will lead to a change in the work performance time; ** Interruptions highlighted in Schedule No. 2 correspond to Figure 5; interruptions highlighted in Schedule No. 4 correspond to Figure 6.

3.2. Sample Risk Assessment (3) for One Critical Path Work Item

Let the work item performance take ten days, or $t = 10$ days, and let the interruption last for one day $\Delta t = 1$. The cost of work, materials included, is 250,000 conventional units. The predictive graph of resources consumption is shown in Figure 7.

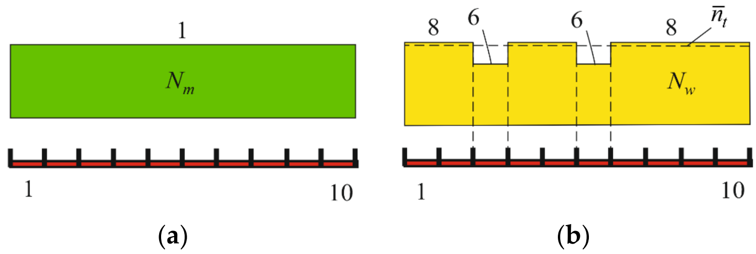

Figure 7. Distribution of resources in time: schedule of machine operations (**a**), schedule of work performance by the core construction workers (**b**).

Work performance requires the failure-free operation of one construction machine and a team of 8 workers for 10 days. Notably, only 6 out of 8 workers worked for two days due to random factors. Costs are evenly distributed in time.

Since the machine was in the failure-free operation mode for all ten days, $S(N_w) = 0$. Let's calculate $S(N_p)$ for the core workers if $\overline{n}_t = (6 \cdot 2 + 8 \cdot 8)/10 = 7.6$ persons (see Figure 6):

$$S(N_p) = \sqrt{1/t \cdot \sum_{1}^{t}(n_t - \overline{n}_t)^2} = \sqrt{1/10 \cdot \left(8 \cdot (8 - 7.6)^2 + 2 \cdot (6 - 7.6)^2\right)} = 0.8 \tag{15}$$

$$\beta_1 = \frac{(N_{m1} + N_{w1})\Delta t}{t\sqrt{S^2(N_{m1}) + S^2(N_{w1})}} = \frac{(1 + 10) \cdot 1}{10\sqrt{0.8^2}} = 1.375; \tag{16}$$

$$p_1 = p(w, m) = 0.5 - \Phi(1,375) = 0.5 - 0.415 = 0.085 \tag{17}$$

In the case of even distribution of costs and a virtual increase in the time of work $\Delta t = 1$, the value of

$\Delta C = C/10 = 25,000$ conventional units,

$R = p\Delta C(t + \Delta t) = 0.085 \cdot 25,000 \cdot 11 = 15,950$ conventional units

Given that 2 out of 8 workers were absent for 2 days, the risk of material damage reached 15,950/250,000 = 6.38% of the cost of work when the time of work was extended by one day.

3.3. Evaluation of the Organizational and Technological Reliability of the Schedule

Let's consider the construction of a frame for a 17-storey apartment building made of monolithic reinforced concrete. Its standard floor area is 600 square meters. Each floor is divided into two equal areas for the purpose of construction of a monolithic reinforced concrete frame (see Figure 8).

Let's assess the reliability of schedules that simulate the erection of a frame for the two floors of a building if the construction time is the same (49 days) but critical paths are different (Figures 9 and 10). The $R(T)$ value (1) is calculated for the critical work of each model. It is assumed that $[R] = 0.05$, i.e., the risk of material damage in the course of the performance of this set of work should not exceed 5% of the total cost of frame construction. It is assumed that preventive measures avert any major accidents. Calculations do not take into account such work items as concrete strength development, curing of concrete, and the removal of structural formwork since these work items are considered as interruptions. During the performance of all items of work, one tower crane was used; it was in operation without failure for all 49 days. Table 2 shows for schedules on Figures 9 and 10 the initial data used in the calculations. It lists only those critical work items that were characterized by deviations caused by the workforce unavailability in the process of construction of a similar facility by the same team of workers. The total cost of building a reinforced concrete frame was 3,500,000 conventional units.

