



## Calendar planning of construction production, taking into account stochastic impacts

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**Abstract.** The objective of this project is to enhance the techniques for creating informational models of alternative scenarios for the execution of the schedule and to expand the timeframe for predicting the progress of construction activities in the face of unpredictable factors. As a result of the study, the structure of a cellular automaton with memory, the cells of which quantitatively describe the states of objects of construction production, and the rules of transition between them were optimized. This paper introduces a comprehensive model framework for analyzing technologically and organizationally intertwined processes inherent in construction production. The model incorporates cellular automata to simulate spatial-temporal dynamics, vectors of complex resources to quantify heterogeneous inputs, and intricate process representations to capture the nuanced interdependencies within the construction system. A meticulously designed methodology has been developed to quantitatively evaluate technological and organizational capabilities, as well as the efficiency of implementing complex processes under constraints on both elemental and aggregated non-storage resources. This approach integrates advanced analytical techniques to assess performance metrics and identify optimization opportunities, ensuring alignment with strategic objectives and resource limitations. The proposed approach provides a robust analytical tool for optimizing construction workflows and enhancing overall project performance, leveraging advanced systems theory and resource optimization techniques. Methods for intensive and extensive optimization of complex process efficiency are formulated. Methods for optimal software implementation of the obtained algorithms are determined. In the shell of the relational database management system, a software package for forming basic and complex structures of a cellular automaton with memory is implemented.

**Keywords:** calendar planning, monitoring, non-storage resources, stochastic effects, scenario method, cellular automaton

**Please cite this article as:** Mishchenko V.Ya., Lapidus A.A., Topchiy D.V., Gorbaneva E.P. Calendar planning of construction production, taking into account stochastic impacts. *Construction Materials and Products*. 2025. 8 (4). 9. DOI: 10.58224/2618-7183-2025-8-4-9

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## 1. INTRODUCTION

In the context of the modern economic paradigm, the construction industry plays a key role in the process of national development, acting as a catalyst for transformational processes in both the economic and social spheres. In the context of the challenges that society has faced in recent years, this industry is becoming particularly important, demonstrating the ability to achieve a synergistic effect, especially in the framework of large-scale projects. The synergetic effect, manifested in a complex system of interaction of various factors, necessitates the optimization of construction project management methods. Effective management at all stages of the project life cycle not only contributes to their successful implementation, but also maximizes socio-economic returns, minimizes costs and lost profits. Within the framework of this issue, special attention is paid to the optimization of project management, which allows not only to increase the effectiveness of the implementation of construction initiatives, but also to ensure the development of the national economy in the long term [1].

The hierarchical decomposition of the cellular automaton's structural framework enables a significant enhancement in the adaptability of the calendar schedule to stochastic perturbations under resource constraints. This capability is driven by the multivariance inherent in the execution of complex processes, which facilitates the activation of diverse, non-storable resources. This intricate interplay of hierarchical structure and process variability forms the foundation for optimizing resource allocation and mitigating uncertainty in dynamic scheduling environments. The criterion for choosing extensive or intensive methods of resource management is determined by the economic priorities of the project and the resource base of the contractor. In the course of this study, the methods of scenario modeling of the dynamics of complex systems are used; methods and algorithms for monitoring and optimal control of complex systems exposed to intense stochastic influences; algorithms of cellular automata with memory; algorithms and methods of relational database management systems.

## 2. METHODS AND MATERIALS

In the field of project management, one of the key tools is the development of a calendar plan. In conditions of uncertainty and unpredictability, this process can be difficult due to limited resources and the need to take into account the priorities of various technological and managerial processes that are closely related to each other [1]. To solve such problems, precise methods that formally guarantee the optimality of the solution with a given error have a minimal field of practical application [2]. The analysis of resolvable scheduling issues, conducted [3], reveals that for practical applications, precise techniques are effective only for single-objective systems. Examples of such optimization are given in the works [4, 5].

The main direction of the development of scheduling methods is adaptation to real problems and the development of approximate methods of discrete optimization. Within the framework of such approaches, genetic algorithms are of great interest to researchers and practitioners [6, 7]; the ant column method [8]; the method of branches and boundaries [9]; greedy algorithms [10, 11]. Practical applications of discrete optimization methods are considered in [12, 13]. In these studies, modeling of organizational and technological factors affecting the final planned indicators was carried out, and the aggregation of indicators made it possible to get rid of unnecessary information.

One of the defining characteristics of the construction industry is its susceptibility to intense external stochastic influence, which precludes the straightforward transfer of successful planning methodologies and operational practices from other sectors of material production. This unique attribute of the construction field can be attributed to its multifaceted and dynamic nature, where unpredictable variables such as weather conditions, regulatory changes, and supply chain disruptions play a significant role in project outcomes. Consequently, the construction industry requires specialized approaches and frameworks that are specifically tailored to mitigate and manage these external stochastic factors [14]. The impact of destabilizing stochastic processes on the construction industry was studied in [15]. However, both precise and heuristic methods of deterministic planning do not take into account the influence of stochastic influences on the processes of construction production.

In the meantime, these effects qualitatively alter the trajectory of the schedule and impose severe constraints on the ability to accurately predict the condition of construction projects [16]. This is a reflection of the general patterns of behavior exhibited by complex systems when subjected to stochastic influence of various kinds [17]. In the context of proactive planning, these constraints in practice necessitate a substantial overprovisioning of non-accumulated resource, which in turn diminishes the overall efficiency of the project [18].

An alternative approach, rooted in adaptive scheduling methodologies, mandates the dynamic adjustment of the construction timeline in response to the outcomes of progress monitoring. This process necessitates a rigorous evaluation of project performance metrics and the implementation of corrective measures to optimize resource allocation and mitigate potential deviations from the initial plan. The integration of real-time data analysis and predictive modeling enables a proactive and responsive management strategy, thereby enhancing the overall efficiency and effectiveness of construction project execution [19]. Methods for monitoring the dynamics of complex systems using information models of the state were studied in [20], and techniques for optimal planning based on the results of monitoring were proposed, in particular, in the article [21]. However, none of these approaches takes into account the specifics of the construction industry. The limitations on the field of practical application of these methods can be overcome by the methodology proposed in the paper [22] for integrating the tools for monitoring the progress of the implementation of the schedule and optimizing the catch-up work schedule. Even more promising is the approach proposed in [23], which integrates methods for scenario modeling of calendar plan implementation, monitoring of its implementation results, and algorithms of cellular automata with memory [24]. The methodology developed by the authors, presented in [24], allows dynamically adjusting the forecast of the implementation of the calendar plan and the dynamics of project implementation, even under conditions of intense stochastic impacts. Comprehensive and accurate forecasting of the system's dynamic behavior will facilitate the formulation of management strategies aimed at mitigating the adverse impacts of stochastic perturbations on the construction process [21, 25]. In a broader sense, effective forecasting will make it possible to optimize the management model, which makes it possible, in particular, to respond to stochastic changes in the external environment, which, in the event of any types of risks, will ensure an effective adjustment of the course of construction production processes in space and time.

