

**RISK ESTIMATION OF IN-PIT CRUSHING SYSTEM
AT THE OPERATIONAL COPPER MINE IN
KAZAKHSTAN**

by

MERUYERT KHUDAIBERGEN

THESIS SUPERVISOR

SERGEI SABANOV

Thesis submitted to the School of Mining and Geosciences of Nazarbayev
University in Partial Fulfillment of the Requirements for the Degree of
Bachelor of Science in Mining Engineering

Nazarbayev University
April 14, 2023

ORIGINALITY STATEMENT

I, Meruyert Khudaibergen, hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at Nazarbayev University or any other educational institution, except where due acknowledgement is made in the thesis.

Any contribution made to the research by others, with whom I have worked at NU or elsewhere is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

Signed on April 14, 2023

ABSTRACT

Due to the existing complicated features and huge scales of operation in open-pit mining sites, the in-pit crushing and conveying (IPCC) system is more efficient compared to the combination of truck and shovel technology [6]. Mine depth or scale expansion leads to an increase in the conveyance distance [6]. Hence, the performance of trucks rapidly reduces as haulage distance increases [6]. The studied copper mine has ambitions to switch from a conventional truck and shovel system to the IPCC system and on the first stage implemented the in-pit crushing (IPC) system. However, several risks associated with truck dumping delays and therefore the IPC productivity loss have been identified. The aim of this study is to produce risk estimation of the in-pit crushing (IPC) system installed at the operational copper open pit in Kazakhstan. As a part of the risk estimation process, stochastic dynamic modelling methodology to examine how an IPC system will behave in the presence of ambiguous causes of delays to predict the system productivity over time has been used. The model analyzed for the real case all data from which a best-case scenario has been proposed. For the model input parameters, the time-tracking study of the in-pit crusher productivity and trucks haulage and dumping cycle has been produced. The time between truck arrivals, the dump time per truck, the spot time per truck, the tons per truck, the bin limit for full dumping, and the crushing rate were taken as basic input parameters. For simulation a Poisson distribution is used for the time between arrivals, a Triangle distribution - for the dump time per truck, the spot time per truck and the crushing rate, a PERT distribution - for the tons per truck. Only the bin limit for full dumping assumed a fixed value for this stage of simulation. By incorporating the dependencies between the variables into the Monte Carlo simulation, the probability of the values was evaluated using stochastic variables. As a result, for the real case, tons dumped per hour varied from 1740 to 1975, number of truck arrivals per hour ranged from 30 to 32, number truck dumped per hour ranged from 14 to 16, delay time per truck at the crusher varied between 52 and 69 minutes. The best-case scenario uses the quickest the dump time per truck and the spot time per truck. Thus, the best case has 3475 to 3600 tons dumped per hour, 30 to 32 trucks arriving per hour, and 28 to 29 trucks dumped per hour with the delay time per truck at the crusher 2.4 and 5.5 minutes. The developed model considered queuing issues at the in-pit crusher and can be used to analyze the impact of changing the bin size by changing the limits for full dumping and the crushing rate. The model is able to forecast the IPC system's future states and calculate the probability of various outcomes.

ACKNOWLEDGMENT

I express my sincerest gratitude to Dr. Sergei Sabanov, my supervisor, for providing me with continuous support throughout my graduate studies and research. His patience and extensive knowledge were instrumental in guiding me through this dissertation's research and writing process. I am genuinely grateful to have had him as my supervisor, who served not only as a professor and advisor but also as a mentor.

I also extend my appreciation to the School of Mining and Geosciences at Nazarbayev University for giving me a chance to pursue a bachelor's program and engage in research projects that have offered valuable experiences for my future.

I express my gratitude to KAZ Minerals and the chief engineer of Bozhsakol, Kenessary Smagulov, for providing all the necessary information and data for this research.

TABLE OF CONTENTS

TABLE OF CONTENTS

TABLE OF CONTENTS	5
LIST OF FIGURES	6
LIST OF TABLES.....	8
1. INTRODUCTION.....	1
1.1 Background	1
1.2 Objectives.....	3
1.2.1 Aim of the study	3
1.2.2 Objectives	3
1.3 Hypotheses	4
1.4 Justification of the R&D	4
1.5 Scope of Work.....	5
2. LITERATURE REVIEW	5
Types of IPCC.....	7
Opportunities of IPCC Systems.....	7
Potential risks and limitations of IPCC Systems.....	12
Economical perspective.....	15
3. METHODOLOGY.....	18
3.1 Mine Site Data collection	18
3.2 Dynamic stochastic modelling.....	20
4. RESULTS.....	26
4.1 Real Case Scenario.....	26
4.2 Worst Case Scenario	30
4.3 Best Case Scenario.....	35
5. DISCUSSION	41
6. CONCLUSIONS AND RECOMMENDATIONS.....	44
7. REFERENCES.....	45
8. APPENDICES.....	49

LIST OF FIGURES

Figure 1. Illustration of Bozshakol Mine Site (KAZ Minerals, 2022)	3
Figure 2. In-pit crusher station distribution by region and type (Osanloo & Paricheh, 2019).	6
Figure 3. Safety index of five transportation systems (Abbaspour et al., 2018)	9
Figure 4. Energy efficiency of different classes of high-way trucks (Osanloo & Paricheh, 2019).	10
Figure 5. Consumed energy and greenhouse gas emissions of IPCC and TS transport modes, (a) energy consumption, (b) greenhouse gas emission (Norgate & Haque, 2013, as cited in Osanloo and Paricheh, 2019).	11
Figure 6. Risk checklist for open mining operations (Pekol, 2019).	14
Figure 7. Typical economic comparison of TS and IPCC systems (Osanloo & Paricheh, 2019).	16
Figure 8. South Crusher's dimensions (KAZ Minerals, 2022).	19
Figure 9. Caterpillar 785 C/D dump truck (Caterpillar 785 C/D Dump Truck, n.d.)	19
Figure 10. Overall tons dumped per hour in the real case	27
Figure 11. Truck arrival per hour in the real case	28
Figure 12. Truck dumps per hour in the real case	29
Figure 13. Delay per truck in the real case	30
Figure 14. Overall tons dumped per hour in the worst case	32
Figure 15. Truck arrival per hour in the worst case	33
Figure 16. Truck dumps per hour in the worst case	34
Figure 17. Delay per truck in the worst case	35
Figure 18. Overall tons dumped per hour in the best case	37
Figure 19. Truck arrival per hour in the best case	38
Figure 20. Truck dumps per hour in the best case	39
Figure 21. Delay per truck in the best case	40
Figure 22. Overall tons dumped per hour in the best case with 800-tons bin limit	42
Figure 23. Delay per truck in the best case with 800-tons bin limit	43
Figure 24. Tons dumped per hour for the real case	49
Figure 25. Truck arrival per hour for the real case	49
Figure 26. Truck dumps per hour for the real case.	50
Figure 27. Truck delay per hour for the real case.	50
Figure 28. Tons dumped per hour for the worst case.	51
Figure 29. Truck arrival per hour for the worst case.	51
Figure 30. Truck dumps per hour for the worst case.	52
Figure 31. Truck delay per hour for the worst case.	52
Figure 32. Tons dumped per hour for the best case.	53

Figure 33. Truck arrival per hour for the best case. 53
Figure 34. Truck dumps per hour for the best case. 54
Figure 35. Truck delay per hour for the best case. 54

LIST OF TABLES

Table 1. Data prepared for modelling with the probabilistic inputs.....	20
Table 2. Real Case Scenario parameters	26
Table 3. Real Case Outputs.....	27
Table 4. Worst Case Scenario parameters	30
Table 5. Worst Case Outputs	31
Table 6. Best Case Scenario parameters	35
Table 7. Best Case Outputs.....	36
Table 8. Best Case Output Comparison	41

1. INTRODUCTION

1.1 Background

This Bachelor Thesis work includes introduction section with problem statement, research objectives, hypothesis, and justification of research and scope of work. As well as sections on literature review, research methodologies, results, discussions, conclusions and recommendations. Overall, the study analyse risks associated with queuing issues using in-pit crusher together with trucks and shovels.

Demand for natural resources increases despite the fact of the world turning to green resources. Therefore, the mining industry is still in high demand. Over 90% of the world's mining is done in open pits (Hartman & Mutmansky, 2002). Open pits mostly rely on trucks as their main source of transportation, or in other words, a haulage system. Dump trucks are mainly used for hauling and transporting the mined ore or waste material from the open pit to further destinations.

Truck and shovel haulage method is a well-known and mostly used method among many mines for daily operations. These daily operations include hauling ore and waste outside of the pit to crushers, stockpiles, or the waste dump, depending on the purpose. Negring et al. (2018) also says that trucks are considered to be the main equipment in the mine and are used for transporting overburden, minerals and rock material to stockpiles or the dump site. The main advantage of the truck haulage system is the mobility as it can travel long distances. However, there are some limitations to this method such as high energy consumption, large labor requirements, and intense water demand. Moreover, as Nehring et al. (2018) states, truck haulage can also cause high safety risks for the labor and impact the environment due to high production of dust and noise. Abbaspour and Drebenstedt (2019) in their research mention that even though one of the most significant sources of environmental problems in mining projects is the transportation system, choosing the most environmentally friendly transportation system is important for the mine planners. Moreover, according to their studies The FMIPCC system achieved the greatest environmental index in all environmental parameters, which may be attributed to the absence of trucks, which are the major drivers of emissions, particulate matter, and water usage (Abbaspour & Drebenstedt, 2019).

Nowadays, one of the most important goals of a mine production is to increase the productivity and decrease the costs (Nehring et al., 2018). As the number of resources decreases

and the demand for them increases, the need for more productive systems is in high demand. That is how the modern mining equipment becomes more and more efficient with dump trucks being able to haul up to 450 tons at once. Unfortunately, larger dump trucks with higher efficiency also bring a vast number of drawbacks such as cost ineffectiveness due to high energy consumption and serious ecological hazards. Such an example can be a case study from Sahoo et al. (2014) paper where in an Indian mine, the dump trucks consumed over 60% of the total diesel usage in the mine. Moreover, according to Purhamadani et al. (2021) dump trucks mostly contribute to production of greenhouse emissions, noises, and the dust. With the current trends towards the more sustainable development of the mining industry, the need for more efficient technologies has arrived.

Purhamadani et al. (2021) states that mines will continue to grow larger in size and depth, but the grade of the minerals will only decrease. This means that the distances between the pit and crushers, waste dumps, or stockpiles increase. Therefore, with the increased haulage distances, the increase of truck fleet, as the most often used method of haulage, has to come. Purhamadani et al. (2021) mentions that with the decrease of mineral grade comes an increase of diesel usage in liters per ton of ore. And that, on the other hand, means an increase in energy consumption, noise effects, and dust production. Another problem related to IPCC is the Open Pit Mine Production Scheduling Problem (OPMPSP) because of the exceptional features of IPCC systems. IPCC requires more detailed optimization of the mine planning. Moreover, one of the largest problems to consider in this research would be the lack of information and particularly case studies on the topic of IPCC in Kazakhstan. Figure 1 is illustrating Bozshakol Mine Site where the in-pit crushing (IPC) system is used. The Bozshakol copper mine has ambitions to switch from a conventional truck and shovel system to the IPCC system and on the first stage implemented the IPC system. However, several risks associated with truck dumping delays and therefore the IPC productivity loss have been identified.

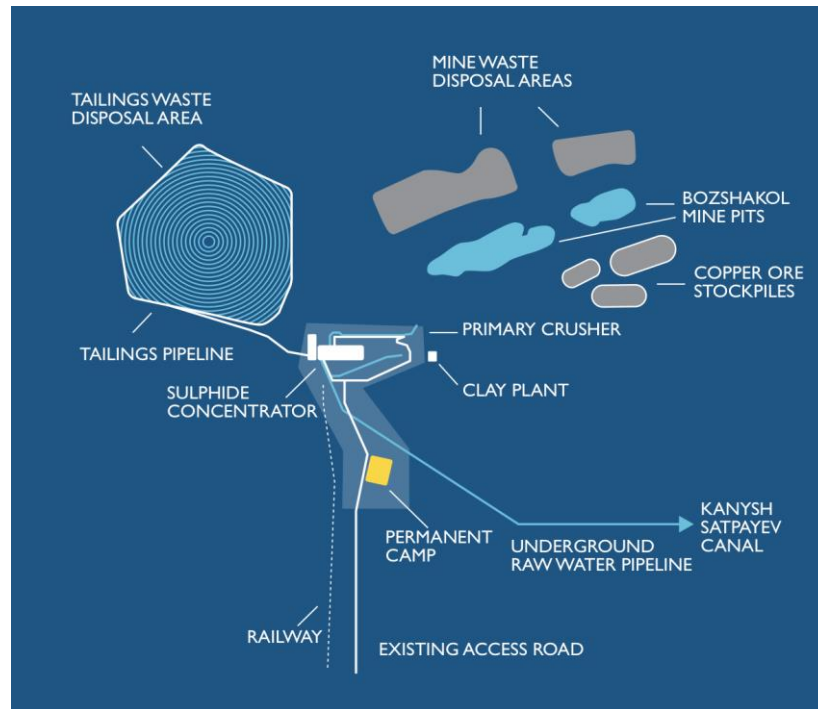


Figure 1. Illustration of Bozshakol Mine Site (KAZ Minerals, 2022)

1.2 Objectives

1.2.1 Aim of the study

The aim of this study is to produce risk estimation of the in-pit crushing (IPC) system installed at the Bozshakol operational copper mine in Kazakhstan.

1.2.2 Objectives

For the objectives of this study the main goals were to collect primary data from the mine site, adapt simulation of risk modeling, build a dynamic stochastic model, receive the results of the simulation, analyze the results as well as interpret and validate the results.

- Conduct literature review for the broad understanding of the topic
- Perform mine site data collection and time-tracking study
- Data analysis and preparation inputs for modelling
- Produce dynamic stochastic model based on the analysed data
- Create Best and Worst scenarios based on Real case data
- Run the model with multiple iteration of Monte Carlo simulation
- Interpret and analyse simulation results

- Provide Conclusions and Recommendations

1.3 Hypotheses

Modern researchers actively study an alternative haulage method - IPCC. IPCC stands for In-Pit Crushing and Conveying Systems. This is a relatively promising in terms of NPV method of haulage which consists of the crusher installed inside the pit and the conveyor which takes the ore to further locations. Samavati et al. (2020) explains that in IPCC, mobile crushing units are located right beside the excavator which then directly loads the ore to the crusher. After that the crushed ore is moved to the conveyor network where it transports to further destinations such as processing plants or the waste dump. So, IPCC acts as a substitute to traditional truck and shovel haulage. This method has several benefits starting from cost effectiveness, lower damage to the environment and higher operational efficiency.

Despite the fact that IPCC is considered to be quite a recent innovation which is extensively studied, some of Kazakhstan's open pit mines have already implemented this system in their work. Examples of such mines can be Koktaszhal Porphyry Copper, Vostochniy coal, Bogatyr coal, Kacharskoye iron ore. However, not much research has been done recently on the topic of local mines using IPCC systems. To develop investigations of implementation of IPC systems at Kazakhstan mines a case study on queuing issues at the in-pit crusher of Bozshakol open pit has been taken as a starting point. Stochastic dynamic risk model can consider risk of delays at the in-pit crusher and can be used to analyse the impact of changing the bin size by changing the limits for full dumping and the crushing rate. The model would be capable to forecast the IPC system's future states and calculate the probability of various outcomes.

1.4 Justification of the R&D

As most important goals of a mine production are to increase the productivity and decrease the costs by implementing more productive systems. However, trucks and shovels with high efficiency also bring a vast number of drawbacks such as cost ineffectiveness due to high energy consumption and serious ecological hazards. With the current trends towards the more sustainable development of the mining industry, the need for more efficient technologies has been raised.

This research is being conducted as the queuing problem of trucks in the mine sites remains one of the most common. With the mining sites getting larger and larger the problem will only increase, therefore the need for IPCC systems will increase.

1.5 Scope of Work

In this study, broad literature review on the topic will be conducted, the primary data will be collected from Bozshakol mine site and on site time-tracking study for in-pit crusher productivity and trucks dumping cycle will be produced. Monte Carlo simulation will be adapted, the dynamic stochastic modelling will be produced, the results of the simulation will be analysed and interpreted.

