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Article

Applications of simulation modeling in mining project risk management: criteria, algorithm, evaluation

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Abstract: Project risk management in the mining industry is necessary to identify, analyze and reduce uncertainty. The engineering features of mining enterprises, by their nature, require improved risk management tools. This article proves the relevance of creating a simulation model of the production process to reduce uncertainty when making investment decisions. The purpose of the study is to develop an algorithm for deciding on the economic feasibility of creating a simulation experiment. At the same time, the features and patterns of the cases for which the simulation experiment was carried out were studied. Criteria for feasibility assessment of the model introduction based on a qualitative parameters became the central idea for algorithm. The relevance of the formulated algorithm was verified by creating a simulation model of a potassium salt deposit with subsequent optimization of the production process parameters. According to the results of the experiment, the damage from the occurrence of a risk situations was estimated as a decrease in conveyor productivity by 32.6%. The proposed methods made it possible to minimize this risk of stops in the conveyor network and assess the lack of income due to the risk occurrences.

Keywords: digital technology; risk mitigation measures; mining enterprise; scenario analysis; potassium salt

1. Introduction

A mining enterprise is a complex integrated business unit consisting of a large number of assets: from dump trucks to drifts and galleries (Babyr et al, 2021, Gabov et al, 2021). A high level of uncertainty due to the specifics of mining production complicates the process of preparing a feasibility study for new mine. At the same time, underestimation of project conditions and factors can lead to incorrect economic efficiency indicators and negatively affect the mining enterprise during operational stage. This is especially relevant in conditions when the amounts of "cheap" resources decreases and there is a need to develop deposits in more difficult conditions: on the shelf, in the Arctic zone (Cherepovitsyn et al, 2021).

Investment project evaluation for the mining enterprise is a time-consuming and complex process associated with the need to analyze a large number of factors and take into account the peculiarities of the mining industry. For example, geological and climate risks, lack of infrastructure, predominance of debt capital, ecological damage (Dirani et al, 2021, Zhang et al, 2023). Despite the fact that production and technological risks of a mining project belong to the diversifiable group of risks, technical solutions developed in the project documentation are initially based on uncertainty of data on the geological structure of the ore body. Therefore, the quality of the technological component development in the project determines the ability of the enterprise to adapt to the manifestation of specific systemic risks of the mining industry.

The features not only have a direct impact on mining project, but also interact with each other, intensifying the effects of each other (Xiong et al, 2023). That means that when uncertainty grows among the possible consequences of only one feature, the overall project vulnerability changes nonlinearly, and it is difficult to assess it by classical methods, for example, using static models (Zhang et al, 2022).

The current methodology of risk management, designed to reduce the degree of uncertainty, is mainly a discrete approach to the analysis and risk assessment; development of risk mitigation measures (Pourander et al, 2021). However, the risk event is dynamic by its nature, which means that the probability of its occurrence in different periods of time is unstable. This justifies the need to apply in risk management additional tools and techniques that describe the production process as a dynamic system (Mostafaei et al, 2022). Improvement of existing risk management mechanisms could have a positive impact on the investment attractiveness of projects in mining industry, which is very important because today we can see a tendency to reduce investment activity in this field (Kruk et al, 2020).

The paper proposes to implement the methods of dynamic systems analysis by creating a production process simulation model of a mining enterprise to minimize project risks. Traditionally, simulation modeling is referred to quantitative methods of project risk assessment. However, the modern paradigm of simulation modeling, embodied in the concept of digital twin, makes it possible to apply it at all stages of the standard risk management algorithm (Baryannis et al, 2019).

The idea that simulation model of production process has an impact on all stages of project risk management leads to a conclusion that, later in the project implementation, new effects could be observed. Effects, that were previously unavailable due to the lower accuracy of prediction (Golovina et al, 2023). Consequently, early analysis of possible risks will reduce the time that would have been spent on eliminating errors and miscalculations in project documentation, in case they would have been detected in the process of operational work (Belsky et al, 2023).

Therefore, the research hypothesis was proposed: additional verification of project decisions using simulation model allows to minimize risks and the probability of their occurrence by taking into account a greater number of factors affecting all stages of project implementation. Underground mining, as a more hazardous method, also imposes certain design impediments related to mining and geological conditions (Snopkowski et al, 2012).