To attain this objective, it is imperative to construct an algorithmic framework for the generation of an information model based on cellular automata theory. This work is devoted to the development of this integral approach.

### 3. RESULTS AND DISCUSSION

The optimal method for building a model of a cellular automaton (CA) is based on identifying basic structures that do not depend on the parameters of a particular project, as well as the connections between them. Such structures are vectors of elementary non-storage resources (hereinafter referred to as ENR), which include, in particular, personnel and equipment. The components of the corresponding vector  $Re = \{r_1, r_2, \dots, r_m\}$  have a text format, and their number  $m$  is determined by the current personnel composition of the contractor and its technological base. The second basic structure of the spacecraft is the vector of elementary processes  $Pe = \{p_1, p_2, \dots, p_k\}$ , the implementation of which is necessary for the implementation of all projects implemented by the contractor. As the personnel and technical characteristics of the contractor change and construction technologies improve, the  $Re$  and  $Pe$  vectors are updated.

Many construction processes cannot be implemented using only ENR. The implementation of such processes requires the use of integrated resources (hereinafter referred to as CR), examples of which are sections, teams, equipment with service personnel, etc.

$$\begin{aligned} \mathbf{p}_j &= \{r_{j,i_1}, r_{j,i_2}, \dots, r_{j,i_{k_j}}\}; \mathbf{n}_j = \{n_{j,i_1}, n_{j,i_2}, \dots, n_{j,i_{k_j}}\}; \\ j &= 1, 2, \dots, Jr; \quad i_{k_j} \leq m \end{aligned} \quad (1)$$

Whose components have an integer format. In the expression Jr, there is a full number of CR, and the parameters  $r_j$ ,  $i$ , and  $n_j$ ,  $i$  are the number of ENR and their number in the complex resource. A comprehensive resource within the contractor is formed either on an ongoing basis for standard projects, or situationally for the implementation of a unique process. An elementary resource is a special case of CR and is described by a one-component vector.

On the other hand, the processes of construction production can also form technologically inseparable sequences described by vectors of complex processes (hereinafter referred to as CP), of the following form:

$$\pi_j = \{p_{j,i_1}, p_{j,i_2}, \dots, p_{j,i_{k_j}}\} \quad j = 1, 2, \dots, Jp; \quad i_{k_j} \leq k. \quad (2)$$

Here  $Jp$  is the total number CP. A complex process, unlike a complex resource, cannot be formed situationally, since it describes the technical and technological properties of the process (for example, the time of solidification of mixtures or cooling of structures below a technologically determined temperature, etc.). At the same time, the elementary process, similar to CR, is a special case of CP and is described by a one-component vector.

The vectors  $\rho_j$  and  $\pi_j$  are not independent. The technical and organizational possibility and economic efficiency of implementing all processes  $\pi_j$  under resource constraints  $\rho_j$  is described by the matrices  $w(\rho, \pi)$  and  $c(\rho, \pi)$ , the elements of which have the format of a real number. The elements  $w_{j,i}$  of the matrix  $w(\rho, \pi)$  are the performance (power) of the  $j$ th resource in the execution of the  $i$ th process; The elements  $C_{j,i}$  of the matrix  $C(\rho, \pi)$  are the specific (i.e., per unit volume of the process) costs for the use of the  $j$ th resource in the execution of the  $i$ th process [26]. For each process, there should be at least one non-zero element  $w_{j,i}$  and  $c_{j,i}$ , which from a practical point of view corresponds to the full staffing and technical support of the contractor.

Since the relationship between processes and resources is not one-to-one, complex processes can be performed with different efficiency using different resources. In contrast, certain complex resources are capable of implementing multiple methods, thereby enhancing their capacity to adapt to stochastic factors while within the constraints of available resources. This multifaceted approach enables a more nuanced and resilient planning strategy, especially in environments characterized by a high level of uncertainty and variation. By leveraging the diverse capabilities of these resources, organizations can optimize their scheduling processes, thereby mitigating potential disruptions and maximizing the efficient utilization of available assets.

The possibilities of resource maneuver in the course of implementing the schedule of construction production increase if there are reserve resources that allow the formation of alternative scenarios for the implementation of the project. From a practical point of view, such redundancy is realized, for example, through additional training of personnel in related professions. Even with an increase in unit costs or a decrease in the productivity of reserve resources compared to the basic ones, the resource maneuver allows you to minimize the total losses arising when lagging behind the proactive plan and reduce the cost of damping the consequences of external negative impacts on the course of the project.

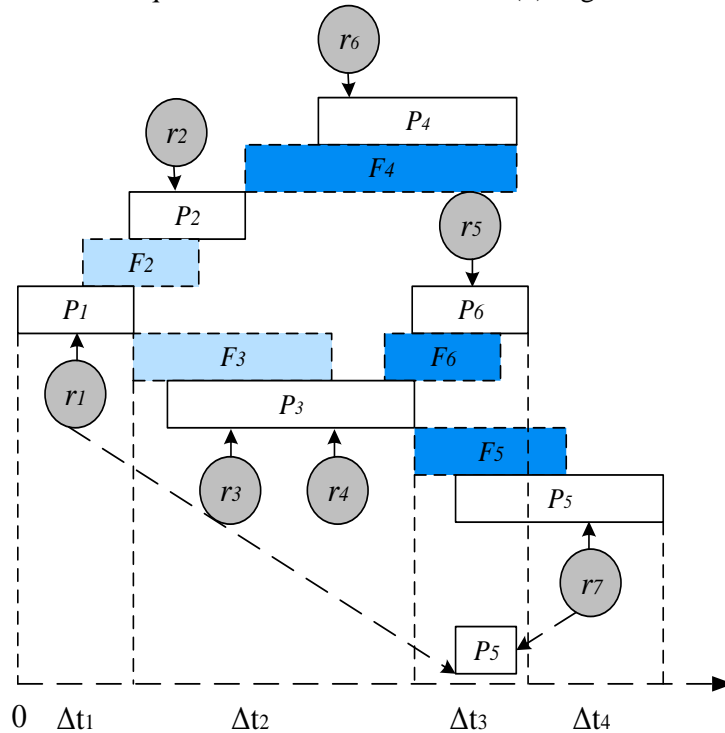
Individual processes are also not independent. The method of quantitative description of the interconnection of elementary processes is formulated in [25]. The generalization of this algorithm into complex processes is based on the matrix  $d_{\pi_a, \pi_d}$  that defines the connection of the fronts of complex acceptor processes  $F_{\pi_a}$  produced by the realized volumes of complex donor processes as follows  $V_{\pi_d}$ :