For Schedule model No. 1 (Figure 9) value $U^{(w)}_{1,1,49}$ = 145.6 thousand conventional units; for Schedule model No. 2 (Figure 10) value $U^{(w)}_{1,2,49}$ = 193.3 thousand conventional units. Risks of material damage are calculated as follows:

$$R^{(w)}_{1,1,49} = 145.6/3500 = 0.0417 < [R] = 0.05,\ R^{(w)}_{1,2,49} = 193.3/3500 = 0.0552 > [R] \quad (18)$$

Hence, the first part of the schedule model developed for the erection of a 2-storey element of a frame has higher reliability, as random deviations emerging in critical work items lead to less substantial total potential damage. The second option of the schedule is unacceptable in the case of this directive value of risk $[R]$.

(**a**)

(**b**)

Figure 8. Work performance broken down into task areas: (**a**) I—floor formwork installation; II—concreting of columns, walls; (**b**) I—floor slab concrete curing; II—slab reinforcement.

Table 2. Input data used in risk assessment for schedules.

Schedule Model No. 1 (Figure 9)					Schedule Model No. 2 (Figure 10)				
No. of Critical Work Items	*t*, Days	Δ*t*, Days	Number of Workers a Day	Δ*C*, Thous. Conventional Units	No. of Critical Works	*t*, Days	Δ*t*, Days	Number of Workers a Day	Δ*C*, Thous. Conventional Units
2	4	0.1	2(14); 2(12) *	180	2	4	0,1	2(14); 2(12)	180
5	4	0.1	2(14); 1(13); 1(12)	180	5	4	0,1	2(14); 1(13); 1(12)	180
11	3	0.1	2(10); 1(8)	120	11	3	0,1	2(10); 1(8)	120
18	4	0.1	1(14); 2(13); 1(12)	180	15	4	0,1	2(14); 2(12)	180
24	3	0.1	1(10); 1(9); 1(8)	120	18	4	0,1	2(14); 1(13); 1(12)	180
31	4	0.1	2(14); 2(12)	180	24	3	0,1	2(10); 1(8)	120
36	3	0.1	2(10); 1(8)	120	28	4	0,1	2(14); 1(13); 1(12)	180
-	-	-	-	-	31	4	0,1	2(14); 2(12)	180
-	-	-	-	-	36	3	0,1	1(10); 1(9); 1(8)	120

* 2(14); 2(12) means that critical work item 2, that takes 4 days, needs 14 employees working for the first 2 days and 12 employees working for the next 2 days; the absence of 2 people is due to accidental causes.