2. LITERATURE REVIEW

According to Osanloo & Paricheh (2019), due to the existing complicated features and huge scales of operation in open-pit mining sites, the IPCC system is more efficient compared to the combination of truck and shovel technology. Mine depth or scale expansion leads to an increase in the conveyance distance. Hence, the performance of trucks rapidly reduces as transit distance increases. In order to achieve the minimum mine production capacity, the number of trucks or other transporters in use needs to be increased (Osanloo & Paricheh, 2019). Overall, all of these factors raise transportation rates by more than 50% of the production costs, which reduces the affordability of trucks. Such incidents typically take place when the stripping ratio is raised, the project enters a new stage or an expansion phase, and the primary fleet of trucks reaches the end of its operational life. On other hand, these variables will increase the expenses of the project, and decrease its profitability as result it will affect the amount of mineral resources (Osanloo & Paricheh, 2019). The authors also imply that although the use of IPCC technologies in open-pit mining is indeed not a new system, over the past couple of decades there has been a significant increase in the number of research and applications that have looked at the IPCC system as a potential replacement for the conventional TS approach. Ritter in his thesis work (2016, as cited in Osanloo and Paricheh (2019)) conducted a survey and found that overall 447 in-pit crusher machines have been implemented since 1956. Figure 2 emphasizes the use of different types of IPCC systems.

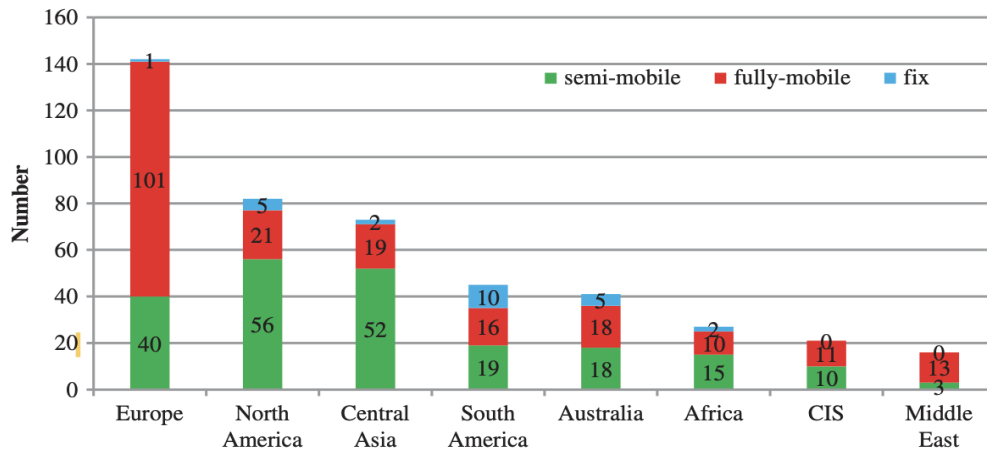


Figure 2. In-pit crusher station distribution by region and type (Osanloo & Paricheh, 2019).

IPCC systems have several advantages over traditional truck haulage methods. An example of such advantages can be the efficiency, long-term productivity, ecological benefits, decreased dust and noise production.

The IPCC system is more cost-effective because of its large production rate (more than 25 million tons annually), extended project lifespans (more than 20 years), and lengthy distances with considerable elevation changes (more than 10 km length or more than 25 minutes of truck cycle time), (Osanloo & Paricheh, 2019). Another advantage of IPCC according to the authors, is that the conveyors are used for hauling both ore and the waste.

McCartney (2011, as cited in Nehring et al., 2018) in his research stated that there are several important factors that are needed to be considered in planning IPCC implementation into the open pit. These are such technical parameters as a) no more than 4 Mtpa of material movement, b) mine life over 10 years, c) less than quarter costs for electricity compared to diesel. Overall, all these parameters are crucial in maintaining Capital Expenditure (CAPEX) and cost effectiveness.

IPCC is a safer alternative to the truck haulage system as it does not require the same number of labors. Nehring et al. (2018) states that some IPCC systems can require only 80 workers, whereas only one truck in truck haulage will need a minimum of 7 workers.

Usually, IPCC's are implemented in the open pit with longer mine life as by this way it can overcome and prevail the operating costs of the project. Nehring et al. (2018) states that IPCC is best used in the deep mines with low sinking ratios, so that one crusher can serve at the same location for more than 5 years.

Russel (2010) provided examples of implemented IPCC systems around the world: in the Baiyinhua coalfields of Inner Mongolia, there are three fully mobile IPCC systems with 6,000 mt/h capacities for overburden and a 3,000 mt/h fully mobile IPCC system for coal; four 5,600 m³/h semi-mobile RollSizer crushing plants handling coal and overburden, with spreader systems, installed at the Coilolar project in Turkey; four 4,250 mt/h semi-mobile crushing plants with gyratory crushers for iron ore are used in Australia, Bulgaria, and Australia. Two fully movable IPCC systems and a spreader are used in a waste rock handling system that can handle 7,000 mt/h of waste rock.

Types of IPCC

There are several types of IPCC systems. For example, Nehring et al. (2018) differentiates several types of in-pit conveyor systems: Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) and Fully-Mobile In-Pit Crushing and Conveying (FMIPCC). Nehring et al. (2018) also mentioned that with the help of SMIPCC and FMIPCC the need for truck haulage during the steady state operation diminishes. Utley (2011, as cited in Paricheh & Osanloo, 2019) states that three categories of IPCC systems—fixed, semi-mobile, and fully mobile—are defined. However, Abbaspour et al. (2018) in their work mentions overall four types of conveyor systems: In-Pit Crushing and Conveying (FIPCC), Semi-Fixed In-Pit Crushing and Conveying (SFIPCC), Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) and Fully Mobile In-Pit Crushing and Conveying (FMIPCC) systems. Moreover, they also mention that in all of these conveyor systems (FIPCC, SFIPCC, and SMIPCC) the conveyor belts move crushed material away from the pit.

Opportunities of IPCC Systems

Ecological opportunities

Talking about ecological advantages of IPCC, Negring et al. (2018) gives an example of IPCC usually being operated by electrical energy rather than diesel compared to conventional truck haulage. Therefore, it can be said that this mining method is considered to be more ecologically safe in comparison to truck and shovel haulage systems. Nehring et al. (2018) mentions that because future mines will get deeper, the haulage distance and consequently the fuel usage will also increase. This will lead to higher noise, CO₂ and dust emissions, which, in its turn, will cause a much more visible environmental footprint. Moreover, according to Negring et al. (2018), traditional truck haulage is highly affected by high Operating Expenditure (OPEX) as one of the main cost effectiveness determining factors. In addition, according to

Nehring et al. (2018), one of the most important factors comprising IPCC's efficiency is that conveyors receive 81% of the consumed energy for hauling the payload, whereas traditional trucks get only 39%. Moreover, because of that, the Operating Expenditure of IPCC can constitute only a third part of the truck shovel (Nehring et al. 2018).

Overall, most researchers believe that the IPCC systems may assist mining operations in making the most potential progress towards sustainable development.

Safety

Abbaspour et al. (2018) in their research compare traditional truck-shovel haulage with Fixed In-Pit Crushing and Conveying (FIPCC), Semi-Fixed In-Pit Crushing and Conveying (SFIPCC), Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) and Fully Mobile In-Pit Crushing and Conveying (FMIPCC) systems. They used safety and social indexes as the indicators of meeting the safety and social criteria for the mines. Abbaspour et al. (2018) used a statistical approach by trying to connect such factors as accidents, injuries, and casualties by trying to develop relationships between them and other factors.

IPCC can be considered a safer option of haulage due to high automation compared to the high maintenance trucks haulage systems. However, Abbaspour et al. (2018) stated that conveyor belts have unsafe potential. Kecojevic et al. (2008, as cited in Abbaspour et al., 2018) developed risk determining technique of using conveyor belts and the ways it can cause fatalities or injuries. For that Preliminary Hazard Assessment (PHA) was used as a method of quantifying the risk. In order to compound their model, Abbaspour et al. (2018) took into consideration such indicators as average truck speed, traffic flow, traffic density, training, lost time injury rate, and number of conveyors sets as the leading factors affecting safety on the mining site.

Case Studies

Abbaspour et al. (2018) mentions that there are several risks particularly associated with moving parts of the conveyor belt. Mine Safety and Health Administration (United States Department of Labor, 2018, as cited in Abbaspour et al., 2018) provided reports starting from 1995 until 2015, where it is mentioned that 31 out of 65 accidents were related to moving parts of the conveyor belt. This shows that the moving part of the conveyor belt plays a large role in causing different types of accidents. Abbaspour et al. (2018) made a model on a hypothetical example of a copper deposit. The authors conducted a simulation based on calculated mine life

and production tonnage as 32.5 years and 21.54 million tonnes per year respectively. Abbaspour et al. (2018) received a model of the safety index of five transportation systems including traditional truck-shovel and different conveyor belt systems (Figure 3):

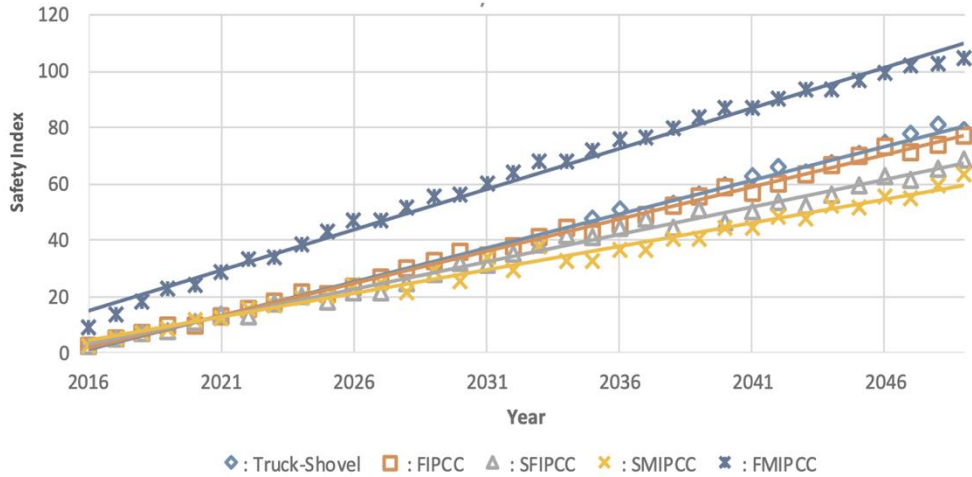


Figure 3. Safety index of five transportation systems (Abbaspour et al., 2018)

As was mentioned previously, safety index here includes different types of haulage systems (Abbaspour et al., 2018). According to the author, Figure 3 shows the compiled model of the safety index where the Fully Mobile In-Pit Crushing and Conveying system has shown the highest results throughout the whole mine life. It means that FMIPCC can be considered as the most safe system compared to others. This method also does not require much labor and is more automated. Overall, according to the results of Abbaspour et al. (2018), FMIPCC has shown the highest safety index, while SMIPCC has shown the lowest using a system dynamic model.

Moreover, Osanloo and Paricheh (2019) in their literature review said that placing the primary crusher inside the pit maintains the average truck transport distance at around one kilometer inside the pit. Consequently, there will be seven fewer trucks overall, or 27 units, each operated and maintained by at least 5 people. Having fewer vehicles in open pit mines could also result in fewer accidents (Osanloo & Paricheh, 2019). As cited in Osanloo and Paricheh (2019), Banda (2016) mentions that in the South African iron mine Sishen almost 90% of fatal accidents were due to truck activities.

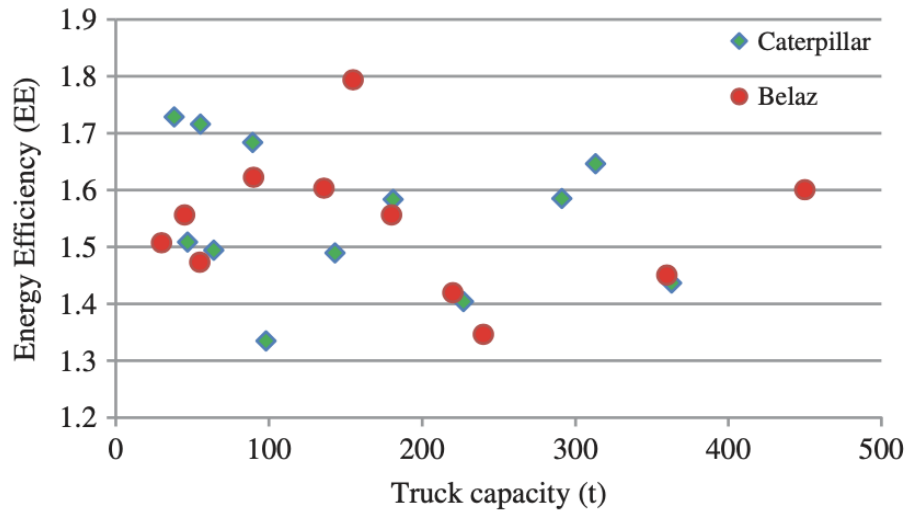


Figure 4. Energy efficiency of different classes of high-way trucks (Osanloo & Paricheh, 2019).

Figure 4 shows that the gross weight of trucks demonstrates that this ratio ranges from 1.3 to 1.8 (Osanloo & Paricheh, 2019). As authors suggest, it means that only 40% of the energy used by a truck cycle is used to shift the payload; the other 60% is used to move the weight of the truck itself. However, when talking about the conveyors, less than half of the total weight of the material is carried by the top and lower portions of the conveyor for each meter of its length. In other words, the energy used to move the material is greater than 70%, while the energy lost is lower than 30% (Osanloo & Paricheh, 2019).

Osanloo and Paricheh (2019) mentioned the work of Norgate and Haque (2013), where they state that the energy required by the IPCC system was 818 MJ/t ore compared to 1024 MJ/t ore for the TS system (Figure 5), according to a life cycle analysis of two IPCC and TS systems. In contrast to the TS system, which has a carbon footprint of 70 kg CO₂ equivalent per tonne of ore, the IPCC system has a footprint of 67 kg CO₂e/t ore, a reduction of 3 kg CO₂e/t ore (Norgate & Haque, 2013, as cited in Osanloo and Paricheh, 2019).

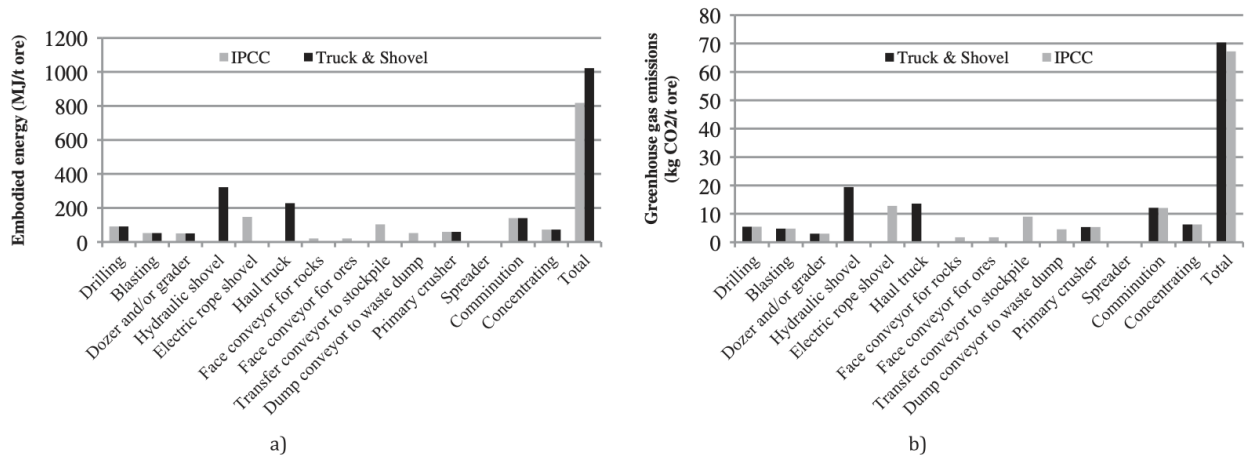


Figure 5. Consumed energy and greenhouse gas emissions of IPCC and TS transport modes, (a) energy consumption, (b) greenhouse gas emission (Norgate & Haque, 2013, as cited in Osanloo and Paricheh, 2019).

Regarding the situation in Kazakhstan, it is known that several mining sites have been using the IPCC systems already, however little to no data was found regarding the implementation of these systems, their productivity, or their potential outcomes.

On the other hand, the study of Sapakov & Kulniyaz (2015) has shown that Aktogay open pit, currently operated by KAZ Minerals LLP, was considering implementing IPCC systems. According to the authors research, Aktogay is planning to reach their productivity to 50 million tons of ore per year, while the pit depth will reach over 700 m. Sapakov & Kulniyaz (2015) suggest implementing IPCC systems as a way to increase the productivity and decrease the costs on truck haulage due to increase in the depth of the pit and, therefore, vast increase in the haulage distance. With the dip angle of 16-18°, IPCC would reduce the cost of transporting rock mass by 30-40% and increase the labor productivity by 1.4-2 times (Sapakov & Kulniyaz, 2015). The authors also mention that their studies have found that the longer the life of the quarry, the lower the operating costs of conveyor transport. Studies have shown that the specific energy consumption of the IPCC quarries is 14-16 % lower compared to the cyclic technology. This is very important in conditions of instability and constant increase in prices for energy resources. The distribution of energy consumption by the main technological processes of IPCC is on average: transportation of rock mass - 75-80 %, crushing - 8-10 %, excavation - 16-18 % (Sapakov & Kulniyaz, 2015).