$$F_{\pi_a} = \sum_{\pi_d} V_{\pi_d} d_{\pi_a, \pi_d}. \quad (3)$$

Summation in expression (3) is made for all donor processes technologically related to the process  $\pi_a$ . The components of the matrix  $\mathbf{d}_{\pi_a, \pi_d}$  are in real number format and are defined by the following formula for related processes:

$$d_{\pi_a, \pi_d} = F_{\pi_a} / V_{\pi_d} . \quad (4)$$

For independent complex processes, the components of the matrix  $\mathbf{d}_{\pi_a, \pi_d}$  take zero values. The formation of a tree of technological interrelations of processes is carried out by the methods of direct or reverse propagation formulated in [26] and, in particular, with a one-to-one correspondence of processes, a one-dimensional sequence is realized and the sum (3) degenerates into a monomial.



**Fig. 1.** Relationship between the complex resource  $\rho$  and the complex process  $\pi$ .

Figure 1 shows the time of accumulation of the work front and the implementation of elementary processes on this basis along the abscissa axis. Graphically, objects have the following meaning:

- Rectangles without filling, bounded by a solid line, reflect the elementary processes that are part of the complex process  $\pi$ ;
- rectangles bounded by a dashed line with filling, the density of which increases with the implementation of technological connections, reflect the fronts of work for these processes;
- circles with radial filling reflect elementary resources;
- the arrows depict the relationship between elementary resources and processes.

The complex process begins with the elementary process  $p_1$ , for which the front was prepared in the previous stage of schedule execution. It is implemented using only one elementary resource  $r_1$  throughout  $\Delta t_1$ .

The process  $p_1$  initializes the fronts  $F_2$  and  $F_3$  for processes  $p_2$  and  $p_3$ , respectively, through a resource management mechanism. Process  $p_2$  is executed sequentially by a single resource  $r_2$ , utilizing its exclusive allocation for the duration  $\Delta t_2$ .

In contrast, process  $p_3$  necessitates a concurrent allocation of two elementary resources,  $r_3$  and  $r_4$ , to complete its execution. It is upon the successful and complete execution of both  $p_2$  and  $p_3$  that the

fronts  $F5$  and  $F6$  are formed, enabling the initiation of processes  $p_5$  and  $p_6$  in the subsequent stage of the workflow. This sequential and resource-dependent execution paradigm ensures the synchronization and coordination of tasks, thereby optimizing the overall system performance and minimizing potential contention for shared resources.

The duration of the third stage,  $\Delta t_3 + \Delta t_4$ , with the activation of elementary resources  $r_5$  and  $r_7$  (solid arrows), as can be seen in Figure 1, is determined by the implementation time of the process  $p_5$ . Under this scheme, the total implementation time of the complex process is determined by the equation  $\Delta t = \Delta t_1 + \Delta t_2 + \Delta t_3 + \Delta t_4$ .

An alternative method of implementing a complex process provides for the use of resource  $r_l$  (dotted arrows) along with  $r_5$  at the third stage. In this scheme, the duration of the third stage is determined by the time of implementation of process  $p_6$ . The time of implementation of the complex process is reduced and is determined by the equation  $\Delta t = \Delta t_1 + \Delta t_2 + \Delta t_3$ . As can be seen from Figure 1, there is another possibility of reducing the time  $\Delta t$ , determined by the resource maneuver in the second stage. Increasing the number of resources  $r_3$  and  $r_4$  will reduce the time of implementation of the process  $p_3$ , which determines the duration of the second stage. Choosing between alternative methods of lowering  $\Delta t$  is determined by the economic priorities and resource base of the contractor. The use of the extensive process of quantitative increase in the use of non-storage resources is effective when they are redundant and low-cost. An intensive optimization method associated with the reuse of the  $r_l$  resource may require significant costs, in particular, with personnel training, additional stimulation, and improvement of the contractor's technical base.

Let us consider the impact of stochastic factors on the temporal dynamics of calendar plan implementation. Stochastic influences engender deviations from the intended trajectory of project execution, necessitating a nuanced approach to model their effects. The methodology for constructing a stochastic cellular automaton must be grounded in the algorithm derived in [26] to effectively capture the influence of external perturbations on the productivity dynamics of non-storage resources and the usage patterns. This analytical framework ensures a rigorous and precise characterization of stochastic influences on project timelines, thereby enhancing the accuracy and reliability of project management strategies.

The algorithm for the transition between the cells of the scenario model and the dynamics of the calendar plan, presented in [26], allows us to determine the planned value of the volume of the  $i$ th operation performed during the  $t$ th planning period (PP) using the planned resource profile and their capacity.

The domain of probability density definition is defined as:

$$f_{i,j} = \frac{w_{i,j}^a + w_{0,i,j}}{w_{i,l}^{plan} \cdot \left( w_{0,i,j} + \left( w_{i,l}^{plan} \right)^a / (a+1) \right)}. \quad (5)$$

This area reflects the negative impact of stochastic factors leading to a decrease in actual productivity compared to the planned values. The upper bound  $[0; w_{i,j}^{plan}]$  represents the exact threshold of the range of definition [26]. The derivative of the function (5):

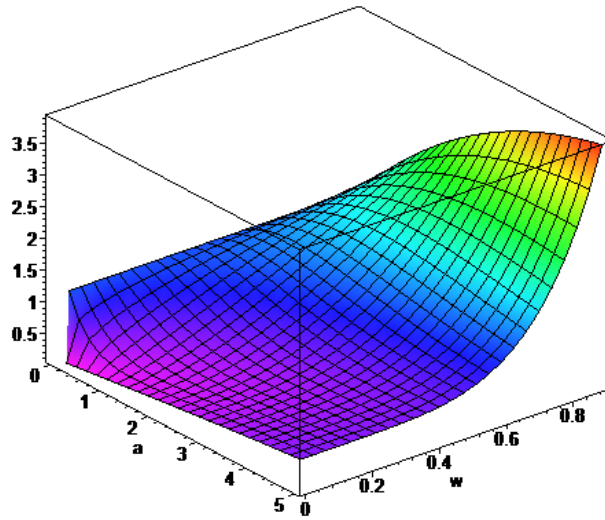
$$\frac{df_{i,j}}{dw_{i,j}} = \frac{a \cdot w_{i,j}^{a-1} + w_{0,i,j}}{w_{i,l}^{plan} \cdot \left( w_{0,i,j} + \left( w_{i,l}^{plan} \right)^a / (a+1) \right)}, \quad (6)$$

with non-negative values of productivity  $w_{i,j}$ ,  $w_{0,i,j}$  and exponent, the degree is strictly positive. As a result, the probability density increases  $f_{i,j}$  monotonously with increasing actual productivity, reflecting the fact that planning is rational. This fact is illustrated in Fig. 2 and 3. Along the axes of