Attitudes towards simulation modeling techniques have changed over the last 25 years (Shabalov et al, 2021). In the business environment, it is beginning to be used more and more to solve complex, multifactorial problems. On the other hand, even in the business environment, simulation modeling is used as an additional tool to confirm analytically calculated results. Due to the development of numerical and simulation modeling programs, it is now possible to work out abnormal situations and test control algorithms on computer simulators (Huerta et al, 2022). This way of research and testing of technological processes is applicable both in training and optimization of the production process (Koteleva et al, 2023).

There is always a risk that the results obtained by the model may not be justified in reality, since the conditions of system functioning are set inside the software product as ideal (Nazarychev et al, 2023). At the same time, the results of experiments obtained in laboratory conditions can serve as a basis for further construction of mathematical models and identification of new dependencies (Serzhan et al, 2023). Many unresolved issues lie in the area of significant factors selection and testing the model reliability (Fedorova et al, 2022). In practice, skepticism towards this method of reducing uncertainty is expressed in the question: "Will it not turn out in the end that the cost of creating a production process simulation exceeds the effect from the solutions developed on its basis?"

The production process simulation modeling is the greatest interest to the authors. Taking into account the problems described in the introduction, it is worth noting that an effective method of testing model adequacy is considered to be conducting a physical experiment with a training facility in laboratory conditions (Ivanov et al, 2021). However, at the stage of project feasibility study, it is difficult to conduct full-scale experiments for risk management purposes due to economic or technological reasons. In this case, to reduce subjectivity in the calculation of economic efficiency and to overcome uncertainty, scenario analysis has become widespread (Matrokhina et al, 2023). Production process reproduction in a virtual form and analysis of its changes over time seems to be the most rational way to assess risk, when there is still insufficient information about the system functioning peculiarities. Theoretical and practical results of simulation modeling application to improve the accuracy of economic forecasting are widely analyzed (Nepsha et al, 2023, Zhukovskiy et al, 2022). Improving the economic efficiency of a project through optimization of production parameters has recently become increasingly common in the literature (Voznyak et al, 2021).

The study is based on the hypothesis that the development of digital technologies has led to an increase in the economic efficiency of dynamic underground planning tools in terms of project risk management. This is due to the fact that, on the one hand, software and computer facilities have become more accessible, and on the other hand, the number of factors that need to be taken into account in the project has increased. The study proves the necessity of introducing new digital tools in the risk management process.

The purpose of this research is to define a number of qualitative criteria which would signify an overall feasibility of simulation model creation with an aim to reduce uncertainty in the design decisions of mining enterprise establishment.

To fulfill this purpose, a methodology for making a management decision on the expediency of simulation model creation has been developed. It consists of a new algorithm which includes the model introduction in the standard risk management process based on a defined check-list of suggested qualitative criteria.

2. Materials and methods

The study formulates the relevance of methodology improvement for overcoming uncertainty in project decisions, and puts forward the assumption of expanding the simulation modeling application possibilities as a risk management tool. Then an improved risk management algorithm with introduced simulation modeling is developed. It is used to formulate the stages of decision making on the expediency of simulation model creation. Qualitative criteria list is developed to verify the presence of features whose impact on the project economically justifies the cost of creating the simulation model. The criteria relevance is checked by using them to solve a real production problem. The economic effect from experimental model introduction in the production process is calculated.

List of qualitative criteria for simulation model feasibility were developed based on scientific literature content analysis, real cases of method application in mining companies, as well as personal experience of the authors. The analysis was carried out on the materials of the scientific database ScienceDirect, companies' information resources.

Since one of the research tasks is to improve the risk management algorithm, the authors consider it necessary to note which version of it is accepted as the basic one. The scheme is prepared by the authors based on the analysis of academic and scientific literature and represents a list of 5 most generalized project risk management stages (**Figure 1**).