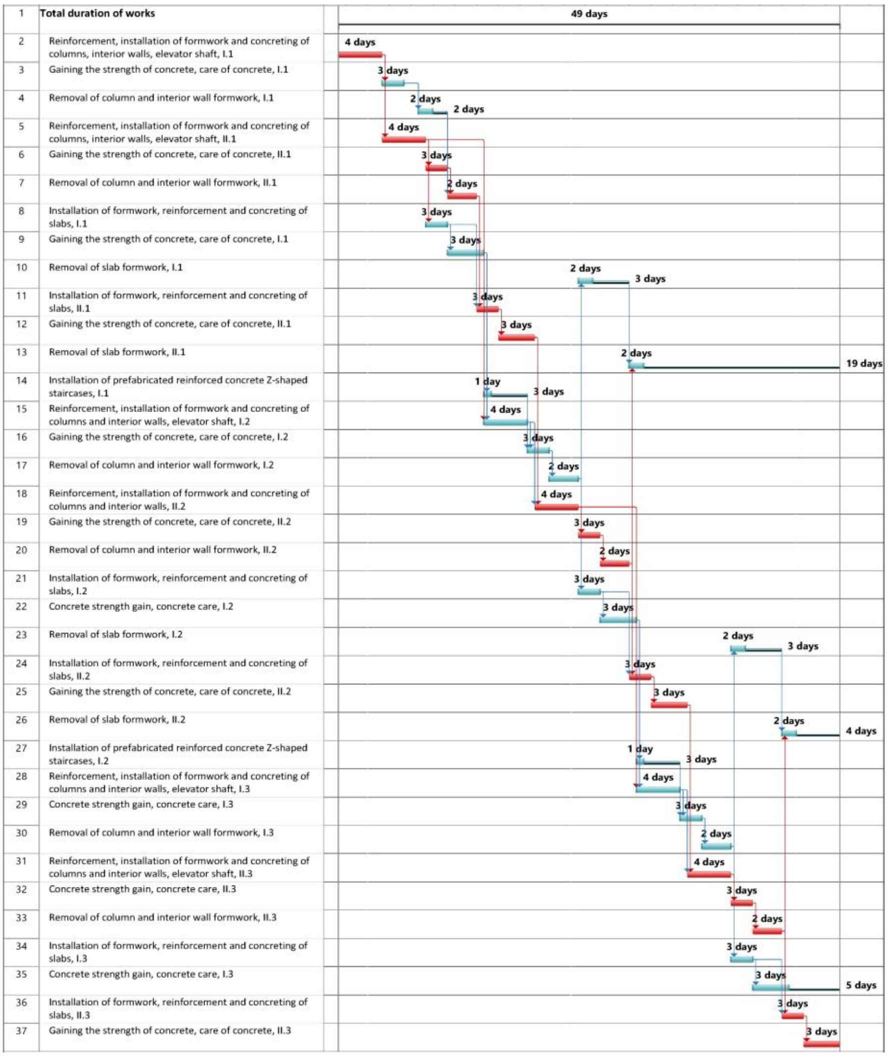

Figure 9. Schedule model No. 1 developed for the construction of a reinforced concrete building frame.