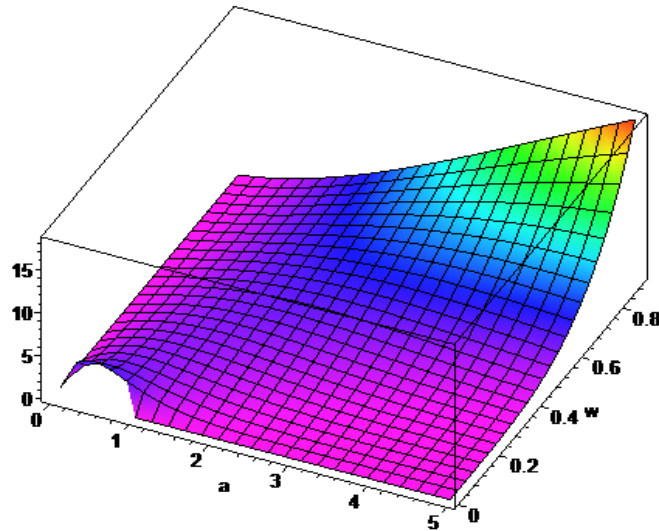
ordinates and abscissas of both graphs, respectively, the values of the exponent and probabilities for and are postponed  $w_{0,i,j} = 0.1$  and  $w_{i,l}^{plan} = 0.9$ .

The lower limit of the range of acceptable values of the function  $f_{i,j}$  is reached at the lower limit of the definition range with the minimum performance value  $w_{i,j} = 0$  and is determined by the expression:

$$(f_{i,j})_{\min} = \frac{w_{0,i,j}}{w_{0,i,j} \cdot w_{i,l}^{plan} + (w_{i,l}^{plan})^{a+1} / (a+1)}. \quad (7)$$



**Fig. 2.** Function  $f_{i,j}$  (fingertip axis).



**Fig. 3.** Function  $\frac{df_{i,j}}{dw_{i,j}}$  (fingertip axis).

Fig. 2 clearly shows the monotony of the probability density over the variable  $w_{i,j}$ , and Figure 3 shows the positive certainty of the derivative of the probability density.

Practical optimization of the scheme for implementing a complex process within the general framework of scenario modeling of the dynamics of the implementation of the calendar plan by the cellular automaton method requires the software implementation of a set of related algorithms in a standard shell. The functionality of the software modules is presented in Table 1. The optimal programming shell for a cellular automaton is a relational database management system (DBMS).

The practical optimality of this methodology is contingent upon the feasibility of segregating the algorithmic and informational components, which are independently developed and executed by distinct stakeholders involved in the construction project. This separation facilitates modularity and scalability, allowing for tailored solutions to specific project requirements. Moreover, it promotes interoperability between different systems, optimizes resource allocation, and enhances decision-making. Consequently, this approach improves project efficiency and minimizes the potential for errors, thus mitigating risks related to construction project management.

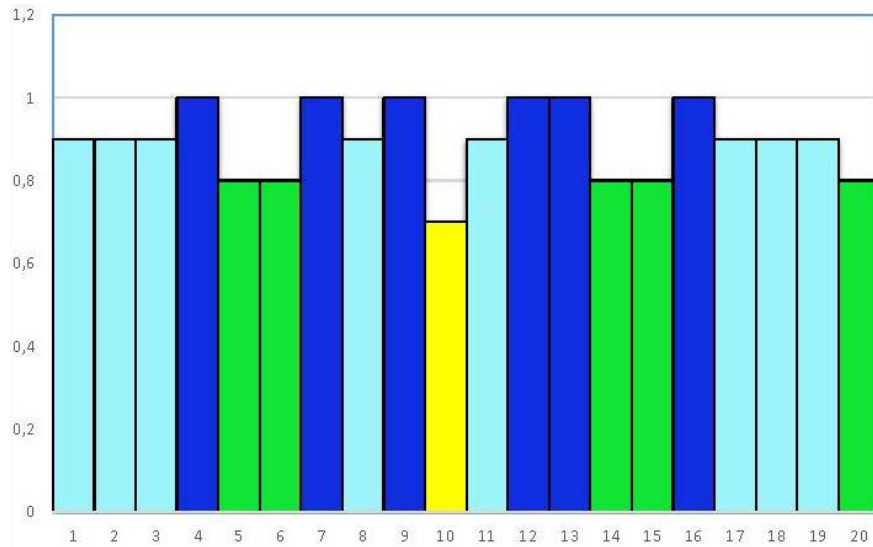
**Table 1.** Functionality of software modules.

Name of the module	Type of module	Module functionality
Process volumes	Form	Defines the terms of implementation and sets the initial front
Production	Request	Implements the transition rule (5)
The work front	Request	Implements the transition rule (6)
Shift production	Report	Analysis of the dynamics of process implementation
Front and development	Report	Analysis of the possibility of implementing processes
Number of resources	Report	Resource usage profile analysis
Resource requirements	Report	Calculating the total number of resources

The algorithmic component defines the fundamental part of the software package, which does not depend on the characteristics of the project and contractors. Only the formation of this component requires the use of highly qualified personnel. In contrast, the information component is formed at the stage of designing the facility and choosing a contractor, and changes dynamically in the process of implementing the schedule plan. Since the DBMS interface coincides with the interface of widely used office programs, the operation of the system at the stage of implementing the schedule does not require additional training of personnel.