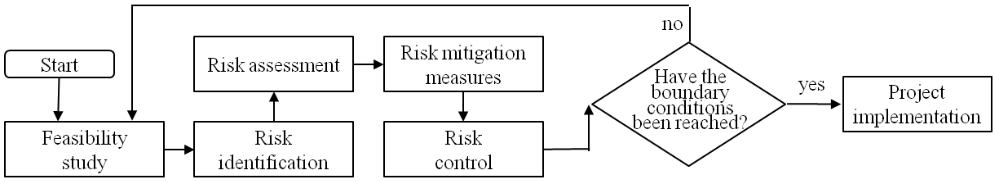

Figure 1. Basic algorithm of project risk management.

Visualized by the authors.

After the feasibility study and calculation of project economic efficiency indicators begins the risk identification process. Then a qualitative risks assessment with risk matrix and quantitative risks assessment special methods are carried out. The most significant and probable risks are dealt with by developing a plan of mitigation measures to overcome them. After the risk control stage it is necessary to return to the first stage, where it is assessed how the impact of mitigation and control measures affected the overall effectiveness of the project. The whole process of risk management is iterative, the algorithm returns to the beginning again and again, until the boundary conditions are achieved (defined by stakeholders or conditioned by legislative, natural or other factors). The risk management process is continued throughout all business stages, even after the start of the project.

AnyLogic: Professional 8.7.2 software product is used to build the simulation model. The experiment was conducted using multi-approach modeling, where the process of chamber mining is set as agent-based, and the process of ore transportation through the conveyor network is implemented using discrete event approach.

3. Results and discussion

3.1. Qualitative assessment of simulation model expediency

The question about developing a simulation model is initially raised after a preliminary qualitative and quantitative risk assessment, risk matrix preparation. That is, when the main sources of risk have already been identified. In the classical risk management algorithm, simulation modeling is used as method of quantitative risk assessment. However, the modern paradigm of simulation modeling, embodied in the concept of digital twin, makes it possible to apply this tool at all other stages. The standard risk management algorithm will then undergo changes, and its improved by authors version is presented in **Figure 2**.

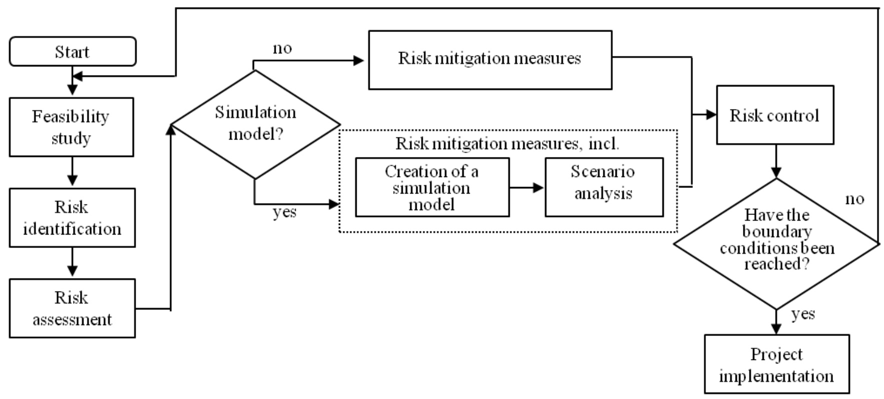

Figure 2. Risk management algorithm using simulation modeling.

Visualised by authors.

In other words, making a management decision on the expediency of a simulation model consists of the following steps:

1) Identification of the uncertainties that have the greatest impact on the project;

2) Identification of the uncertainties source and the greatest risk;

3) Evaluating the economic efficiency of the model according to a set of qualitative criteria;

4) Preliminary quantitative model economic efficiency assessment;

5) Making a management decision on the feasibility of creating a model;

6) Creation of the simulation model in the appropriate software;

7) Development of a plan to overcome uncertainties and reduce the risks of experimentation with the model (multi-criteria scenario analysis);

8) Re-iteration of the algorithm stages x-y if necessary;

9) Finishing the risk management process after reaching the boundary conditions.

Let is talk about the 3rd stage. At the moment, there is no unambiguous methodology for assessing the economic efficiency of simulation models implementation for mining production problems solution in scientific works. In this connection, the following list of qualitative criteria was formulated, the presence of which economically justifies the development of a simulation model at the planning stage:

1) The project has a non-linear influence of stochastic factors on the result;

2) The risks assessment associated with these factors is difficult or impossible by analytical methods;

3) Consequences of ignoring risks, occurrence of a risk situation are high;

4) The production process is not flexible enough, it is difficult to overcome risk

situation in future;

5) In the course of the project realization it is necessary to provide consistent output of production;

6) It is necessary to study the change in the behavior of the system over time.