Potential risks and limitations of IPCC Systems

Optimization limitations of IPCC

The biggest deterrents to deploying the system are high capital expenditure, ore-body characteristics, mine planning, and operational dependability (Osanloo & Paricheh, 2019). Therefore, more in depth research must be done on the planning and optimization.

Negring et al. (2018) discusses potential risks associated with Ultimate Pit Limit optimization being used mostly for truck haulage systems and not for the conveyor systems. Osanloo and Paricheh (2019) also mention in their research that optimization continues to be one of the most difficult aspects of implementing IPCC in the open pits.

Samavati et al. (2020) mentions that nowadays due to increase of the interest in IPCC systems, the problem of lack of sequencing constraints in the production scheduling and optimization of this process. He explains how optimization is mostly taking into consideration truck haulage systems, while neglecting the IPCC systems which gain more recognition among worldwide mines. In their research Samavati et al. (2020) tried to present a new integer programming model for production scheduling. Their programming formulation was aimed at moderating the Open Pit Mine Production Scheduling Problem (OPMPSP). They called it OPMPSP-IPCC referring to the specific case of IPCC systems. In order to comprehend IPCC systems, Samavati et al. (2020) had to add additional constraints and variables in their algorithm. According to Samavati et al. (2020) this OPMPSP-IPCC is used for creating a network of conveyors inside the deposit and regulating material extraction movement. These extra limitations make the already complicated large scale OPMPSP even more complicated (Samavati et al., 2020). However, with their algorithm optimization process computation would decrease to only 1442 s.

Paricheh and Osanloo (2019) in their research mention that the issue of design and planning is linked to two additional open-pit mining issues, namely truck fleet replacement planning and OPMPSP. To simultaneously provide the best solutions, these issues were merged into a single optimization model by the authors. The newly designed MILP model's (M1) practical performance was then assessed by contrasting it with two other models (M2 and M3) that do not include IPCC planning (Paricheh & Osanloo, 2019). The second model takes into account fleet sizing in line with OPMPSP, whilst the third model is a traditional OPMPSP model. Paricheh and Osanloo (2019) also state that by maximizing the system application time, the crusher site and relocation plan, and the ideal number of ex-pit or in-pit crushers, the

computational results demonstrated that the suggested model could successfully address the IPCC planning issue. In this approach, the IPCC planning also optimized the extraction sequences, material destinations, and truck fleet size (Paricheh & Osanloo, 2019). The total cash flows of the cases and their NPVs were likewise improved when compared to the traditional model, by \$28.5 million and \$23.8 million, respectively, and 3.3% and 2.4%, respectively (Paricheh & Osanloo, 2019).

Osanloo and Paricheh (2019) in their literature review describe several potential problems of IPCC systems related to the planning process. The authors state that given that transportation costs make up about half of mining expenses, even a little adjustment in those costs can have a significant impact on block value. An increase in block value is strongly correlated with a decrease in transportation costs. The primary crusher is moved within the pit solely to cut down on hauling expenses (Osanloo & Paricheh, 2019).

Block extraction sequences vary beyond a doubt when block values are changed. Authors also mention that the ore block that is situated nearer to the in-pit crusher generally has a higher value when two ore blocks with the same metal content are compared. As a result, it would have a higher extraction priority. On the other hand, the profit made from altering the transportation infrastructure could have a visible effect on how far the ultimate pit limit can be extended (Osanloo & Paricheh, 2019). Overall, according to Osanloo and Paricheh (2019), both of these IPCC issues include time and place variables. One involves the time and place of block extraction and the other involves the time and place of the system installation.

Another research of Bernardi et al. (2020) was studying the problem of optimization of IPCC systems. They proposed that the changes to the number of haul trucks needed and the intervals at which they were added to the fleet were made as part of the optimization, which resulted in increased NPV for each configuration (Bernardi et al., 2020). Bernardi et al. (2020) describe the technique that enables rapid and easy comparison of suggested and implemented materials handling systems, as demonstrated by the iterative optimization of the proposed systems using DES and Process Analyzer. The suggested systems analysis technique has the potential to be used repeatedly to emphasize the advantages and disadvantages of different mine designs, with the possibility to test several ideas for relatively little money and effort (Bernardi et al., 2020). As a result, the objective of developing a technique to enhance accessibility and practicality of testing IPCC systems in massive mining operations has been realized (Bernardi et al., 2020).

Moreover, because of the linear bench and flat floor limitations placed by conveyor systems, fully mobile in-pit crushing and conveying systems have different pit form requirements than conventional truck haulage systems (Hay et al., 2019). Moreover, Hay et al. (2019) state that since the ultimate pit limit primarily determines the form of a pit, it is preferable to consider the extra shape requirements of fully mobile in-pit crushing and conveying systems in the process of determining the final pit limit. Overall, the authors imply that as the more restricted scheduling of FMIPCC options has a more detrimental effect on NPVs than conventional scheduling, it is crucial to schedule each FMIPCC option for a deposit (Hay et al., 2019).

General risks associated with IPCC

Overall, there are more risks associated with IPCC systems rather than optimization problems. Pekol (2019) described potential risks associated with conveyor systems in his work. He mentioned that the most critical risk factors are determined to be those relating to the environment, financial considerations, upkeep, safety, repair, availability, offer, geology, and reliability. Throughout the reading of relevant literature and brainstorming, 99 dangers were found (Pekol, 2019). He developed a check-list of potential risks (Figure 6). However, it is vital to mention that these risks may not apply directly to IPCC, but more to the general open pit operations. Pekol (2019) also mentioned that because fully mobile crushers are installed in fixed crushing stations that are placed in the same location and left there for a number of years, these crushers are made to move with the loading system. Therefore, fully mobile crushers (FMIPCC) require a greater workspace than stationary crushers, which must be taken into account (Pekol, 2019).

TABLE 1 Risk checklist for open-pit mining operations							
Number	Stage	Risk Issue	Risk Event/ Issue	Causes	Preventative Controls	Impact	Mitigating Controls
6	Operation	Operability conditions	Coal fire	Self-ignition of pyrite due to oxygen reaction; Poor heat emission due to unfavourable fill	Early detection of pyrite bearing layers/formations; Alternative extraction/ventilation method; Fully extraction of coal seam	Damage to environment; Standstill of mining operation; Injury to personnel	Measurements of temperature, gas content; Geophysical measurements (e.g. magnetic properties of country rock); Prevention of oxygen supply (e.g. usage of covers, barriers); Monitoring of fire area

Figure 6. Risk checklist for open mining operations (Pekol, 2019).

Phill Morris (2008) in his works describes how it is necessary to determine the appropriate hours for each link in the IPCC "chain" and then consider how they interact in order to establish realistic estimates for the effective operating hours for an IPCC system as well as the hours that the system must run in order to achieve those effective hours (the Service Meter Unit or "SMU" factor). Moreover, the fact that there is no established method for obtaining or presenting this data in the mining industry. The "standard" nomenclature used by the majority of large mining corporations use reporting systems (like Modular Mining) to give data that serves as the foundation for calculations (Phill Morris, 2008).

Another risk associated with IPCC is the problem of setting the correct parameters for steepness (dip angle) and the material chosen for the conveyors. According to this article, because high-performance conveyor belts transport bulk materials up the opencast mine's steep embankment and out of the mine by receiving primary crushed ore or rock overburden from an upstream primary crusher at the mine's base (Minkin et al., 2018). In this study, Minkin et al. (2018) were investigating the material behavior inside the conventional Mega-Pipe belt and the Deep Through belt. In their study they found the optimum parameters for the conveyors in this case: directly following a primary crusher in up to 1000 m-deep open pit mines with slope angles of up to 30°, a system with the up to 3200 mm wide and up to 10,000 N/mm strong deep trough chevron-belt can achieve volume flows of up to 12,000 m³/h or an annual conveying capacity of about 100 million m³ per year (8,322 h) (Minkin et al., 2018).

Another potential issue is choosing the location of the conveyor system, as it is known they are mostly static for a long period of time. Paricheh and Osanloo (2019d) in their research introduce a new search method for selecting the candidates with the lowest opportunity cost and most usability. In order to group the blocks that are located in the same azimuth domains, pushbacks, and benches, a new clustering method was also devised (Paricheh & Osanloo, 2019d). The algorithm looks for the best options while taking into account a number of general and specialized rules among the aggregated blocks included inside the eventual pit limit (Paricheh & Osanloo, 2019d).

Economical perspective

One if not the most important factor in considering a mining project is the economical perspective, as cost effectiveness continues to be the primary factor of deciding whether the project is valuable or not. Therefore, this perspective will be discussed in this section based on the case studies and current research implementations.

According to Turnbull and Cooper (2010), conveying presents a desirable option for the difficult times ahead and into the ostensibly energy-depleted future since it uses energy significantly more efficiently than vehicles do and has lower operational expenses per ton transported. When Sandvik and Snowden compared IPCC with truck-optimized pit designs in 13 of their 15 experiments, they found that IPCC produced operating savings of between \$0.18 and \$0.82 per ton moved (Turnbull & Cooper, 2010).

Osanloo and Paricheh (2019) in their work describe how the previous studies (Dean et al., 2015) defined the economical comparison of these two systems (IPCC and Truck-Shovel) by consideration of technical safety and environmental factors. The following Figure 7 illustrates the net present value (NPV) of the two systems over the lifetime of the mine.

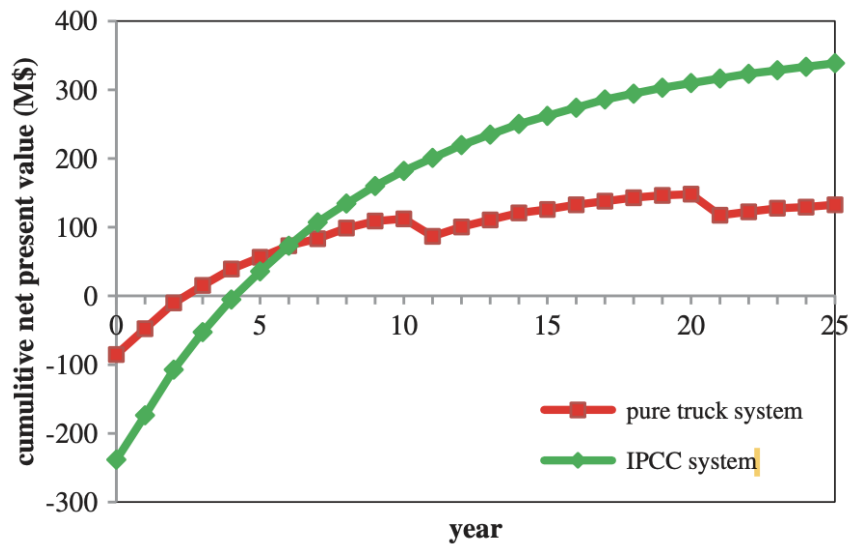


Figure 7. Typical economic comparison of TS and IPCC systems (Osanloo & Paricheh, 2019).

Taking into account the necessity to replace the trucks as they become worn out, it is important to emphasize that the conveyor system has a lower initial investment cost over the mine's operational lifetime, while the machine's expected lifetime also impacts profitability and depreciation charges. On the other hand, as the mining operation develops, the transport length increases, and as a result, it increases the cost of transportation for both the truck and the conveyor. However, compared to truck haulage, conveyor transportation does not respond as significantly to an expansion in the mobility path.

However, despite the general thinking about the high CAPEX of these systems, they impose much lower OPEX to the project (Abbaspour & Drebenstedt, 2019b). Moreover, Abbaspour & Drebenstedt's (2019b) research have shown that the FMIPCC method has a

higher economic index for the remaining five years of the mine's life, but the Truck-Shovel system is preferred for the first five years of the project. Additionally, it was demonstrated that choosing the optimal transportation system based solely on the capital or operating costs might be detrimental. In this study, Truck-Shovel and FMIPCC had the lowest capital and running expenses, respectively (Abbaspour & Drebenstedt, 2019b).

The trucking system's operating costs (OC) are driven upward by rising costs per ton of amortization, infrastructure maintenance, gasoline, and tires, which results in a reduction in cash flow. Figure 6 illustrates that beyond a period of three to seven years, the NPV of the IPCC system will approach that of a conventional truck system. The economic benefits of this technology will then rise to the optimum point for mining transportation activities and become more prevalent. Throughout that period, the two curves will be moving much farther apart and more rapidly. As shown in Figure 6, the NPV of the IPCC system is two times more than the truck system.

3. METHODOLOGY

3.1 Mine Site Data collection

For this research work the data from KAZ Minerals' open pit Bozshakol was collected that will be used for Risk Analysis. The data contained such parameters as both crushers' dimensions, spotting and dumping (backing and tipping) time of the trucks, and actual data on the operation of the primary crusher.

Actual data on the operation of the primary crusher was collected and contained information about tonnage of the crushed ore (DMT), operating hours of the crusher, and tonnes per operating hours for the year of 2022 (starting from January 1st to December 19th 2022).

According to KAZ Minerals' data, the maximum performance stated by the manufacturer of the crusher is 5100 tons per hour. However, the company does not use it to the full capacity as the capacity of the mill fluctuates between 3500 to 4000 tons per hour. As stated by KAZ Minerals' chief engineer, the bin limit of the crusher for full dumping is 406 tons or 242 m³ in volume.

Bozhsakol mine site has two in-pit crushers: South and North. The study utilize data from the South crusher. Figure 8 shows the South crusher's dimensions where it can be seen that the height of the crusher is 10 meters.

Moreover, several assumptions must be made. Trucks conditions are assumed to be the same. Operators' behavior and skills are also assumed to be the same.



Figure 8. South Crusher's dimensions (KAZ Minerals, 2022).

According to the data provided by KAZ Minerals (2022), the truck fleet consists of 28 dump trucks from Caterpillar 785 C/D with a maximum capacity of 140 tons. Figure 9 represent a dump truck model (Caterpillar 785 C/D Dump Truck, n.d.).



Figure 9. Caterpillar 785 C/D dump truck (Caterpillar 785 C/D Dump Truck, n.d.)

For data analysis time-tracking study for in-pit crusher productivity and trucks dumping cycle for it has been produced. In addition, video-recorded materials from Bozhsakol mine site were used for confirmation of produced estimations. Shooting of trucks dumping in the crusher were looked at and observed in order to understand the arrival time

and the dump time of each truck. In Table 1, collected, interpreted and analysed data prepared for modelling with the probabilistic inputs.