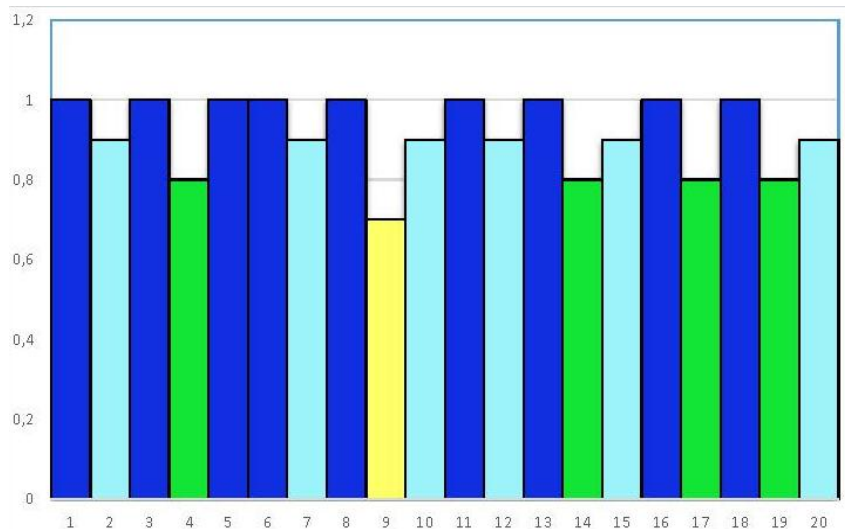
Consider the results of computer modeling examining the dynamics of non-storage resource utilization under stochastic impact conditions.

For greater clarity, let us consider the results of computer modeling designed to simulate the potential stochastic realization of nonrenewable resources (NR) over a 20-day period of operation at various levels of planned use ( $N_j^{plan} = const = 10$ ). The probability of such scenarios can be characterized by a distribution  $p_n = 0.9$ . The simulation results were obtained using the extended mathematical package MAPL V and are shown in Fig. 4 and 5.



**Fig. 4.** The result of monitoring the execution of the resource profile for  $p_n = 0.9$ .

In the presented graphs (Figures 4 and 5), the profile is normalized to the planned value. In the first case, the normalized mathematical expectation for a given probability  $p_n = 0.9$  is  $\langle N_j \rangle = 18/20 = 0.9$ . As Fig. 4 shows, the average value is close to the a priori mathematical expectation.

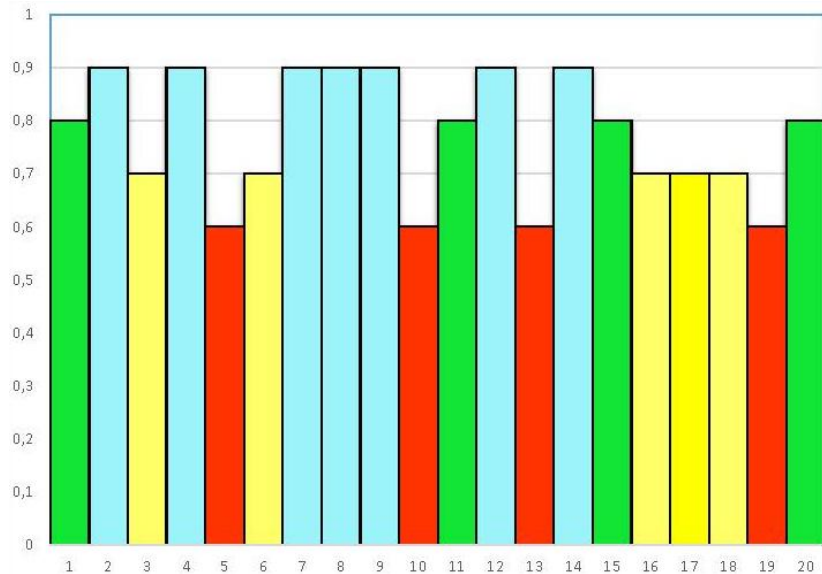


**Fig. 5.** The result of monitoring the execution of the resource profile for  $p_n = 0.95$ .

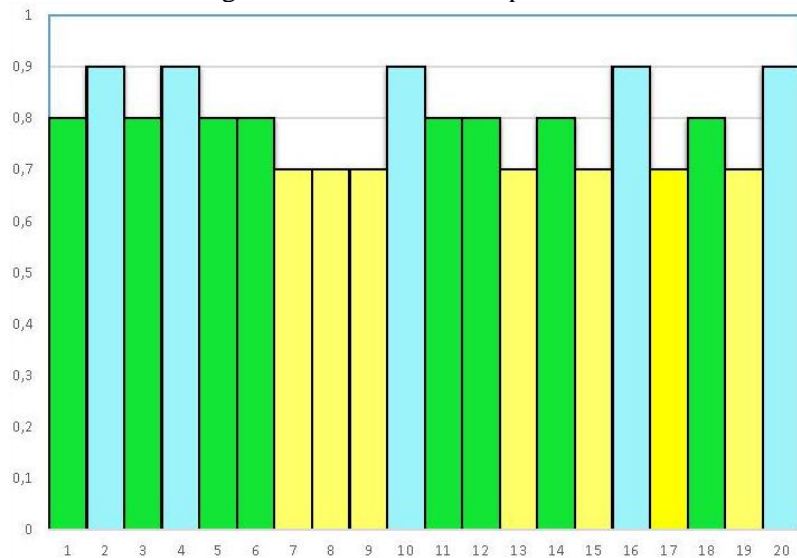
The probability of full utilization of the Network Resource (NR) is confirmed by the simulation outcomes. Fig. 5 reveals an average value of 0.95, which aligns with the theoretical mathematical expectation. During the simulation, this value was attained in nine out of twenty shifts, surpassing the anticipated statistical probability. This divergence may suggest the influence of unidentified or latent factors impacting the process dynamics.

Fig. 6 and 7 present alternative simulation scenarios, demonstrating the model's sensitivity to variations in initial conditions. The empirical averages observed in these implementations are consistent with the theoretical probability and mathematical expectation. Notably, the mathematical expectation in both cases remains close to the specified value, underscoring the model's robustness and

stability. However, the over the entire observation period in these scenarios remains below 1, with no instance of complete NR utilization observed across the 20 simulation iterations. This result highlights the limitations and constraints within the system. It necessitates further investigation to elucidate factors that impede full NR exploitation.



**Fig. 6.** The initial configuration of the resource profile. The mean value is 0.81.



**Fig. 7.** The initial configuration of the resource profile. The mean value is 0.83.

The presented results underscore the necessity for a reevaluation of the initial probabilistic hypothesis. A sudden deviation in system behavior may be attributable to the activation of supplementary stochastic effects, including meteorological conditions or epidemiological parameters. This necessitates a more comprehensive analysis and, potentially, the modification of the existing model to enhance its predictive precision and adaptability to heterogeneous external influence.