The authors postulate that if the considered production task meets 4 or more of these criteria, it means that the effect from the simulation modeling will justify its creating cost. In order to prove this statement, simulation modeling of a real production task was carried out.

3.2. Assessment of criteria relevance based on the example of potassium salt mining

To conduct this, experiment the conveyor network optimization project is introduced in the mine, where potash salt extraction is carried out with the use of chamber and pillar mining system. The work is carried out simultaneously in 8 faces, in each of which there is a heading-and-winning machine and a shuttle car. From the shuttle car, the ore enters the heading-and-measuring bin, from where it is consistently fed to the conveyor (**Figure 3**).

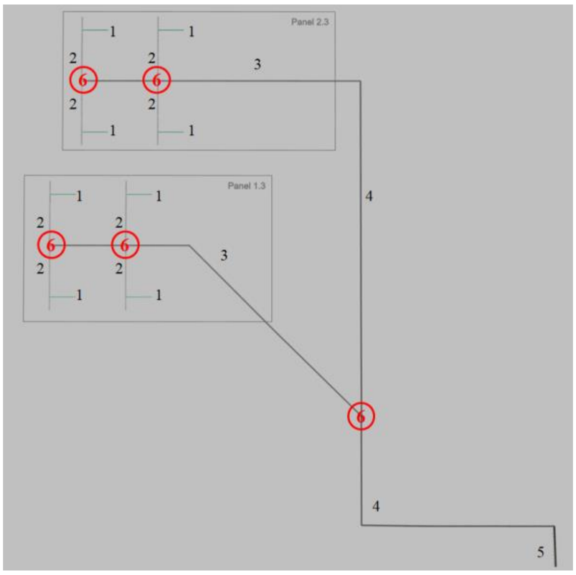

Figure 3. Modeled section, top view.

1—chambers; 2—block conveyors; 3—panel conveyors; 4—trunk conveyors; 5—head conveyor; 6—nodes. Screenshot from AnyLogic. Designed based on the authors data.

The timing results show that the shuttle car speed, the duration of loading and unloading operations are subjected to fluctuations and vary within a certain range specified in the project documentation. Consequently, the time of ore getting to the conveyor differs from face to face and from cycle to cycle. The enterprise has to solve the task of determining the maximum permissible capacity of the heading-and-measuring bin in order to get the ore to the surface as quickly as possible and to prevent the accumulation of cargo flows in the places where the conveyors are combined at the same time. In total there are 5 such nodes on the considered section of the network, they are marked in **Figure 3** by red circles with the number 6. In other words, the task is to analyze the risk of downtime during ore lifting to the surface.

According to the proposed list of criteria, it is advisable to create a simulation model to solve the task at hand. The analysis of the project features according to the criteria is presented in **Table 1**.

Table 1. Assessing the feasibility of the model creation according to the proposed criteria list.

No.	Criteria	Project features
1)	The project has a non-linear influence of stochastic factors on the result	Loading and unloading time, speed of shuttle car is not constant
2)	The risks assessment associated with these factors is difficult or impossible by analytical methods	8 faces, each discharges ore onto the conveyor at different time periods
3)	Consequences of ignoring risks, occurrence of a risk situation are high	Congestion at a node leads to a full system stop
4)	The production process is not flexible enough, it is difficult to overcome the already occurred risk situation in future	The only way to bring the ore to the surface is by conveyor network
5)	In the course of the project realization, it is necessary to provide consistent output of production	Yes, it's important for optimizing further stages of project logistics
6)	It is necessary to study the change in the behavior of the system over time	A single conveyor stop due to a traffic jam results in more stops

* **Table 1** verifies the relevance of the production problem posed and the criteria developed. We will describe each item in more detail in the next section, analyzing the conditions and constraints of the model.