Table 1. Data prepared for modelling with the probabilistic inputs

Truck No.	Arrival Time	Time between Arrivals - Min.	Spot Start Time	Spot Time Minutes	Dump Time Minutes	Actual Dump Time - Min.	T. in Truck	Dump Rate T. / Min.	Beg. Bin Qty. T.	Crushing Rate T. / Hr.	Crushing Rate T. / Min.	End Bin Qty. T.	Finish Time	Delay Time Minutes
1	0.00	0.00	0.00	3.66	1.19	1.19	122.59	102.75	200.00	3490.40	58.17	40.14	4.88	0.00
2	2.00	2.00	4.88	1.32	1.15	1.15	133.38	115.59	40.14	3198.80	53.31	41.58	7.33	2.86
3	4.07	2.07	7.33	4.25	1.65	1.65	129.23	78.30	41.58	3637.88	60.63	0.00	13.23	3.26
4	6.28	2.22	13.23	3.76	0.94	0.94	126.88	134.63	0.00	3604.27	0.00	126.88	17.93	6.94
5	8.30	2.02	17.93	1.94	1.49	1.49	126.20	84.84	126.88	3580.81	59.88	48.32	21.36	9.63
6	10.25	1.95	21.36	4.03	1.65	1.65	120.83	73.01	48.32	3577.48	59.62	0.00	27.04	11.11
7	12.23	1.98	27.04	1.84	1.52	1.52	120.26	79.87	0.00	3558.82	0.00	120.26	30.41	14.81
8	14.20	1.97	30.41	2.11	1.06	1.06	128.66	121.54	120.26	3558.63	59.31	60.82	33.58	16.21
9	15.98	1.78	33.58	1.21	1.15	1.15	129.46	112.15	60.82	3605.33	60.09	47.93	35.95	17.59
10	17.90	1.92	35.95	4.71	0.81	0.81	125.37	155.21	47.93	3555.78	59.26	0.00	41.47	18.05
11	19.82	1.92	41.47	1.66	1.30	1.30	122.78	94.24	0.00	3362.48	0.00	122.78	44.43	21.65
12	21.90	2.08	44.43	2.33	1.48	1.48	124.76	84.31	122.78	3806.27	63.44	5.83	48.24	22.53
13	23.90	2.00	48.24	2.12	1.58	1.58	129.09	81.58	5.83	3623.10	60.39	0.00	51.94	24.34
15	25.87	1.97	51.94	0.94	1.16	1.16	128.63	110.46	0.00	3225.08	0.00	128.63	54.04	26.07
16	27.82	1.95	54.04	3.70	1.35	1.35	124.72	92.25	128.63	3280.13	54.67	0.00	59.10	26.23
17	30.05	2.23	59.10	3.59	0.74	0.74	121.57	164.30	0.00	3591.26	0.00	121.57	63.43	29.05
18	32.33	2.28	63.43	5.22	1.74	1.74	134.22	77.35	121.57	3669.18	61.15	0.00	70.38	31.09
19	34.03	1.70	70.38	0.76	1.40	1.40	121.61	87.05	0.00	3692.48	0.00	121.61	72.54	36.35
20	36.20	2.17	72.54	2.02	1.26	1.26	127.42	101.08	121.61	3657.93	64.30	38.28	75.81	36.34
21	38.13	1.93	75.81	4.12	1.87	1.87	127.62	68.18	38.28	3460.78	57.68	0.00	81.80	37.68
22	39.82	1.68	81.80	2.99	1.69	1.69	124.95	73.79	0.00	3515.39	0.00	124.95	86.48	41.99
23	41.65	1.83	86.48	1.61	1.56	1.56	122.72	78.66	124.95	3255.15	54.25	75.77	89.65	44.83
24	43.28	1.63	89.65	2.48	1.33	1.33	127.96	95.90	75.77	3714.60	61.91	0.00	93.47	46.37
25	45.32	2.03	93.47	3.10	1.70	1.70	123.24	72.37	0.00	3297.34	0.00	123.24	98.28	48.15
26	47.20	1.88	98.28	1.50	1.19	1.19	127.62	106.87	123.24	3635.10	60.58	87.75	100.97	51.08
27	49.22	2.02	100.97	3.28	1.72	1.72	128.60	74.87	87.75	3542.98	59.05	0.00	105.96	51.75
28	51.63	2.32	105.96	2.47	1.15	1.15	133.13	116.01	0.00	3304.79	0.00	133.13	109.58	54.43

3.2 Dynamic stochastic modelling

As part of the methodology, risk estimation methods is conducted. There are several types of risk analysis methodologies: Qualitative Methods, Quantitative Methods, and Semi-quantitative Methods. In the scope of this research, Quantitative risk analysis methods will be used. A mathematical approach called stochastic dynamic modeling is used to examine and project how complex systems will behave in the presence of random or ambiguous causes. This kind of modeling is frequently used to predict the behavior of systems over time. Stochastic dynamic models are defined by the incorporation of random variables and the evolution of those variables across time. These models are frequently employed to forecast system future states and calculate the probability of various outcomes.

Research about stochastic dynamic models presume that decisions are based on the accumulation in continuous time of noisy, time-varying sensory information (Smith, 2001c). These models of decision-making are used in simple perceptual and cognitive tasks. Stochastic differential equations are used to mathematically depict the dynamics of information accumulation in these models (Smith, 2001c).

For the experimental work of this research, Palisade @Risk software was used. The software is based on Excel and acts as an extension for it which allows it to perform different estimates of the risk analysis.

In this research, Monte Carlo simulation used in order to run dynamically stochastic model. In this simulation, a random value is given to the unknown variable in a Monte Carlo simulation. After that, the model is used to produce a result. It then will be repeated multiple times using different random variables in order to achieve the higher accuracy of the outcome. Important to mention, that as Stochastic Modeling uses random variables, the repeatability will only increase the randomness.

For the Monte Carlo Simulation random variables are used in the sample. Moreover, Monte Carlo is a simulation technique that computes the outcomes using statistical analysis and many times repeated random sampling. This simulation technique is quite similar to random tests, in which the precise outcome is initially unknown. In other words, as Raychaudhuri (2008) calls this technique “what-if” analysis as the main purpose of the model to predict as many results as possible. Since the values of these input parameters are their most likely values, a deterministic model that ignores these variances is frequently referred to as a base or real case. The risks related to diverse input factors should be included in an efficient model. Therefore, an effective model must include three scenarios: Real, Worst, and Base Cases as an initial version of the model. As a result, mathematical model produced will show the result for output of each case which will show a more realistic and critical approach to a problem. According to the study of Raychaudhuri (2008) for each of the input parameters, we find a statistical distribution in Monte Carlo simulation that we can use as the source. The values of the input variables are then represented by random samples that were taken from each distribution. A set of output parameters is obtained for each set of input parameters. Each output parameter's value corresponds to a certain simulation outcome scenario.

As Raychaudhuri in his research suggests (2008), in order to build Monte Carlo simulation, four main steps must be performed. First step is a Static Model Generation, or in other words a Deterministic Model, where the most real values are usually used in order to receive the most realistic scenario (base case). Second step is an Input Distribution Identification where from deterministic, the model must become stochastic to fulfill the realness of the risks. In this step the input variables' underlying distributions should be identified. Next step is a Random Variable Generation or in other words random samples. Here, the deterministic model will produce one set of output values by using one set of random integers, one for each of the input variables. Then, by producing additional random number sets, one for each input distribution, this procedure is repeated and gathers several sets of potential output values. Then, Analysis and Decision making, statistical analysis is performed in order to choose

the best version. As a last step, dynamic simulation is produced, meaning that the trucks in simulation are coming continuously without stop.

Raychaudhuri in his study (2008) presents several formulas used in the basic statistical analysis that was used in this study: Mean (1), Median (2), Standard Deviation (3), Variance (4), Coefficient of Variability (5), Minimum (6), Maximum (7), Range Width (8), and Mean Standard Error (9). All of these formulas are used in the Monte Carlo Simulation's statistical analysis.

$$\bar{x} = \frac{1}{n} \sum_i x_i \quad (1)$$

Median is used in 50th percentile (2)

$$s = \sqrt{\frac{1}{N-1} \sum_i (x_i - \bar{x})^2} \quad (3)$$

$$s^2 = \frac{1}{N-1} \sum_i (x_i - \bar{x})^2 \quad (4)$$

$$\text{Coeff. of Variability} = \frac{s}{\bar{x}} \quad (5)$$

$$x_{min} = \min x_i \quad (6)$$

$$x_{max} = \max x_i \quad (7)$$

$$\text{Range Width} = x_{max} - x_{min} \quad (8)$$

$$\text{Mean Std. Error} = \frac{s}{\sqrt{n}} \quad (9)$$

Several distributions were used in the inputs of the Monte Carlo such as Poisson distribution, PERT distribution and the triangle distribution.

In statistical analysis, the Poisson distribution is a probability distribution that is frequently used to simulate the occurrence of events. The predicted number of occurrences of the event of interest within a specific time or space interval is represented by the Poisson distribution's sole parameter, denoted as λ (lambda).

In statistical analysis, the Poisson distribution is a probability distribution that is frequently used to simulate the occurrence of events. The predicted number of occurrences of the event of interest within a specific time or space interval is represented by the Poisson distribution's sole parameter, denoted as λ (lambda). Given the predicted number, the probability mass function of the Poisson distribution calculates the likelihood of observing k

instances of the event during the interval (Ross, 2014). This probability mass function has the following formula (10):

$$P(k; \lambda) = (e^{-\lambda} * \lambda^k) / k! \quad (10)$$

where k is a non-negative integer, e is the mathematical constant, and $k!$ denotes the factorial of k . (i.e., the product of all positive integers up to and including k).

The fact that the Poisson distribution's mean and variance are equal to λ is one of its key characteristics. This implies that as λ rises, the distribution's shape becomes increasingly symmetric around its mean. Also, when the number of trials is very large and the likelihood of success is very low, the Poisson distribution is frequently utilized as an approximation of the binomial distribution (Johnson et al., 1995).

In this study Poisson distribution will be used for time between truck arrivals. It is useful as Poisson allows dependencies.

According to Inouye et al. (2017), univariate count-valued data have been examined and modelled extensively using the Poisson distribution. Although they are much less common, multivariate versions of the Poisson distribution that allow for dependencies. Moreover, Inouye et al. (2017) in their article describe that using three different underlying assumptions, there are three basic methods for creating multivariate distributions generated from the Poisson distribution: the marginal distributions are obtained from the Poisson, the joint distribution is a combination of independent Poisson distributions, and the node-conditional distributions are derived from the Poisson.

Next distribution method used in the risk analysis of this research work is PERT. The time of a project or assignment can be estimated statistically using the Program Evaluation and Review Technique (PERT) distribution. It is a three-point estimation method that considers the most likely, worst-case, and best-case scenarios to establish the anticipated time for project or task completion.

The PERT distribution presupposes that the duration needed to finish a project or work follows a continuous probability distribution called the beta distribution, which has a range of values between 0 and 1 (Johnson, 1949). The PERT distribution considers the likelihood of the best-case scenario, worst-case scenario, and most likely scenario to produce a more precise estimate of the time needed to finish a project or activity. This gives an estimate range rather than a single point estimate, which can be useful for project planning and risk management. In

the case of this research work, worst case, regular case, and best-case scenarios were used. Moreover, PERT distribution was used in order to find tons per truck for the simulation.

The PERT distribution's formula is (11):

$$f(x;a,b,c) = \frac{(x-c)/(c-a)}{B(a,b)} * (c-b) \quad (11)$$

$$\frac{1}{B(a,b)} * (c-b) * \frac{1}{\Gamma((a+b)/2)} * \left(\frac{x-c}{c-a} \right)^{\frac{(a+b)}{2}-1} * \left(1 + \frac{x-c}{c-a} \right)^{-\frac{(a+b)}{2}}$$

where $f(x;a,b,c)$ denotes the probability density function of the pert distribution for a given value of x , a , b , and c denote the four distribution parameters that stand for the smallest, most likely, and largest values of the uncertain time, respectively, and $B(a,b)$ denotes the beta function (Pendharkar et al., 2005).

In this study PERT was used for tons per truck input as it is used for continuous probability.

Triangle distribution is another distribution method that was used in this research. The triangle distribution is a continuous probability distribution that is frequently used in statistics, notably in simulation studies. Its name refers to the probability distribution's triangular shape. Three factors— a , b , and c —are used to define the distribution. While a and b represent the lower and upper bounds, c represents the median, or most likely value. The triangular distribution's probability density function (PDF) is linear, with the mode showing the highest value. Since the area under the PDF curve is always equal to 1, it is symmetric about the mode. Because it allows for variation in the input parameters, the triangle distribution is usually applied in simulations. By utilizing the triangle distribution, it can be taken into consideration the ambiguity of the input parameters. Therefore, the decisions can be based on the likelihood of various outcomes in a more accurate way.

The formula for the triangular distribution (12) is:

$$\text{If } x \leq a, \text{ then } f(x;a,b,c) = 0; \text{ if } a \leq x \leq c, \text{ then } f(x;a,b,c) = \frac{2(x-a)}{(b-a)(c-a)}; \text{ if } c \leq x \leq b, \text{ then } f(x;a,b,c) = \frac{2(b-x)}{(b-a)(b-c)}; \text{ and if } x > b, \text{ then } f(x;a,b,c) = 0 \quad (12)$$

Where a is the lowest value, b is the highest value, and c is the distribution's mode (Kendall & Stuart, 1977).

Triangle distribution was used for determining dump and spot time per truck and the crushing rate in the scope of this work. It is needed for the even distribution with higher accuracy needed for simulation.

The results of the simulation were produced in form of graphs using probability density and the normal distribution.

Probability density is a term used in probability theory to describe the likelihood that a random variable will take a particular value. It is a function, more specifically, that expresses the probability that a continuous random variable will take any particular value inside a given range.

The distribution of probabilities for a continuous random variable is described by a mathematical function called a probability density function (PDF). The likelihood that the random variable will take a value inside a given range is determined by the area under the curve within that range, which is how the PDF is defined. The probability density, or relative likelihood that a random variable will take any particular value within a range, is represented by the PDF's curve.

The normal distribution, also referred to as the Gaussian distribution, is a continuous probability distribution that is frequently utilized to model random variables that have a tendency to cluster around a central value, with the majority of observations falling close to that central value and fewer observations at extreme.

The mean and standard deviation of a normal distribution are two parameters that describe it. While the standard deviation indicates the distribution's spread, the mean represents the distribution's symmetrical tendency.

A bell-shaped curve with symmetry around the mean makes up the normal distribution's probability density function (PDF). The distribution's mean is shown by the curve's highest point, after which the curve gradually falls off in either direction.

Dynamic stochastic models involve multiple stage events for more complex operations often featuring queuing, limited resource and other issues.

Many dynamic models utilize the Poisson distribution. The Poisson distribution is a discrete probability distribution of the occurrence of independent events often expressed events per period of time or the fixed interval of time between these events.

Dynamic models provide to decision-makers data in the form of probabilities on the variability that can result from operations or support activities.

The dynamic stochastic models can be utilized to test the results of applying alternatives to unacceptable circumstances to find an acceptable solution.

4. RESULTS

Queuing issue at the in-pit crusher in the open pit mine has been solved with help of Dynamic Stochastic Modeling. Data has been analysed for three scenarios: Real, Best and Worst. For this time-tracking study for in-pit crusher productivity and trucks dumping cycle for it has been produced.

4.1 Real Case Scenario

Real case has been produced on the database collected during long-term period and considered different situations of breakdowns related with weather conditions, repair works, maintenances etc. In the regular case time between arrivals, dump time per truck, spot time per truck, tons per truck, bin limit for full dumping, and crushing rate were taken as basic parameters of input.

Table 2. Real Case Scenario parameters

Parameters	min	mean	max	units	Distribution
Time between arrivals	120			sec	Poisson
Dump time per truck	0.6	1.2	2.2	minutes	Triangle
Spot time per truck	0.1	2.1	6.1	minutes	Triangle
Tons per truck	120	125	140	tons	PERT
Bin Limit for Full Dumping	400			tons	Fixed
Crushing rate	3 000	3 500	4 000	tons per hour	Triangle

Table 2 shows the information regarding the parameters needed for the Palisade@Risk software simulation input.

Truck arrivals at the crusher fit a Poisson distribution with a value of 120 seconds between truck arrivals. The dump time per truck is a triangle distribution with values of 0.6, 1.2 and 2.2 minutes respectively. Spot time per truck is also a triangle distribution with values of 0.1, 2.1 and 6.1 minutes respectively. The truck payloads are a PERT distribution with values of 120, 125 and 140 tons. The bin ahead of the crusher has a capacity of 400 tons. The crushing rate is a triangle distribution with values of 3,000, 3,500 and 4,000 tons per hour.

Desired outputs include tons dumped per hour, truck arrivals per hour, number of trucks dumped per hour and average delay time per truck at the crusher.

Table 3. Real Case Outputs

Tons dumped / hour	1867	tons
Truck Arrival / hour	31	trucks
Truck dumps / hour	15	trucks
Delay / truck (minutes)	61	minutes

Table 3 shows the output results for the regular case. Tons dumped per hour was found to be 1867. Truck arrival rate was found to be approximately 31 trucks per hour. Hourly dump rate was estimated to be about 15 trucks. The average truck delay was approximately 61 minutes.

Simulations on the model has been run for 1000 iterations.