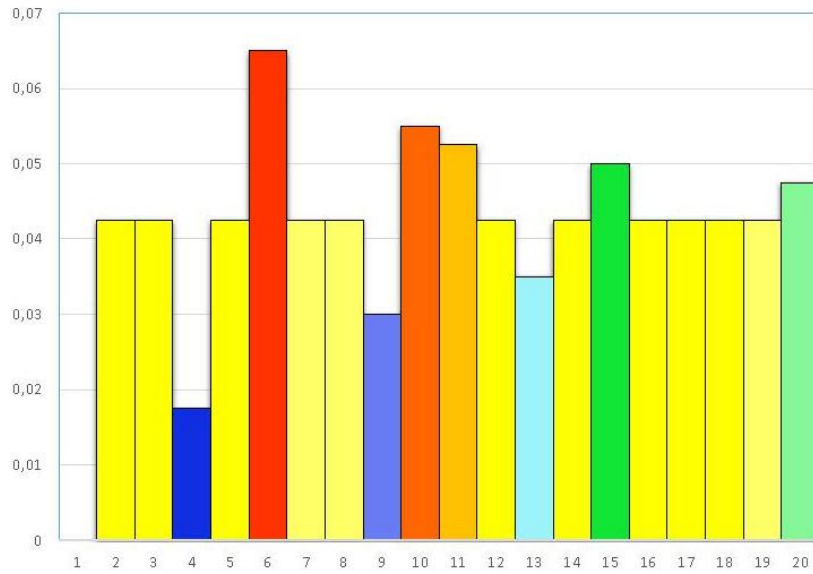
In scenarios where the probability of resource realization remains invariant, implying the stability of external random influence sources, the impact of stochastic factors on the implementation of the

calendar plan can be quantified by multiplying the planned resource quantity by the average active resource value derived from monitoring data.

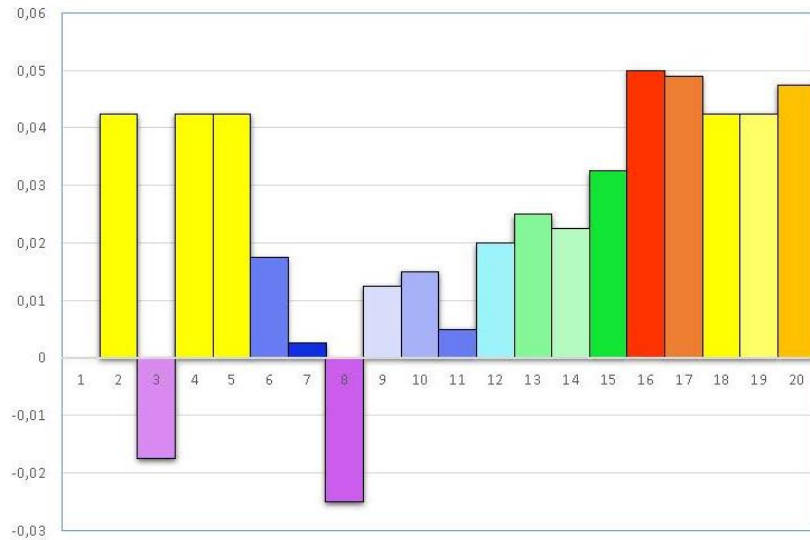
As the planning horizon expands, the relative forecasting error exhibits minimal accumulation, as evidenced by Fig. 8 and 9, which illustrate the dependency of the relative error in predicting the total resource profile  $\delta_k$  on the shift number for various probability  $p_n$  values calculated using formula [24]:

$$\delta_k = \sum_{j=1}^k N_j^{mon} / \sum_{j=1}^k N_j^{plan}, \quad (8)$$

where  $N_j^{mon}$  and  $N_j^{plan}$  are the actual and planned resource profiles, respectively.



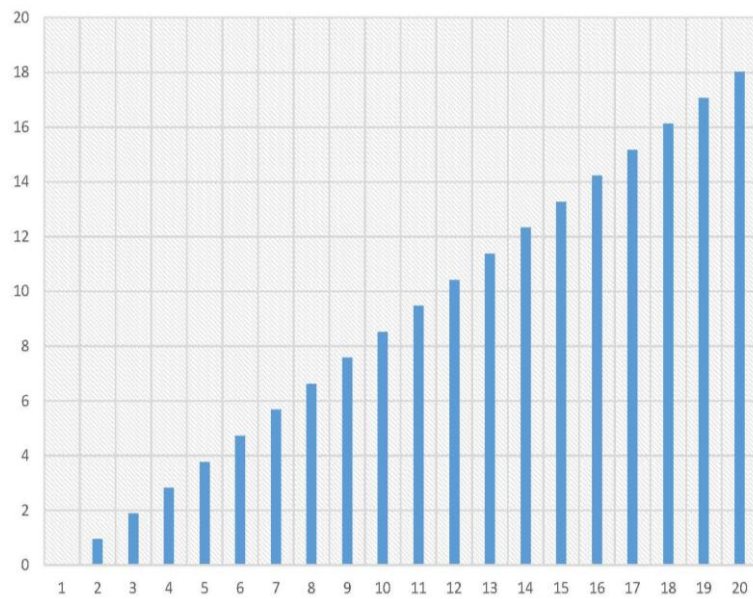
**Fig. 8.** The relative error in predicting the total resource profile with probability  $p_n \approx 0.9$ .



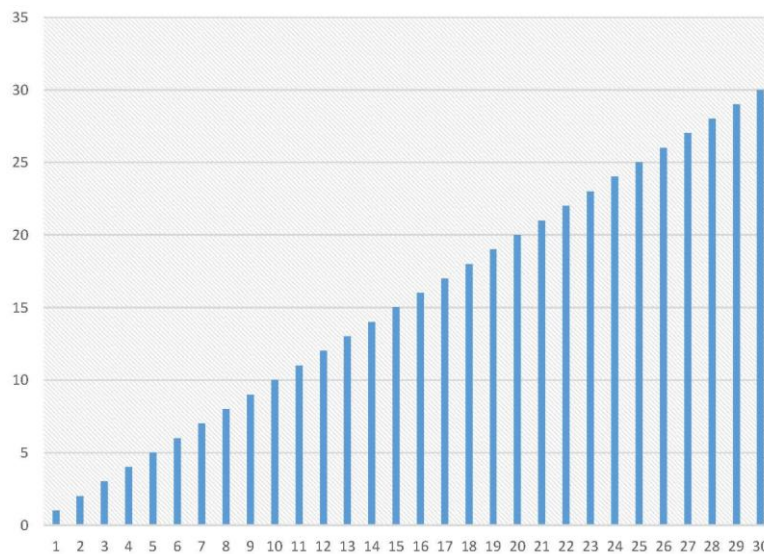
**Fig. 9.** The relative error in predicting the total resource profile with probability  $p_n \approx 0.6$ .

From the graphs (Fig. 8 and 9), it can be seen that even with a high probability of resource failure, the relative prediction error in the fixed probability  $P_n$  model does not exceed 5%.