3.3. Description and results of the simulation experiment

The purpose of the experiment is to determine the minimum and maximum productivity of ore unloading on the conveyor, regulated by means of a transfer scraper unit (also known as UPS-25P, also known as heading-and-measuring bin). UPS-25P is a scraper transfer unit and is designed to receive ore from a self-propelled wagon and subsequently transfer it onto a conveyor during mining works.

The time taken to lift 1 ton of ore to the surface depends on the following parameters:

1) Capacity of the heading-and-winning machine, t/min.

2) Mass of extracted ore per cycle, tons.

3) Load capacity of shuttle car, tons.

4) Time of loading and unloading operations from the heading-and-winning machine to the shuttle car, min.

5) Time of loading and unloading works from shuttle car to the heading-and-measuring bin, min.

6) Rolling shoulder, m.

7) Speed of shuttle car, m/sec.

8) Capacity of the scraper reloading unit, t/min.

9) Capacity of conveyors.

10) Belt speed, m/s.

The limits adopted in the simulation model are:

1) The conditional model start time is 1 January 2023. The units of model time are minutes.

2) The model considers a conveyor network section covering two panels and the head conveyor leading to the surface.

3) The experiment is conducted within the framework of mining one chamber located at the end of each block conveyor, with total of 8 chambers. The results obtained for mine productivity are extrapolated to the remaining chambers of the panel.

4) The simulation is stopped when the last load flow from the last chamber reaches the surface (end of the head conveyor).

5) The animation of the conveyor network is set with a scale of 1:5 for the length of the conveyor and chambers, 1:1 for the width of the belt for the convenience of analyzing the visual component. The difference in scale is taken into account in the logic and does not affect the correctness of the results.

6) Verification and validation of the model was carried out on the real industrial measuring of the working time

7) The model does not take into account such a factor as secure and immutable process data sharing.

According to the UPS-25P passport the productivity is in the range of 6–20 t/min. Timely regulation of ore unloading value on the conveyor from the unit allows to reduce the risk of jamming in the places where conveyors are combined. It is known that in case of simultaneous arrival of 6 or more load flows to the node, the whole system of conveyors above the node stops until the ore from the overloaded node will not be lifted to the surface. This means that the greatest risk to the process is the risk of conveyor shutdown. The source of this risk lays in incorrect or untimely corrections of the current capacity of UPS-25P. Logical block diagram of the model operation is presented in **Figure 4**.

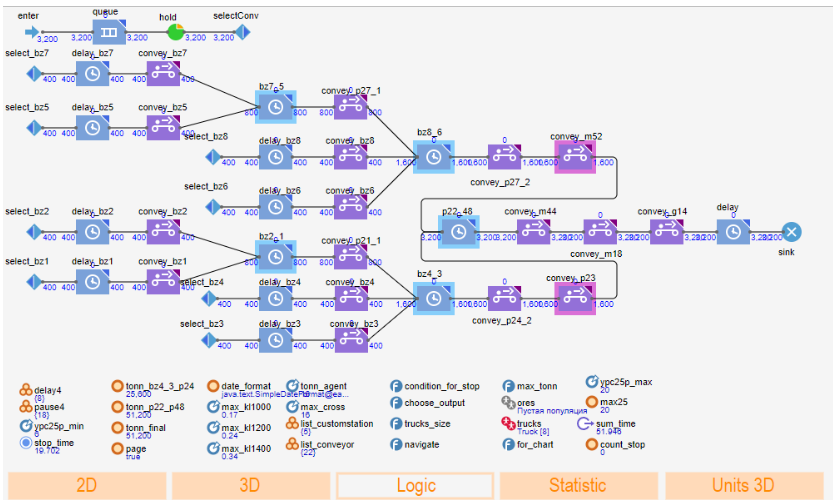

Figure 4. Part of the ore transportation logic diagram at the end of the simulation. Screenshot from AnyLogic, designed by the authors

As can be seen from **Figure 4**, the logic circuit consists mainly of “Delay” and “Convey” type blocks. Delay blocks are used to model the calculation of the time taken to unload ore onto the conveyor, the time to pass nodes, and the time to get stuck at a node. The “conveyor” blocks are responsible for the movement of material objects (cargo flows) along the conveyor belt.