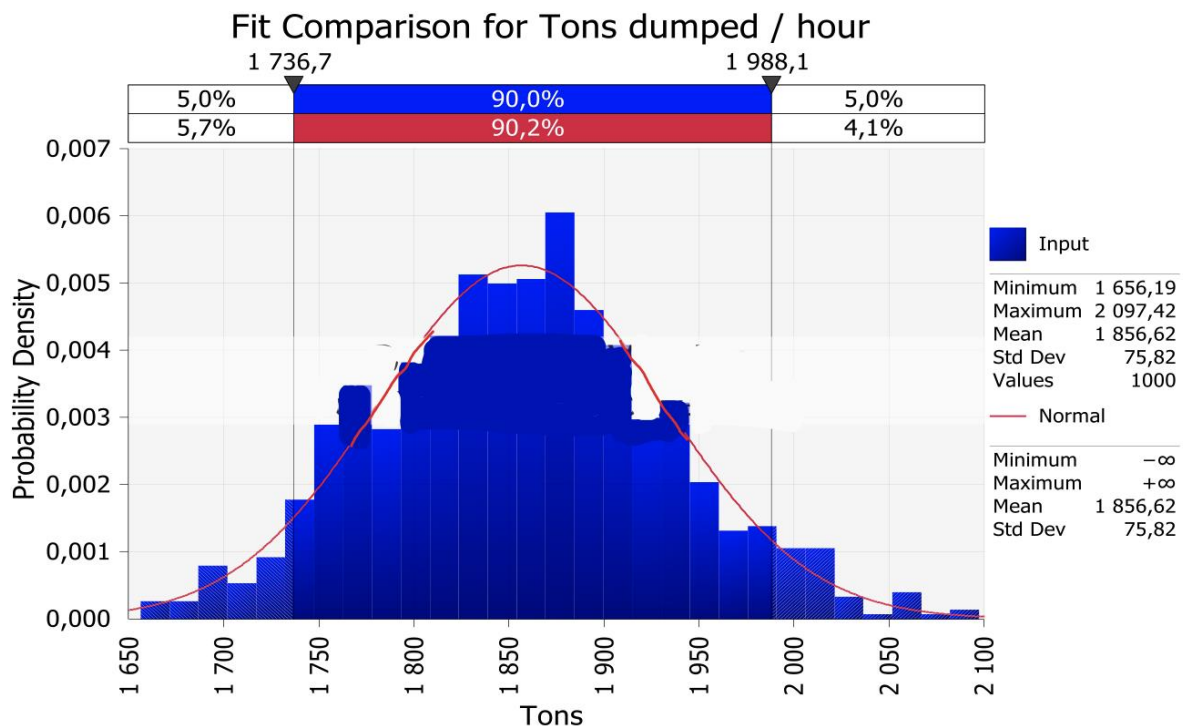


Figure 10. Overall tons dumped per hour in the real case

Figure 10 displays the dump rate per hour in tons for the real case. By incorporating the dependencies between the variables into the Monte Carlo simulation, the probability of the operational events occurring was evaluated using stochastic variables. The Y-axis in the

histogram shows the probability density. X-axis shows tons. As a result, overall tons dumped varied from 1736.7 to 1988 per hour with the probability of 90% occurrence. Mean value was found to be 1856.6 tons per hour with the standard deviation being 75 tons per hour. Normal distribution shows that the output achieved fits in the distribution.

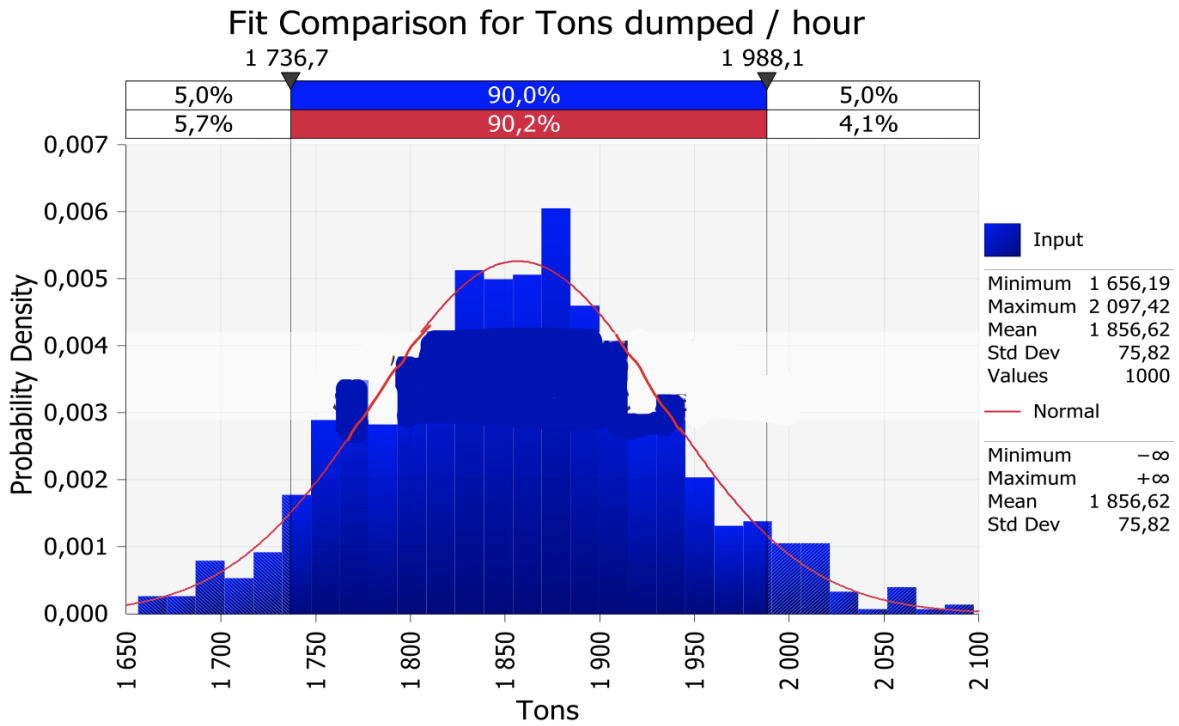


Figure 11. Truck arrival per hour in the real case

Figure 11 displays the truck arrival rate per hour in tons for the real case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows number of trucks arrived. As a result, the overall number of trucks arrived per hour ranged from 30.4 to 31.6 with the probability of 90% occurrence. Mean value was found to be 31 trucks per hour with the standard deviation being 0.37 trucks per hour. It is vital to mention that decimal numbers of trucks are taken as the method of statistic approach and in real life case number of trucks is measured as integer number.

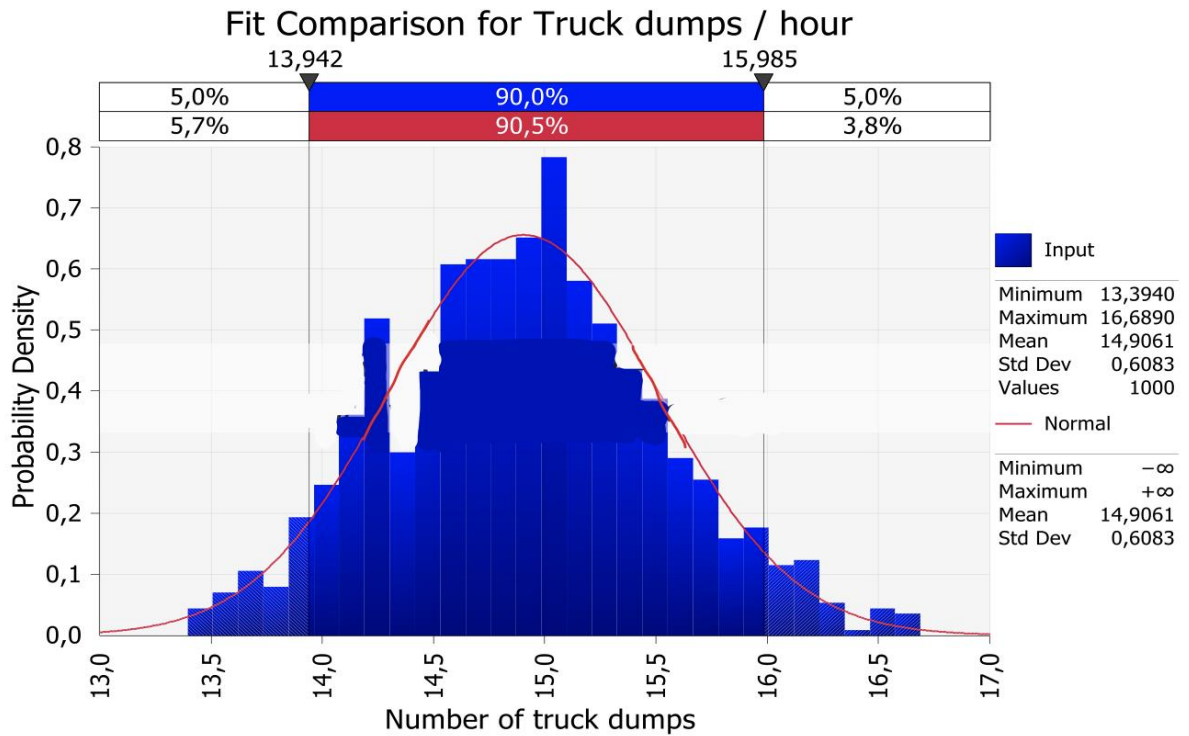


Figure 12. Truck dumps per hour in the real case

Figure 12 displays the truck dump rate per hour in tons for the real case. The Y-axis in the histogram demonstrates the probability density or the number of times the event has occurred in the simulation over the total number of trials. As a result, the overall truck dumping rate per hour ranged from 13.9 to 15.9 with the probability of 90% occurrence. Mean value was found to be 14.9 truck dumps per hour with the standard deviation being 0.6 truck dumps per hour.

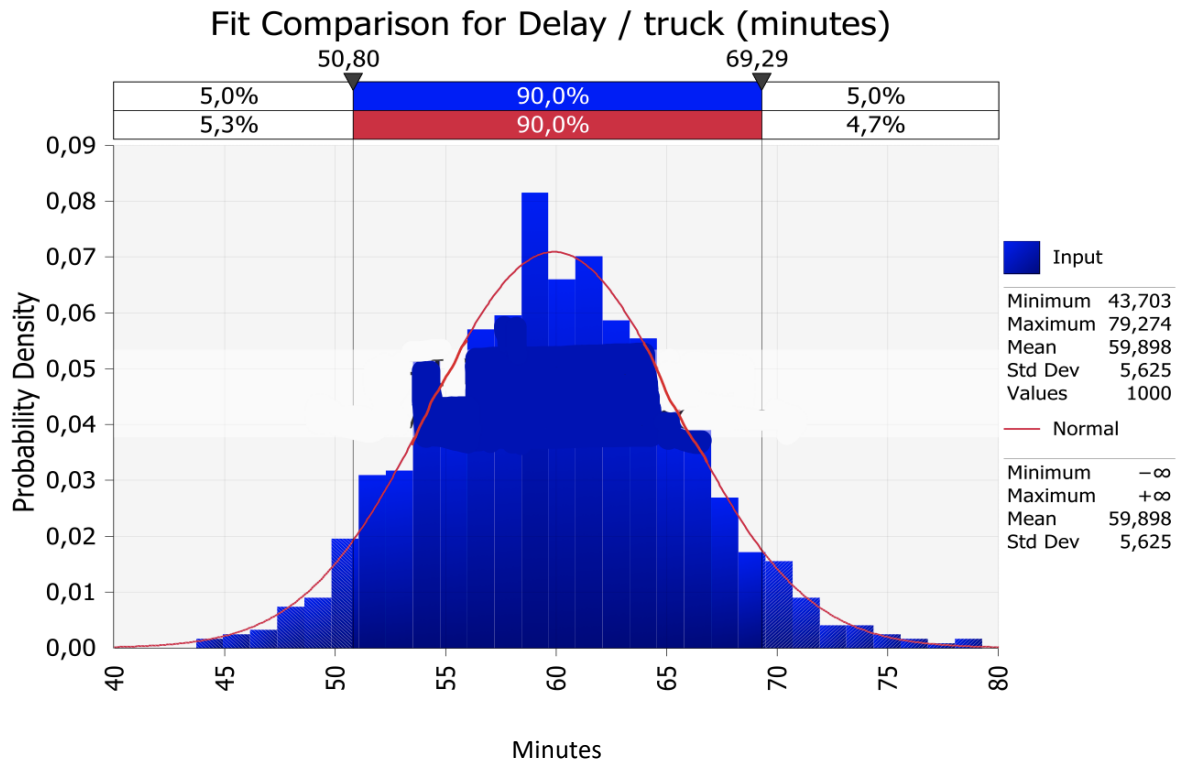


Figure 13. Delay per truck in the real case

Figure 13 displays the delay per truck in minutes for the regular case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows the number of trucks delayed. As a result, the overall time the trucks have been delayed for fluctuated between 50.8 and 69.3 minutes with the probability of 90% occurrence. Mean value was found to be 59.9 minutes with the standard deviation being 5.6 minutes.

Analysis shows that based on the inputs a truck queue is formed inconsistently therefore parameters can be optimized. The truck arrivals are based on annual time-tracking study, and it is presented based on minimum and maximum values for Best and Worst scenarios.

4.2 Worst Case Scenario

Table 4. Worst Case Scenario parameters

Parameters	min	mean	max	units	Distribution
Time between arrivals	120			sec	Poisson
Dump time per truck	1	1.5	2.2	minutes	Triangle
Spot time per truck	3.1	4.1	6.1	minutes	Triangle
Tons per truck	120	125	140	tons	PERT

Bin Limit for Full Dumping	400			tons	Fixed
Crushing rate	3 000	3 500	4 000	tons per hour	Triangle

Information about the parameters required for the @Risk Simulation input for the worst-case scenario is provided in Table 4. Time between arrivals displays the number of seconds that pass between each truck's arrival. The input was a Poisson distribution with the value set to 120 seconds. Triangle distribution was used to determine the amount of time required for each truck to deposit its load of ore into the crusher (dump time). The times were calculated as 1, 1.5, and 2.2 minutes, respectively. Spot time was estimated in the same manner using Triangle distribution and was estimated to be 3.1, 4.1 and 6.1 minutes respectively. PERT distribution was used to estimate the tons per truck, which came out to be 120, 125, and 140 tons. Bin limit for full dumping is a fixed value of 400 tons as stated by the company. Crushing rate for the worst case was estimated using Triangle distribution and found to be 3000, 3500, and 4000 tons per hour.

Table 5. Worst Case Outputs

Tons dumped / hour	1273	tons
Truck Arrival / hour	31	trucks
Truck dumps / hour	10	trucks
Delay / truck (minutes)	114	minutes

The output results for the worst-case scenario are displayed in Table 5. An estimated 1273 tons were dumped each hour. The average number of trucks arriving each hour was found to be 31 trucks. Approximately 10 trucks were dumped every hour. And estimated delay per truck was equal to 114 minutes.

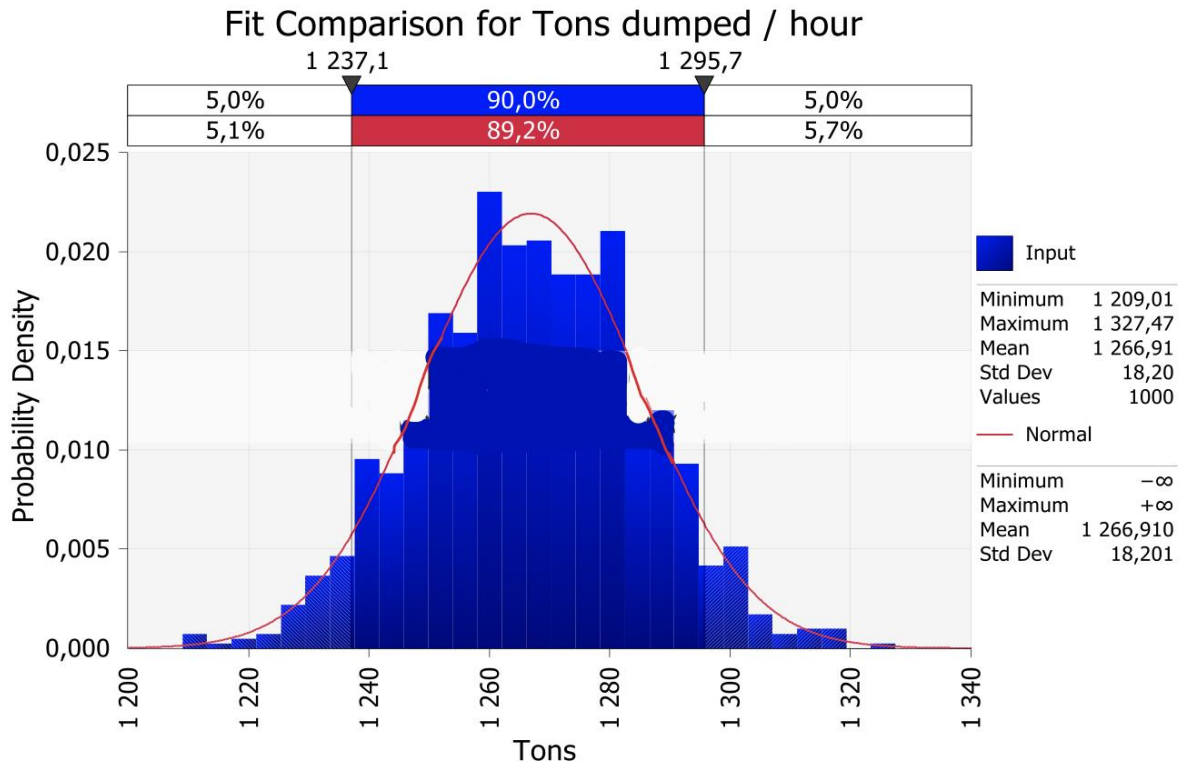


Figure 14. Overall tons dumped per hour in the worst case

Figure 14 displays the dump rate per hour in tons for the worst case. By incorporating the dependencies between the variables into the Monte Carlo simulation, the probability of the operational events occurring was evaluated using stochastic variables. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows tons. As a result, overall tons dumped varied from 1237 to 1295.7 per hour with the probability of 90% occurrence. Mean value was found to be 1267 tons per hour with the standard deviation being 18.2 tons per hour. It can also be seen that the input goes out of the distribution slightly.