In the context of absolute forecasting errors, the situation undergoes a significant transformation. Given a constant productivity level, the magnitude of the error in predicting the work volume is directly attributable to the precision of forecasting the dynamics of resource utilization. The accuracy of these forecasts is contingent upon the temporal horizon of the projection. This intricate relationship is vividly illustrated in graphs 10 and 11, which meticulously depict the outcomes of monitoring the absolute error in resource utilization dynamics under varying probabilities of external stochastic influences and different planning horizons. These visual representations provide a comprehensive empirical basis for understanding the complexities of predictive modeling in resource-intensive environments.



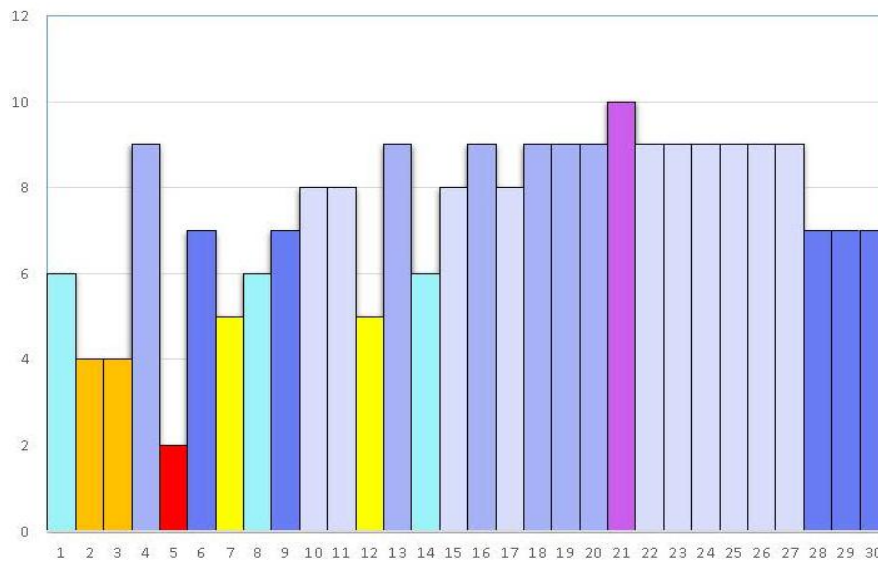
**Fig. 10.** Absolute error in predicting the total resource profile with a probability  $p_n \approx 0.6$  planning horizon of 20 shifts.



**Fig. 11.** Absolute error in predicting the total resource profile with a probability  $p_n = 0.9$  planning horizon of 30 shifts.

Analyzing the graphs depicted in Fig. 10 and 11, it becomes evident that a small relative error in forecasting the total resource profile does not necessarily ensure the precision of predicting the amount of work accomplished. The error exhibits a cumulative nature and is constrained by the planning horizon. In both scenarios, the error converges towards the target value within 10 shifts. However, on the planning horizon spanning 30 shifts, there is a low probability that the accumulated error will not exceed three times the planned value, despite being less than half of the planned amount within a 10-shift horizon.

In numerous practical scenarios, the planning horizon is additionally delimited by the fact that algorithms for accounting for stochastic influences on the implementation of the calendar plan, which are based on fixed probability models over the planning horizon, may not accurately reflect the actual situation. Fig. 12 presents examples of monitoring results illustrating a qualitative alteration in stochastic influences, underscoring the limitations of such deterministic models in dynamic and uncertain environments.



**Fig. 12.** The result of modeling the resource usage profile with a variable probability value, the planning horizon is 30 shifts.

The graphical representation depicted in Fig. 12 conclusively demonstrates that stochastic influences exert disparate effects during the initial and subsequent phases of the monitoring period. Specifically, within the interval spanning shifts 1 to 15, the likelihood of resource consumption activity exhibits a probability of 0.47. This probability undergoes a significant increase during the subsequent interval from shift 16 to shift 30, nearly doubling to reach 0.81. This phenomenon signifies a qualitative transformation in the operational mechanisms of stochastic influences.

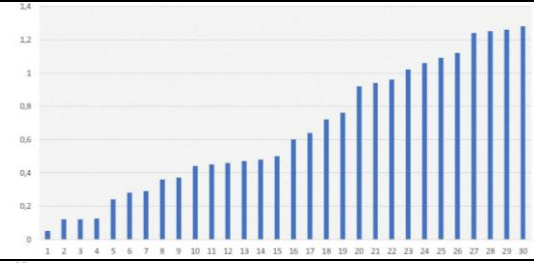
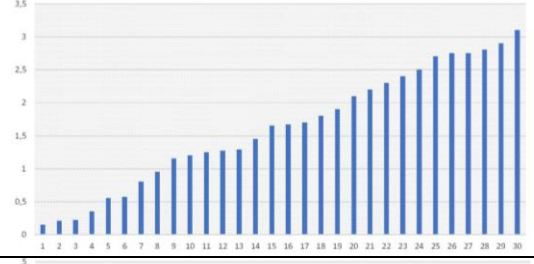
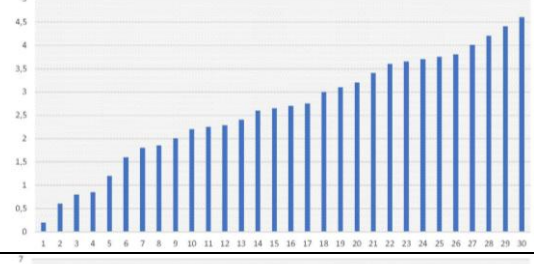
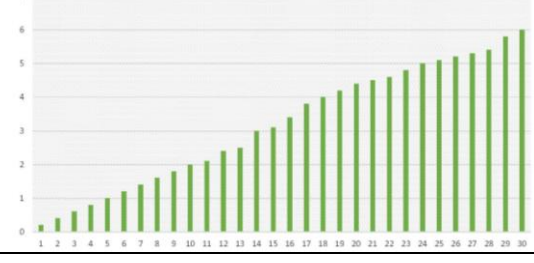
The results of the modelling pertaining to the dynamics of the calendar plan's execution emphasize the intricate interplay between discrete and continuous stochastic mechanisms that collectively generate a synergistic effect. This complex interaction challenges the effectiveness of additive models that traditionally isolate stochastic factors in comprehensively describing the complex dynamics of implementing the calendar plan. This inherent characteristic of the implementation process manifests a basic principle underlying the development of complex systems subject to stochastic disturbances. The interaction between discrete and continuous random processes is not simply additive, but rather exhibits non-linear emergent behavior that requires a more advanced modelling approach to accurately describe the temporal and spatial features of the system evolution. This finding aligns with broader principles governing stochastic dynamic systems, where collective influences of random variables lead to phenomena not reducible to their individual components.