Basic experiment: It represents a production process as it exists in the mine with some assumptions. The performance of the heading-and-measuring bin stays the same, regardless of the state of the conveyor interconnection points. Then, using the parameter variation experiment interface, the results of restarting the model with different variations of the maximum capacity of the heading-and-measuring bin are displayed on the screen. There are 14 iterations in total, with variation in the range from 7 t/min to 20 t/min. The results of the experiment is shown in **Figure 5**.

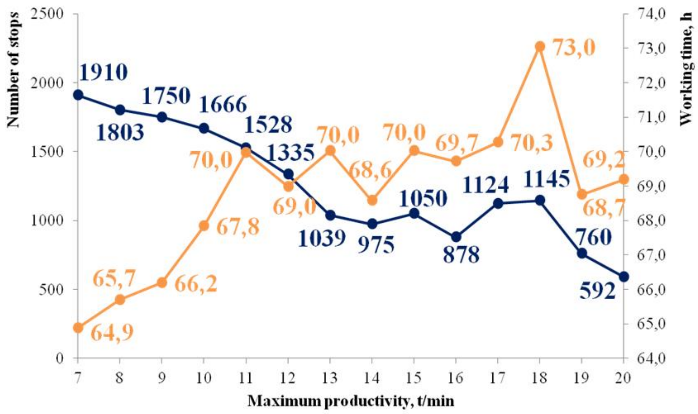

Figure 5. Results of varying the parameter of the maximum heading-and-measuring bin capacity in the basic experiment. **(a)** dependence of the working time on the maximum capacity; **(b)** dependence of the number of stops on the maximum capacity.

Visualized by the authors.

As can be seen from **Figure 5a**, there is no obvious linear relationship between the constant maximum productivity and the chamber mining rate. The same is true for the effect of the number of stops on mine productivity (**Figure 5b**). This is due to the fact that an increase in productivity, on the one hand, accelerates the rate of ore rise to the surface, and on the other hand, it is difficult to predict at what point a jam will occur. At the same time, there is a decrease in the number of stops with increasing capacity of the loader. This is explained by the fact that with higher ore unloading speed on the conveyor, the length of the load flow is shorter, while the weight is unchanged. This means that the time for one load flow to pass the conveyor node will also be shorter and the probability of simultaneous arrival of the critical mass of ore will be reduced.

Optimization experiment. Optimization of the conveyor network consists in adding to the model the dynamic control of the UPS-25P productivity: at the moment of unloading the cargo flow on the conveyor, the time of its passing the node is calculated and recorded in the data set. While the ore is in the heading-and-measuring bin, the calculated time for this load is compared to the values in the dataset. If 5 or more other flows are detected whose estimated times are in the same range as the analyzed agent, the algorithm selects the unloading speed value that minimizes the probability of collision. The performance of the algorithm is tested using a parameter variation experiment in the same manner as in the basic experiment. At the end of each iteration, the simulation time (the number of hours spent on working out the last chamber and lifting all ore to the surface), the number of stops, and the maximum productivity of the UPS-25P are recorded in an external excel file. The results are presented graphically using the optimization experiment interface (**Figure 6**).

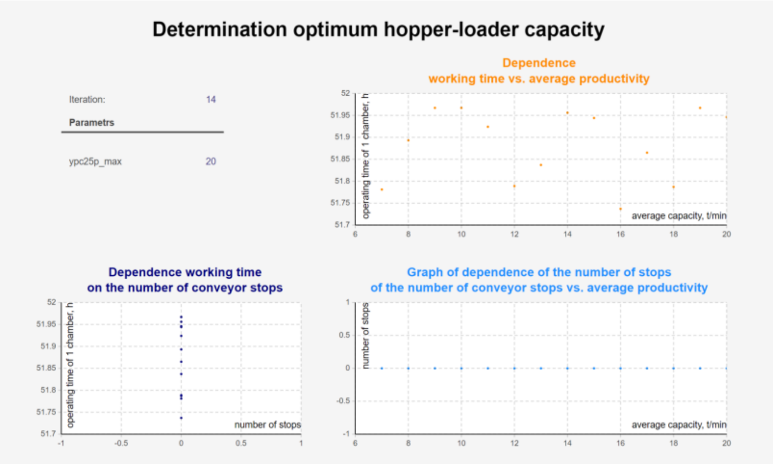

Figure 6. Optimization experiment results in AnyLogic interface.
Designed based on the authors data.