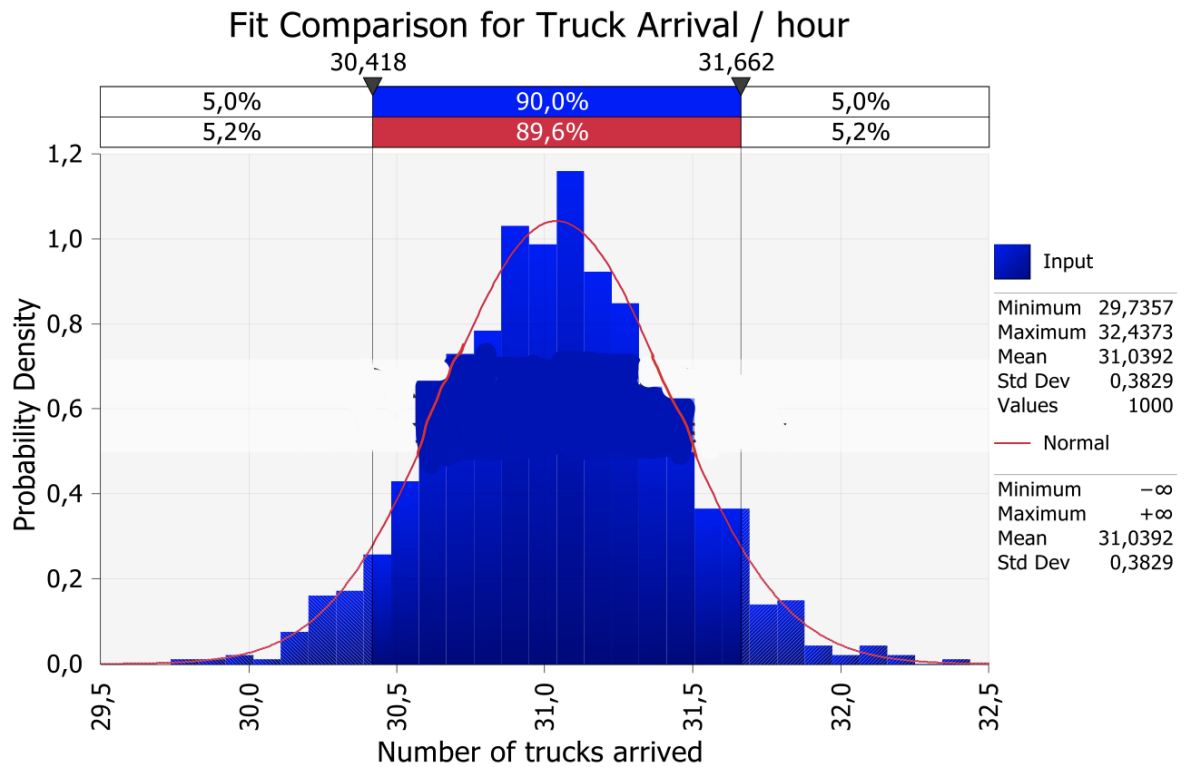


Figure 15. Truck arrival per hour in the worst case

Figure 15 displays the truck arrival rate per hour in tons for the worst case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows number of trucks arrived. As a result, the overall number of trucks arrived per hour ranged from 30.4 to 31.6 with the probability of 90% occurrence. Mean value was found to be 31 trucks per hour with the standard deviation being 0.38 trucks per hour.

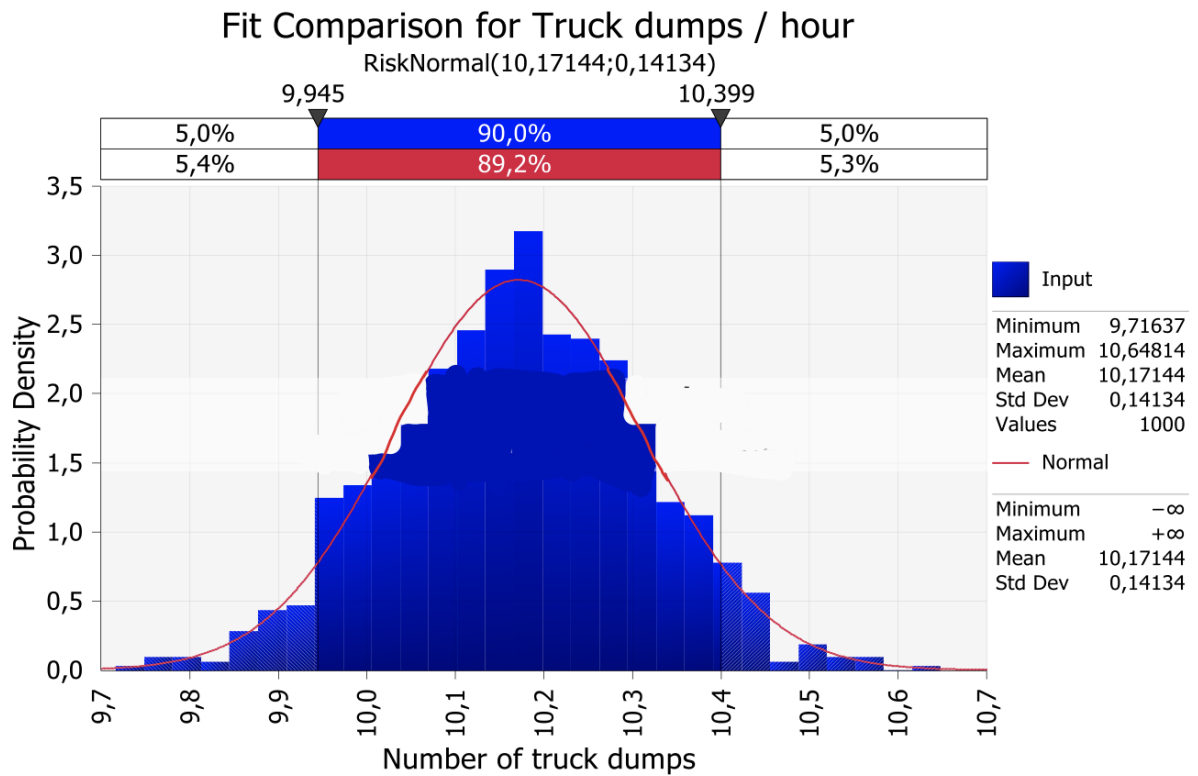


Figure 16. Truck dumps per hour in the worst case

Figure 16 displays the truck dump rate per hour in tons for the worst case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. As a result, the overall truck dumping rate per hour ranged from 9.9 to 10.4 with the probability of 90% occurrence. Mean value was found to be 10 truck dumps per hour with the standard deviation being 0.14 dumps per hour.

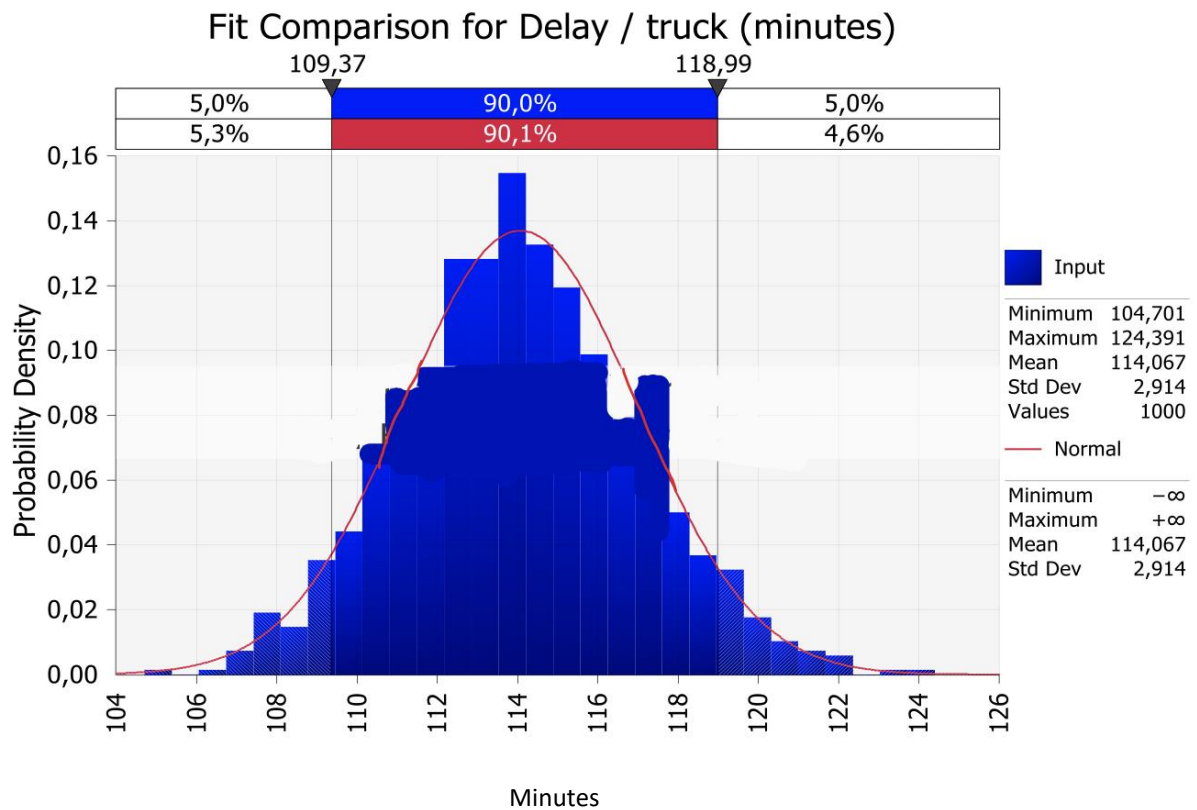


Figure 17. Delay per truck in the worst case

Figure 17 displays the delay per truck in minutes for the worst case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. As a result, the overall time the trucks have been delayed for fluctuated between 109 and 119 minutes with the probability of 90% occurrence. Mean value was found to be 114 minutes with the standard deviation being 3 minutes.

4.3 Best Case Scenario

Table 6. Best Case Scenario parameters

Parameters	min	mean	max	units	Distribution
Time between arrivals	120			sec	Poisson
Dump time per truck	0.6	1	1.2	minutes	Triangle
Spot time per truck	0.1	1	2	minutes	Triangle
Tons per truck	120	125	140	tons	PERT
Bin Limit for Full Dumping	400			tons	Fixed
Crushing rate	3 000	3 500	4 000	tons per hour	Triangle

Table 6 shows the information regarding the parameters needed for the @Risk Simulation inputs for the best-case scenario. Time between arrivals shows the seconds between

each truck's arrival in seconds. The value was taken to be 120 seconds and Poisson distribution was used for this input. Dump time per truck or the time needed for each truck to dump the ore into the crusher was estimated using Triangle distribution and was estimated to be 0.6, 1, and 1.2 minutes. Spot time or waiting time of each truck before the arrival of the next truck, was estimated to be 0.1, 1, and 2 minutes respectively using the Triangle distribution. Tons per truck were estimated using PERT distribution and found to be 120, 125, and 140 tons. Bin Limit for full dumping or the capacity of tons in the crusher's bin. This input is fixed and is equal to 400 tons according to KAZ Minerals. The last variable is the crusher rate. This input was estimated using Triangle distribution and found to be 3000, 3500, and 4000 tons per hour as in the previous scenarios.

Table 7. Best Case Outputs

Tons dumped / hour	3545	tons
Truck Arrival / hour	31.5	trucks
Truck dumps / hour	28.6	trucks
Delay / truck (minutes)	4	minutes

Table 7 shows the output results for the best case. Tons dumped per hour was found to be 3545. Truck arrival rate was found to be approximately 31.5 trucks per hour. Hourly dump rate was estimated to be about 28.6 trucks. The average truck delay was approximately 4 minutes.

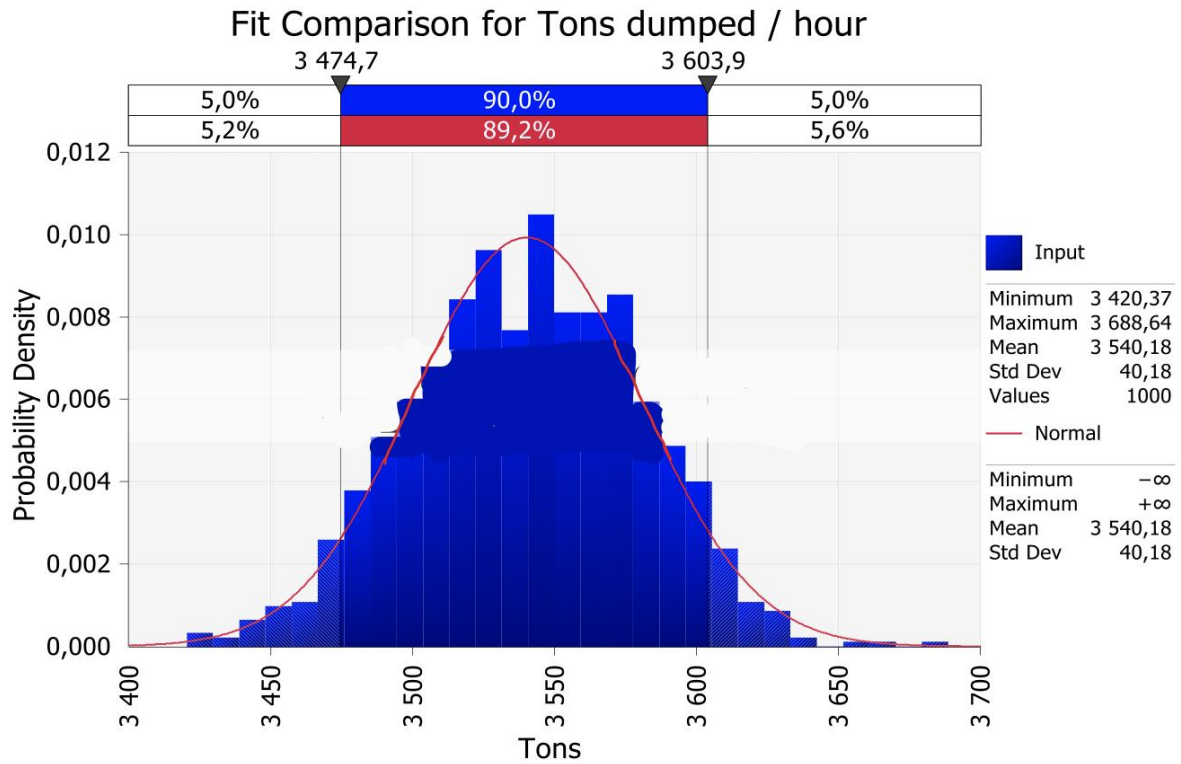


Figure 18. Overall tons dumped per hour in the best case

Figure 18 displays the dump rate per hour in tons for the best case. By incorporating the dependencies between the variables into the Monte Carlo simulation, the probability of the operational events occurring was evaluated using stochastic variables. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows tons. As a result, overall tons dumped varied from 3474.7 to 3603.9 per hour with the probability of 90% occurrence. Mean value was found to be 3540 tons per hour with the standard deviation being 40 tons per hour. Here the normal distribution fits well with the inputs.