The optimal planning horizon for such systems is contingent upon the system's complexity and the intensity of stochastic influences. In the context of the system under investigation, this is elucidated in Table 2, which presents normalized graphs relative to the planned value:

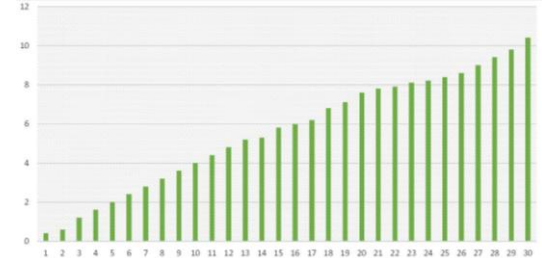
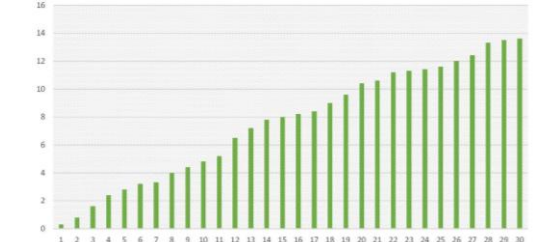
$$R_{plan} = K_j c_l^{plan}. \quad (9)$$

Upon normalizing equation (9), the height of the graphical column serves as a quantitative indicator of the number of shifts required to eliminate the backlog under ideal conditions, where external negative influences on the construction process are non-existent. Consequently, the calculated value represents the lower bound of the actual time reserve necessary, provided the non-storage resource (NR) consumption profile remains fixed.

**Table 2.** Results of the optimal planning system taking into account stochastic impacts.

Line number	Probability value	Degree indicator	Histogram
1	$p_n = 0.9$	$a = 5.5$	
2	$p_n = 0.9$	$a = 2.5$	
3	$p_n = 0.9$	$a = 0.5$	
4	$p_n = 0.6$	$a = 5.5$	

Continuation of Table 2

5	$p_n = 0.6$	$a = 2.5$	
6	$p_n = 0.6$	$a = 0.5$	

An exhaustive examination of the data presented in rows 1-3 of Table 2 reveals a significant inverse correlation between the probability of stochastic distortions in the resource utilization profile and the planning time horizon for workload allocation. Specifically, as the probability of stochastic perturbations increases, there is an exponentially proportional reduction in viable planning timeframes, indicating a highly responsive and nonlinear system. The highlights the critical importance of accurate stochastic modeling and risk management for optimizing resource allocation. This is because stochastic fluctuations in resource use have a nonlinear effect on system performance, leading to a rapid reduction in the predicted completion time for tasks.

Data from rows 4 to 6 of Table 2 emphasizes the importance of considering stochastic influences when developing resource management strategies and planning construction processes, especially under conditions of high uncertainty. Findings suggest that there is a significant probability of distortion in the resource profile, regardless of the magnitude of stochastic factors influencing production processes. As a result, the planning horizon is limited to a few shifts, requiring a comprehensive understanding of and proactive management of stochastic impacts to optimize allocation and minimize potential disruptions. These observations emphasize the need for a rigorous and evidence-based assessment of stochastic impacts in resource management planning to ensure the resilience and effectiveness of construction projects in unpredictable environments.

#### 4. CONCLUSIONS

The prevalent methods of proactive and reactive scheduling used in the construction industry, particularly in areas characterized by significant random fluctuations, have limitations in their ability to predict the temporal development of project milestones. These limitations are highlighted by the inherent limitations of their forecasting horizons, which are not sufficient to adequately capture the complex and unpredictable nature of the construction process. As a result, these scheduling approaches often fail to provide an effective framework for optimizing the allocation of resources and mitigating adverse effects from random disruptions. Techniques for improving the reliability of plans, based on prior reservation of resources, can lead to deterioration in various indicators of project performance. A method that is free of these limitations, based on dynamic monitoring of schedule implementational and adaptive adjustment of work schedules, mitigates adverse effects on project metrics caused by random influences. This approach uses real-time analysis of data and predictive models to improve operational efficiency and allocate resources optimally, creating a resilient framework for project management.

Advancement of this approach combines techniques for simulating schedule implementation dynamics and monitoring results to formulate effective strategies to mitigate adverse effects of outside factors on construction project, even under intense random influences. The ideal mathematical

framework for quantitatively simulating the dynamics of construction is the formalism of cellular automata with memory, which has recently experienced a surge in development and has greatly expanded its practical applications. The adequacy of such an approach to the description of construction production, even in the basic setting, is ensured by the discreteness of the system (space, time, and state); locality of connections; homogeneity of basic structures (cells). And, although in practice at least one of the fundamental properties of the model of cellular automata can be violated, in the process of development, hybrid models have been formulated, within the framework of which one of the modifications of the basic model is reduced to taking into account the stochastic nature of local transition functions.

The optimal methodology for constructing a model is predicated upon the identification of fundamental structural elements that encapsulate the broadest conceivable class of objects and processes. This entails a hierarchical assembly of structures of progressively higher order, thereby fostering a systematic and comprehensive understanding of the phenomena under investigation. This approach ensures that the model is both robust and adaptable, capable of accommodating a wide range of variables and scenarios within its conceptual framework. In particular, the structures of the first level built in this work do not depend on the parameters of a specific project and contractor. The structures of the second level of the hierarchical scheme, describing complex processes and resources, characterize a broad class of projects implemented by the contractor. Intensive and extensive methods can optimize structures of the second level. The choice of an optimization approach should be made based on an analysis of the economic priorities and resource base of the contractor.

Restrictions on the field of practical application of the results obtained in the work are determined by the volume of the information base of the model and the depth of accounting for hierarchical links. In this regard, the development of this approach involves constructing higher-order structures, describing a wider class of processes and resources, and expanding the functionality of the software implementation of algorithms.

Thus, the optimal management of the construction production process during the implementation phase of the schedule can be achieved through the integration of active and reactive planning methodologies, continuous monitoring of schedule progress, scenario modeling of production dynamics, and the application of cellular automata with memory. The practical implementation of this diverse array of tools necessitates the development of an information model for the process and the software realization of the resulting algorithms within a user-friendly interface accessible to a wide spectrum of project stakeholders. These criteria are met by a relational database management system, within which it is possible to separate the algorithmic and factual components. Such a division makes it possible to optimize the methods of information transfer between heterogeneous participants in the implementation of the project.

## 5. ACKNOWLEDGEMENTS

The research presented in this work was carried out as part of implementing the Strategic Academic Leadership Program “Priority - 2030”, a grant from the National Research University MGSU.

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