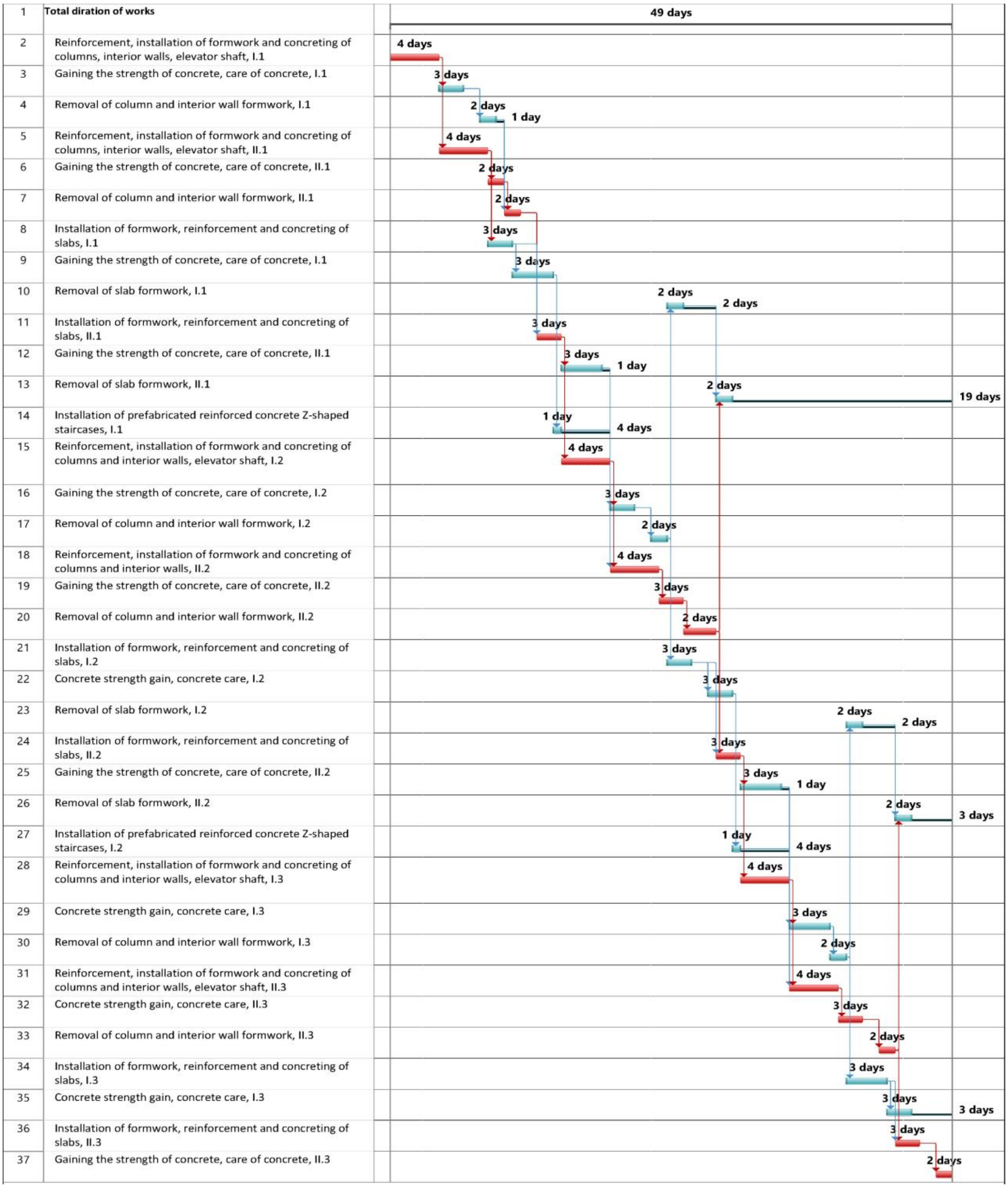

Figure 10. Schedule model No. 2 developed for the construction of a reinforced concrete building frame.

4. Discussion

Calculations of the schedule model time made using the interval estimation technique $[T_{\min}, T_{\max}]$, have shown that in some cases $T_{\max} \gg T_{\min}$. It strongly relies on a selection of points of potential interruptions. Consequently, when analyzing such models, the construction manager should avert any interruptions by taking preventive measures. Such measures can include supplier reliability checks [30,33], provision of larger amounts of warranty and insurance reserves in respect of stored structures and materials, the conclusion of leasing agreements for the principal construction machinery and their potential prompt replacement, etc.

The proposed scheduling model does not consider factors associated with the adjustment and approval of design solutions and revisions in the course of construction. In this case, no interruption is deemed to occur; some work items are performed while the design documentation is being approved and revised.

The strength of the proposed approach is its ability to make a relatively quick and reliable assessment of minimal and maximal durations of work subject to the presence of random factors. Besides, each random factor is presented not as an expectation, as in [13,14,16], but as a set of random values. It allows for identifying minimal and maximal durations, unlike the majority of studies that generate some optimal duration corresponding to specific values of random factors.

This research project has great prospects. It may be developing towards the generation of a database or a cloud service that will contain interruptions, caused by poor process organization and engineering factors, as well as sets of their values. It will allow for a more accurate application of an optimization model to various construction facilities. Alternatively, this research project may address the development of an approach to integration with BIM technologies and their application in the course of scheduling the reconstruction of facilities and changing their functions. Besides, this project may focus on the optimization of resource distribution with due regard for their limited amount and random factors that influence the process.

5. Conclusions

A probabilistic method of construction scheduling optimization, taking into account such random factors, as delays caused by the unavailability of construction machines, materials, equipment, and workforce, as well as extreme changes in weather conditions, is developed.

A novel approach, which has two values describing schedule duration, is proposed. Minimal duration takes into account the pace of construction without schedule overruns. Maximal duration allows prognosticating construction delays as a result of differentiated or joint effects of random factors.

The method of evaluating the organizational and technological reliability of solutions was developed for the purpose of construction implementation. The evaluation is based on the risk of material damage as a result of the virtual extension of construction time.

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