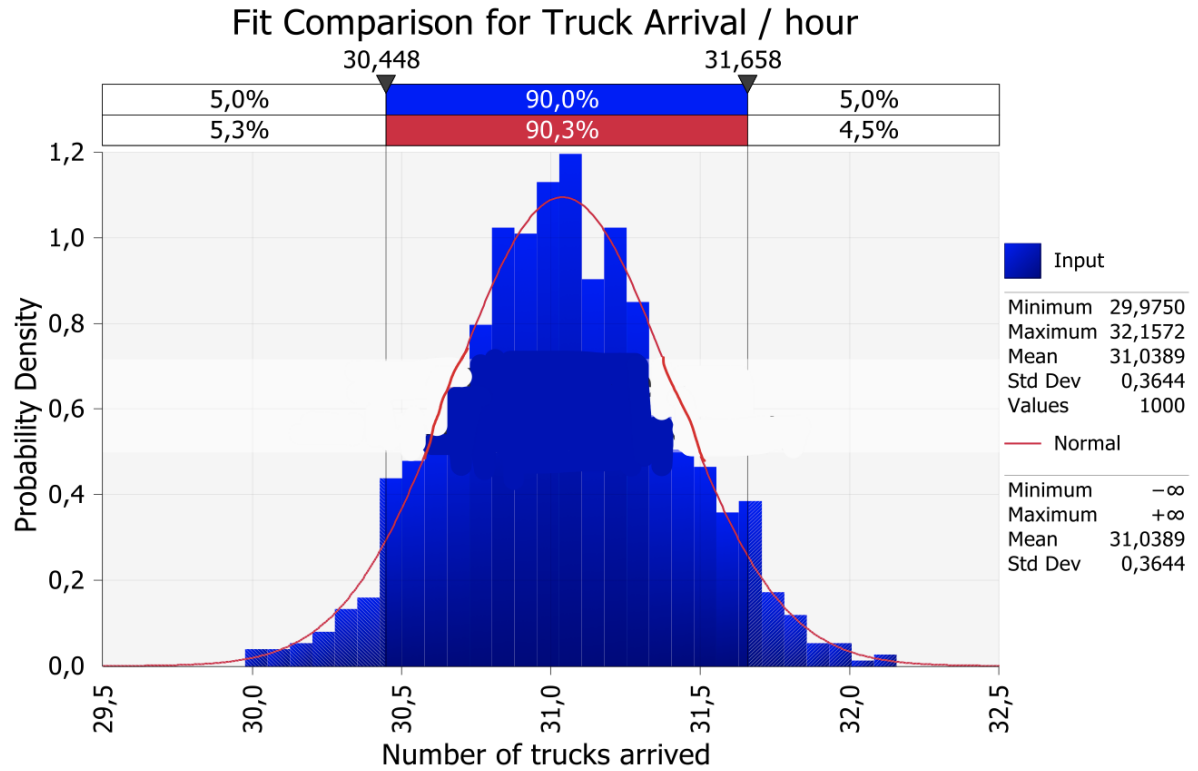


Figure 19. Truck arrival per hour in the best case

Figure 19 shows the truck arrival rate per hour in tons for the best case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. X-axis shows number of trucks arrived. As a result, the overall number of trucks arrived per hour ranged from 30.4 to 31.6 with the probability of 90% occurrence. Mean value was found to be 31 trucks per hour with the standard deviation being 0.36 trucks per hour.

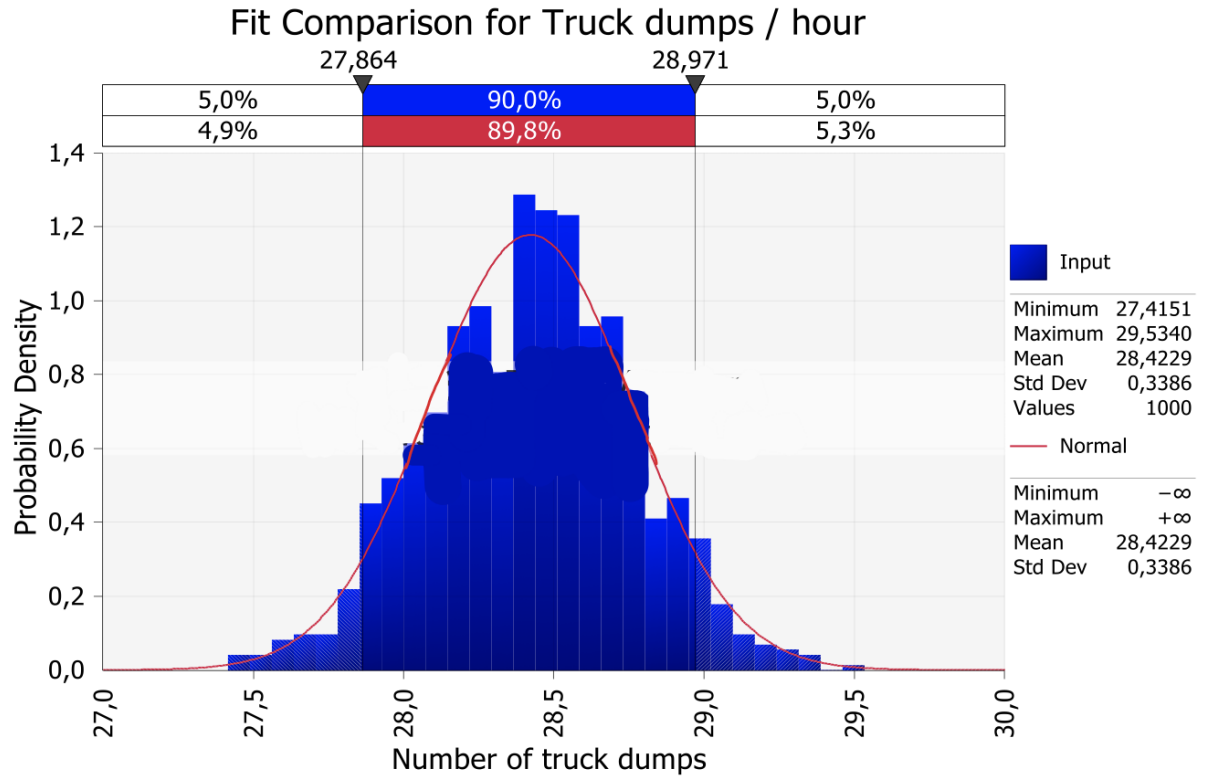


Figure 20. Truck dumps per hour in the best case

Figure 20 displays the truck dump rate per hour in tons for the best case. The Y-axis in the histogram demonstrates the probability density or the number of times the event has occurred in the simulation over the total number of trials. As a result, the overall truck dumping rate per hour ranged from 27.8 to 28.9 with the probability of 90% occurrence. Mean value was found to be 28.4 truck dumps per hour with the standard deviation being 0.33 truck dumps per hour.

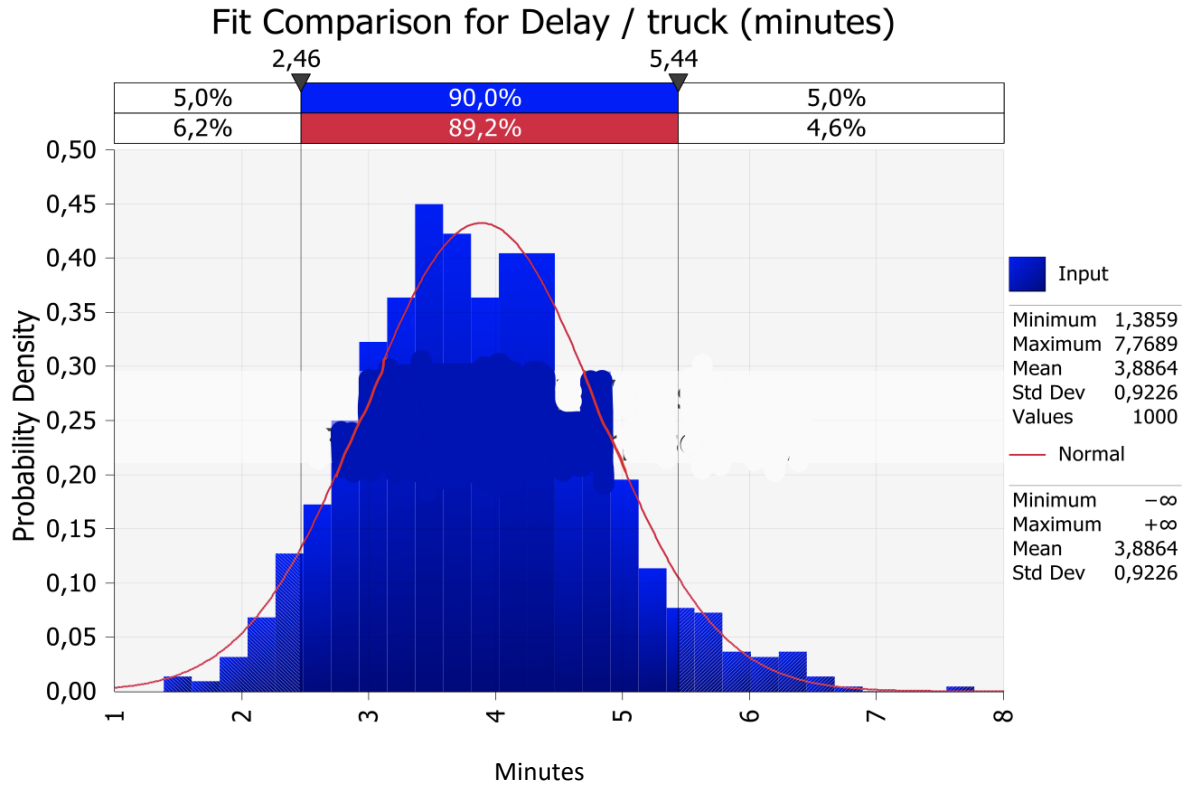


Figure 21. Delay per truck in the best case

Figure 21 displays the delay per truck in minutes for the best case. The Y-axis in the histogram shows the probability density or the number of times the event has occurred in the simulation over the total number of trials. As a result, the overall time the trucks have been delayed for fluctuated between 2.4 and 5.44 minutes with the probability of 90% occurrence. Mean value was found to be 3.8 minutes with the standard deviation being 0.9 minutes.

5. DISCUSSION

Potential solution of the queuing problem alternative bin limits was examined to see the change in the outputs.

There are many factors affecting these variables, such as weather conditions during specific day or the driver's experience, the road condition etc. One of the most important factors, however, is the weather during specific day.

In the scope of this work three case scenarios were checked: real, worst, and best. By comparing these cases it can be seen how the outputs of the simulations vary. Real case has shown the real situation in the mining site, the worst case has shown the situation with the most negatively affecting factors, and the best case has shown the situation with the most positively affecting factors.

In the next phase mining engineers could decide to examine the impact of changing the bin size by changing the limits for full dumping to 800 tones. Therefore, Bin Limit for Full Dumping has to be a variable. However, the examination of the output statistics reveals that with the larger bin the dumping rate increases, and the delay time declines but consistent delays and queuing remain. Therefore, increasing bin size is not a solution to the queuing problem. Next step is to examine crushing rates by increasing crushing them. Examining the outputs of the simulation can show that the delay could be reduced by increasing the crushing rate but not eliminated. For this case the mining company may then undertake a cost / benefits analysis to determine which size crusher to specify for the installation.

Moreover, it is clear that when checking best case but varying one variable (Bin limit) the results of the simulations have not changed significantly. Therefore, the current bin limit (400 tons) has shown the best results.

Table 8. Best Case Output Comparison

Bin Limit	400	800	
Tons dumped / hour	3545	3731	tons
Truck Arrival / hour	31.5	31	trucks

Truck dumps / hour	28.6	31	trucks
Delay / truck (minutes)	4	0.5	minutes

Table 8 displays the comparison between best case outputs for different bin limits: 400 tons (actual data) and 800 tons. When comparing tons dumped per hour it can be seen that by increasing bin limit, the tonnage has increased visible. The number of trucks arrived and dumped did not vary significantly. However, the delay time in the increased bin limit has decreased from 4 minutes to only 0.5 minutes.

Figure 22 and Figure 23 represent tons dumped in one hour and delay per truck respectively. Tons dumped per hour have normal distribution with mean being 3751 tons and standard deviation being 58 tons. Delay per truck has lognormal distribution with mean being 1.1 trucks and standard deviation being 0.7 trucks.

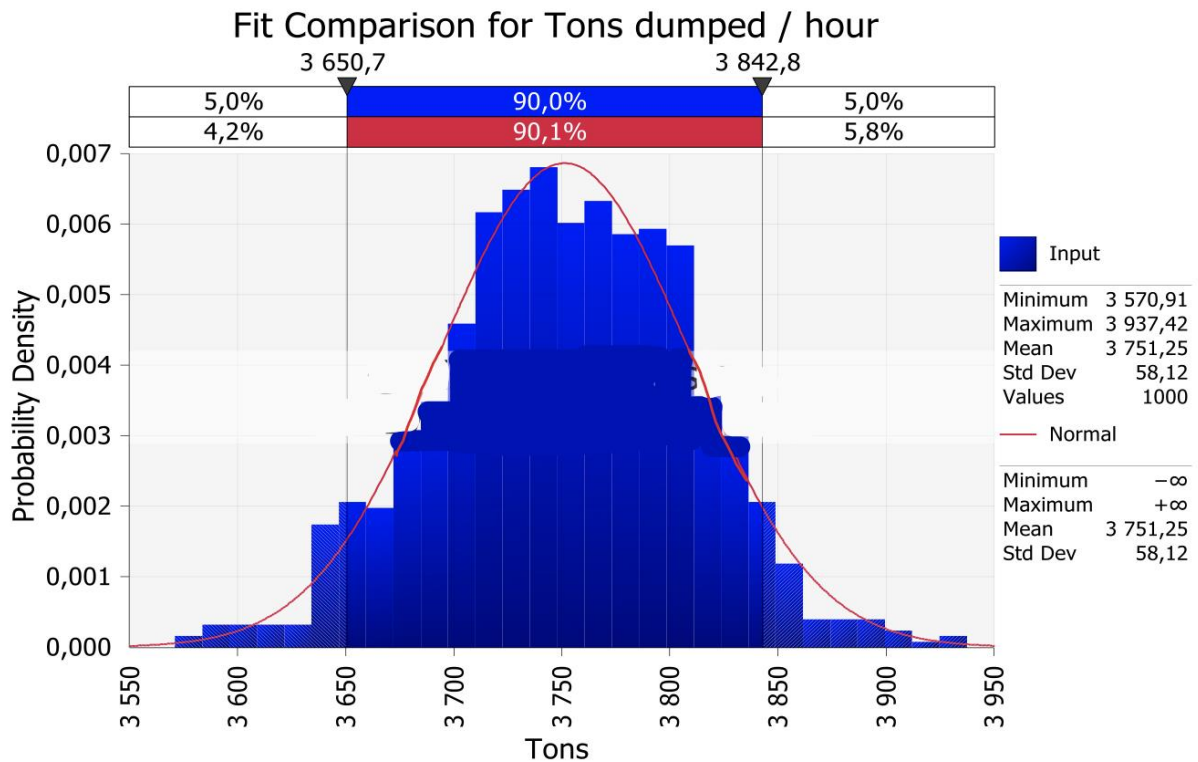


Figure 22. Overall tons dumped per hour in the best case with 800-tons bin limit

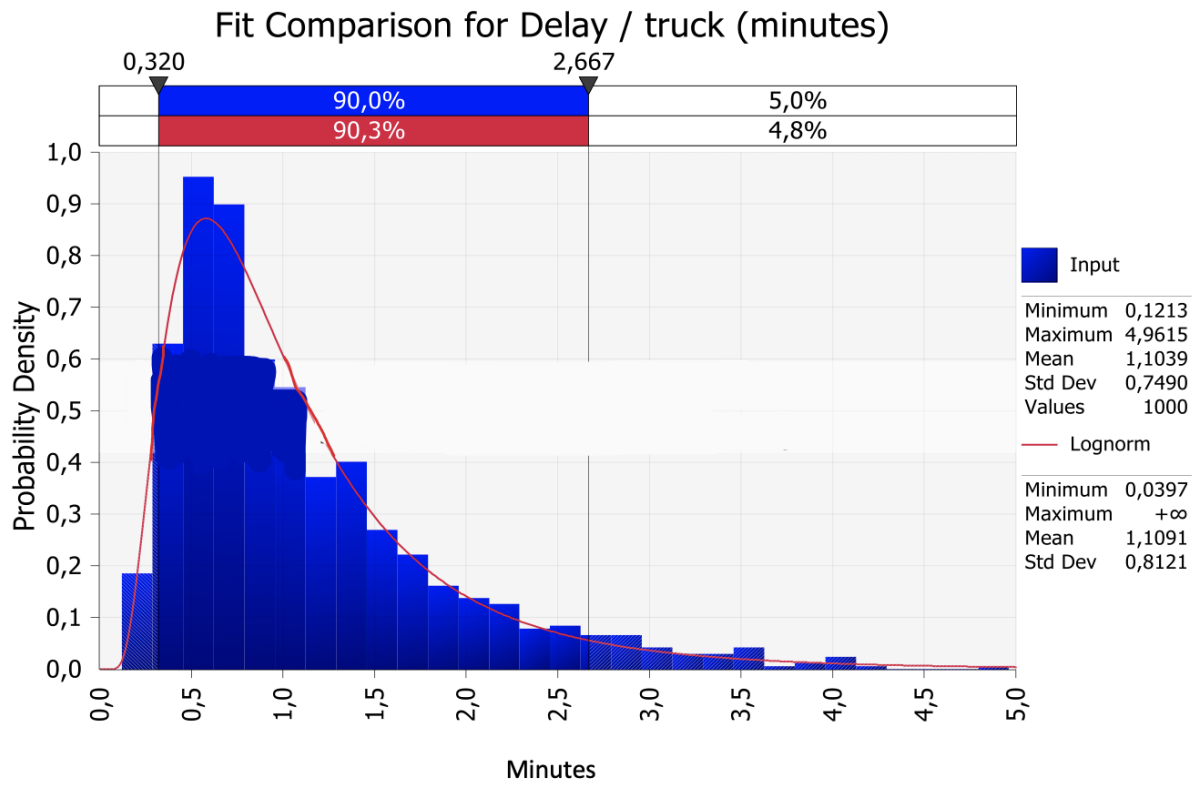


Figure 23. Delay per truck in the best case with 800-tons bin limit

Overall, it can be seen that increasing bin limit up to 800 tons increases the dumped tonnage and decreases the delay per truck. Therefore, it can be suggested as a potential solution for the queuing problem.