Based on the graphs, we can conclude that due to the implemented method of dynamic capacity control at each installed UPS-25P it was possible to avoid shutdowns of the conveyor network due to jamming. Let's analyze the results of the experiment in more detail with the help of **Figure 7**.

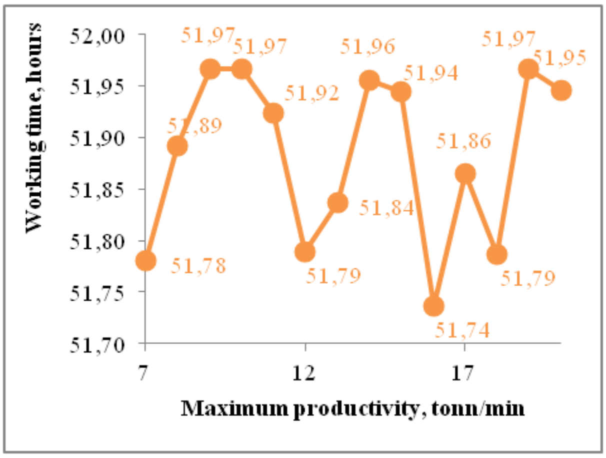

Figure 7. Results of varying the parameter of maximum hopper capacity in the optimization experiment.
Designed based on the authors data.

The results of the experiment show that in the case of no stops of the conveyor network (thanks to the system of dynamic regulation developed in the model), regardless of the set limit for the capacity of the transfer scraper unit, the final time taken to work off and raise the ore to the surface from one chamber is in the range of 51.7–52 h. When compared with calculated analytically, limits of time required for UPS-25P scraper to unload ore from one operational cycle to the conveyor, which are equal to 0.8–2.7 min, we can see same range of accuracy rate. From the total time required for ore delivery to the destination point, it takes 2–7% (without dynamic control). We can conclude that the results are correct.

To assess the simulation model economic efficiency, the average mine productivity in the base case (before the creation of the model) and after the modeling results implementation was compared. Increased productivity due to reduced downtime in conveyor movement allows ore to be lifted to the surface faster, which means that it can be processed and, eventually, sold on the market faster. The average value from **Figure 7** is taken as the working time in the optimization experiment. Calculated productivity at the considered mine section is extrapolated to all adjacent to the conveyor network panels. The price per ton of production is chosen at the average market level, according to open sources from the Internet. The effect in value is between annual revenue with the simulation results implementation and revenue in the basic experiment. The costs of creating the simulation model are taken at the market level and consist of development costs, as well as the cost of one license for the software product in the most complete set. Approximately it amounts to 3.6 million rubles. The results of the calculation are presented in **Table 2**.

Table 2. Economic effect calculation of creating a simulation model in the MS Excel.

Variant	Ore weight, thousand tons	Working time, h	Mine capacity, th. tons/hour	Ore price, RUB/thousand tons	Revenue, RUB/hour	Total revenue, thousand RUB/year	Economic effect from model implementation, thousand RUB
Formula	m	t	$B = \frac{m}{t}$	p	$R = B \times p$	$R_{\text{year}} = \frac{R \times 24 \times 365}{1000}$	$E_0 - E_{\text{optimal}}$
Basic, E_0	51.2	68.8	0.74	2,000,000	1,488,397	543,265	
E_{optimal}	51.2	51.9	0.99	2,000,000	1,973,675	720,392	177,127

It can be concluded that with the help of solutions developed by the simulation model, a quantitative risk assessment was carried out in case of conveyor shutdown, measures to prevent the risk situation emergence were proposed, and the model interface allows in real time to predict the jams formation at the conveyor nodes, in case of change in the initial data. The experiment results show an increase in mine productivity by 32.6%. However, one should not take this number as a realistic achievable number in case of simulation solution implementation in production. Rather, it expresses the potential risk value and the maximum damage amount in case of ignoring the conveyors stop threat. Obviously, in a real mine, no one will keep the heading-and-measuring bin at maximum capacity ignoring the high possibility of jamming. At the same time, the simulation model allows predicting the probability of overloading at earlier stages than a human can notice it. In monetary terms, the risk damage cost can be estimated at 177 million rubles. This effect exceeds the cost of creating the simulation model almost 50 times. Hence, we can conclude that the criteria for qualitative assessment of the feasibility of creating a simulation model proposed in this study are relevant.

4. Discussion

It is worth noting that the simulation model acts as an additional tool for improving the business plan, because on its basis it becomes possible to conduct scenario analysis with the variation of many parameters.

The main problem of any modeling methods is that the model is not a simplification of reality but a representation of reality through the prism of a theoretical approach or expert opinion. Simulation models are not an exception here, and all other scientific problems related to the application of simulation modeling for project risk management of a mining enterprise, one way or another, stem from the subjectivity of perception of the modeled system.

Simulation modeling requires high computational power to produce a reality-like result. This need arises due to the growth of simulation input data, creating capacity issues related to data acquisition, data transfer from one place to another, storage and analysis. Thus, alternative means of data transfer are required to support the big data produced by simulation models. The need for large computing power ultimately affects the total cost of an investment project, however, there is no unambiguous methodology that allows us to correctly assess how much more expensive is the project, for the implementation of which simulation modeling capabilities were involved. The simulation model itself also acts as an additional source of risk, because in the end the cost of its construction may not be justified by the results obtained due to changes in the project. Often a model, which has sufficient accuracy to obtain results, is completely impossible to verify with reasonable development costs due to the huge number of parameters taken into account. This also affects the final cost of model implementation.

Despite the fact that the market is seeing an increase in investment in simulation modeling solutions by capital-intensive enterprises, the scientific literature lags behind on the issues of compiling methodologies for incorporating simulation modeling into risk management schemes. This, in turn, is reflected in the increasing cost of implementation of simulation modeling methods in real practice: for each new project it is necessary to develop from scratch an algorithm for creating a model, to choose a methodology for optimizing parameters. These problems also lead to the lack of a sufficient number of competent specialists on the market, who can meet the demand for the introduction of simulation modeling methods in the production environment. This state of affairs, in turn, leads to an even greater increase in the cost of the final model.

Taking into account the mentioned problems and the results of the conducted research, further development of the work is aimed at a complex assessment of simulation modeling introduction for industrial mining enterprises, including a new methodology that will allow to quantitatively assess the economic efficiency of creating a simulation model to reduce the degree of uncertainty.

5. Conclusion

1) It is established that the factors inherent in mining projects nonlinearly affect various aspects of enterprise construction, increasing the overall degree of uncertainty. The need for rapid adaptation of the production process with changing conditions, consideration of time as an integral factor of the project, continuity of the planning process—form the prerequisites for changing the existing methods of reducing uncertainty.

2) It is revealed that an additional limitation in the development of tools aimed at improving the quality of project risk management is imposed by the fact that it is

difficult to conduct empirical experiments. Therefore, the paper suggests the expediency of using mathematical modeling, in particular, simulation modeling.

3) The paper proposes the use of simulation modeling at all stages of project risk management. For this purpose, an improved algorithm of the main stages of risk management was developed by introducing experiments with simulation of the production process in virtual form.

4) The criteria by which it becomes possible to decide on the feasibility of creating a simulation model to reduce uncertainty at the stage of feasibility study were substantiated. To test the relevance of the criteria, a simulation experiment was conducted on the example of the optimization of the conveyor network at the deposit, where potash salt production is carried out.

5) Recommendations were developed, according to which it becomes possible to prevent a risk situation affecting mine productivity - conveyor stoppage due to a jam. With the help of modeling results, a quantitative assessment was carried out, the potential damage from it amounts to 177 million rubles, prevention of the risk situation ensures the mine productivity by 32.6% compared to the base case. The effect of the model implementation exceeds the cost of its creation, which allows us to conclude that the developed criteria are significant.

Author contributions: Conceptualization, MN and TK; methodology, LN; software, AS; validation, AS, TK and LN; formal analysis, MN; investigation, TK; resources, MN; data curation, AS; writing—original draft preparation, AS; writing—review and editing, AS; visualization, TK; supervision, MN; project administration, MN; funding acquisition, LN. All authors have read and agreed to the published version of the manuscript.

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