6. CONCLUSIONS AND RECOMMENDATIONS

The study produced risk estimation of the in-pit crushing (IPC) system installed at the operational copper open pit in Kazakhstan. For this research all of the objectives, based on assumptions of truck conditions and operators' characteristics being the same, were achieved: primary data from the mine site was collected, simulation of risk modeling was adapted, a dynamic stochastic model was built, the results of the simulation were obtained and analyzed, and later interpreted and validated. As a part of the risk estimation process, stochastic dynamic modelling methodology to examine how an IPC system will behave in the presence of ambiguous causes of delays to predict the system productivity over time has been used. The model analyzed all data for the real case from which the best-case scenario has been proposed.

As a result, for the real case, tons dumped per hour varied from 1740 to 1975, number of truck arrivals per hour ranged from 30 to 32, number truck dumped per hour ranged from 14 to 16, delay time per truck at the crusher varied between 52 and 69 minutes. The best-case scenario uses the quickest the dump time per truck and the spot time per truck. Thus, the best case has 3475 to 3600 tons dumped per hour, 30 to 32 trucks arriving per hour, and 28 to 29 trucks dumped per hour with the delay time per truck at the crusher 2.4 and 5.5 minutes. Thus, the best case has twice higher tones dumped per hour and about 60 minutes shorter delays.

The developed model considered queuing issues at the in-pit crusher and can be used to analyse the impact of changing the bin size by changing the limits for full dumping and the crushing rate. The model is able to forecast the IPC system's future states and calculate the probability of various outcomes.

7. REFERENCES

- Abbaspour, H., & Drebenstedt, C. (2019). Environmental Comparison of Different Transportation Systems—Truck-Shovel and IPCCs—In Open-Pit Mines by System Dynamic Modeling. *Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection - MPES 2018*, 287–305. https://doi.org/10.1007/978-3-319-99220-4_24
- Abbaspour, H., & Drebenstedt, C. (2019b). Determination of Transition Time from Truck-Shovel to an IPCC System Considering Economic Viewpoint by System Dynamics Modelling. *Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection - MPES 2019*, 289–295. https://doi.org/10.1007/978-3-030-33954-8_36
- Abbaspour, H., Drebenstedt, C., & Dindarloo, S. R. (2018). Evaluation of safety and social indexes in the selection of transportation system alternatives (Truck-Shovel and IPCCs) in open pit mines. *Safety Science*, 108, 1–12. <https://doi.org/10.1016/j.ssci.2018.04.020>
- Bernardi, L., Kumral, M., & Renaud, M. (2020). Comparison of fixed and mobile in-pit crushing and conveying and truck-shovel systems used in mineral industries through discrete-event simulation. *Simulation Modelling Practice and Theory*, 103, 102100. <https://doi.org/10.1016/j.simpat.2020.102100>
- Caterpillar 785 C/D dump truck*. (n.d.).
ArtStation. <https://www.artstation.com/artwork/14NNnG>
- Gravetter, F. J., & Wallnau, L. B. (2016). *Statistics for The Behavioral Sciences*. Cengage Learning.
- Hartman, H. L., & Mutmanský, J. M. (2002). *Introductory Mining Engineering* (2nd ed.). Wiley.
- Hay, E., Nehring, M., Knights, P., & Kizil, M. S. (2019). Ultimate pit limit determination for fully mobile in-pit crushing and conveying systems. *International Journal of Mining and Mineral Engineering*, 10(2/3/4), 111. <https://doi.org/10.1504/ijmme.2019.104444>
- Inouye, D. I., Yang, E., Allen, G. I., & Ravikumar, P. (2017). A review of multivariate distributions for count data derived from the Poisson distribution. *WIREs Computational Statistics*, 9(3). <https://doi.org/10.1002/wics.1398>

- Johnson, N. L. (1949). SYSTEMS OF FREQUENCY CURVES GENERATED BY METHODS OF TRANSLATION. *Biometrika*, 36(1–2), 149–176. <https://doi.org/10.1093/biomet/36.1-2.149>
- Johnson, N. L., Kotz, S., & Balakrishnan, N. (1995). Continuous Univariate Distributions. *Journal of the American Statistical Association*, 90(432), 1490. <https://doi.org/10.2307/2291547>
- Kendall, M. G., & Stuart, A. (1977). *The Advanced Theory of Statistics*. Macmillan Publishers.
- Minkin, D. A., Wolpers, D. F. M., & Hellmuth, D. T. (2018). NEW STEEP CONVEYING CONCEPT FOR OPENCAST MINES USING AN IN-PIT CRUSHING AND CONVEYING SYSTEM (IPCC). *Ugol'*, 05, 34–38. <https://doi.org/10.18796/0041-5790-2018-5-34-38>
- Nehring, M., Knights, P., Kizil, M., & Hay, E. (2018). A comparison of strategic mine planning approaches for in-pit crushing and conveying, and truck/shovel systems. *International Journal of Mining Science and Technology*, 28(2), 205–214. <https://doi.org/10.1016/j.ijmst.2017.12.026>
- Osanloo, M., & Paricheh, M. (2019). In-pit crushing and conveying technology in open-pit mining operations: a literature review and research agenda. *International Journal of Mining, Reclamation and Environment*, 34(6), 430–457. <https://doi.org/10.1080/17480930.2019.1565054>
- Palisade. (2022, November 11). @RISK / Risk Analysis using Monte Carlo Simulation in Excel. <https://www.palisade.com/risk/>
- Paricheh, M., & Osanloo, M. (2019). Concurrent open-pit mine production and in-pit crushing–conveying system planning. *Engineering Optimization*, 52(10), 1780–1795. <https://doi.org/10.1080/0305215x.2019.1678150>
- Paricheh, M., & Osanloo, M. (2019d). A New Search Algorithm for Finding Candidate Crusher Locations Inside Open Pit Mines. *Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection - MPES 2019*, 10–25. https://doi.org/10.1007/978-3-030-33954-8_2
- Pekol, A. (2019). Evaluation and Risk Analysis of Open-Pit Mining Operations. *BHM Berg-Und Hüttenmännische Monatshefte*, 164(6), 232–236. <https://doi.org/10.1007/s00501-019-0854-9>

- Pendharkar, P. C., Subramanian, G. H., & Rodger, J. A. (2005). A probabilistic model for predicting software development effort. *IEEE Transactions on Software Engineering*, 31(7), 615–624. <https://doi.org/10.1109/tse.2005.75>
- Phill Morris. (2008). KEY PRODUCTION DRIVERS IN IN-PIT CRUSHING AND CONVEYING (IPCC) STUDIES. In *SAIMM*. The Southern African Institute of Mining and Metallurgy. https://www.saimm.co.za/Conferences/SurfaceMining2008/023-034_Morriss.pdf
- Purhamadani, E., Bagherpour, R., & Tudeshki, H. (2021). Energy consumption in open-pit mining operations relying on reduced energy consumption for haulage using in-pit crusher systems. *Journal of Cleaner Production*, 291, 125228. <https://doi.org/10.1016/j.jclepro.2020.125228>
- Raychaudhuri, S. (2008). Introduction to Monte Carlo simulation. *2008 Winter Simulation Conference*. <https://doi.org/10.1109/wsc.2008.4736059>
- Ross, S. M. (2014). *Introduction to Probability and Statistics for Engineers and Scientists*. Elsevier Gezondheidszorg.
- Russell A. Carter. (2010). Latest IPCC systems provide improved operational flexibility, higher capacity. *Coal Age*, 115(5), 42–45.
- Sahoo, L. K., Bandyopadhyay, S., & Banerjee, R. (2014). Benchmarking energy consumption for dump trucks in mines. *Applied Energy*, 113, 1382–1396. <https://doi.org/10.1016/j.apenergy.2013.08.058>
- Samavati, M., Essam, D., Nehring, M., & Sarker, R. (2020). Production planning and scheduling in mining scenarios under IPCC mining systems. *Computers & Operations Research*, 115, 104714. <https://doi.org/10.1016/j.cor.2019.05.019>
- Sapakov, E. A., & Kulniyaz, S. S. (Eds.). (2015). *SUBSTANTIATION OF CYCLIC-FLOW TECHNOLOGY ADAPTATION WHILE DEVELOPING THE AKTOGAY COPPER DEPOSIT*. Contemporary Innovation Technique of the Engineering Personnel Training for the Mining and Transport Industry.
- Smith, P. (2001c). Stochastic Dynamic Models (Choice, Response, and Time). *Elsevier EBooks*, 15115–15121. <https://doi.org/10.1016/b0-08-043076-7/00680-x>

Turnbull, D., & Cooper, A. (2010). In-pit crushing and conveying (IPCC) - a tried and tested alternative to trucks: Part 1. *AusIMM Bulletin*, 5, 60–
64. <https://search.informit.org/doi/abs/10.3316/informit.606047206778820>

8. APPENDICES

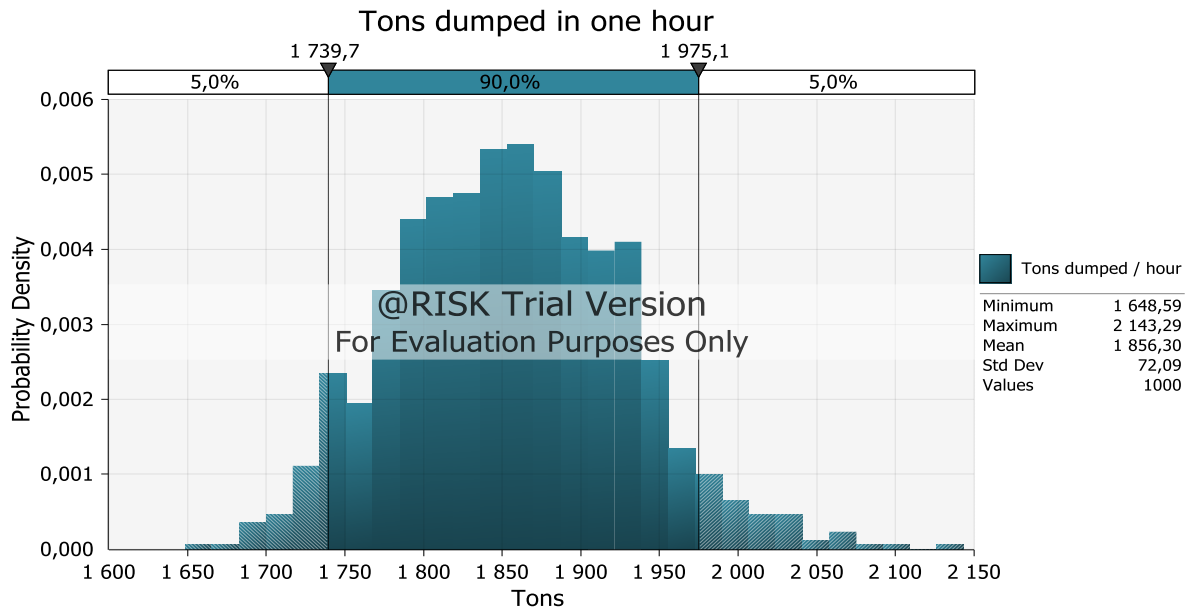


Figure 24. Tons dumped per hour for the real case.

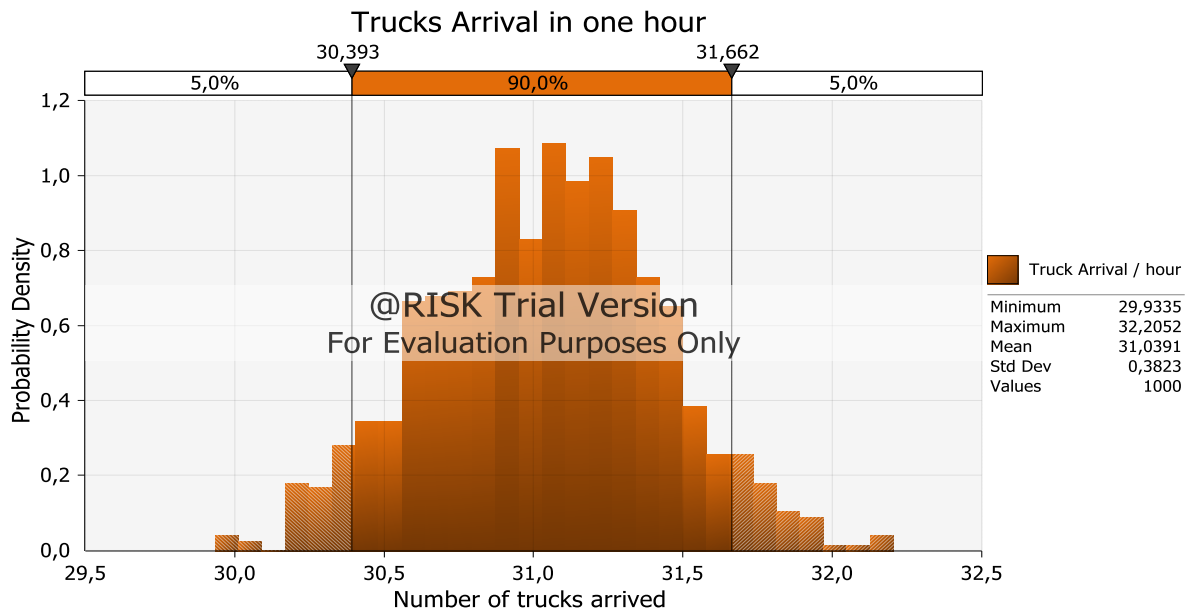


Figure 25. Truck arrival per hour for the real case.

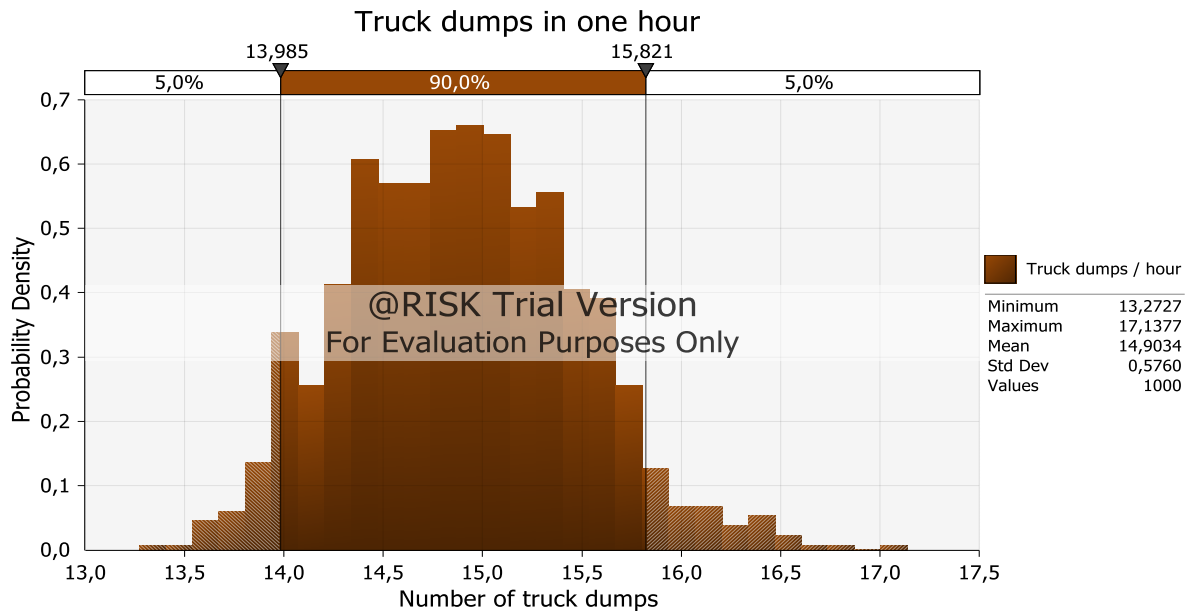


Figure 26. Truck dumps per hour for the real case.

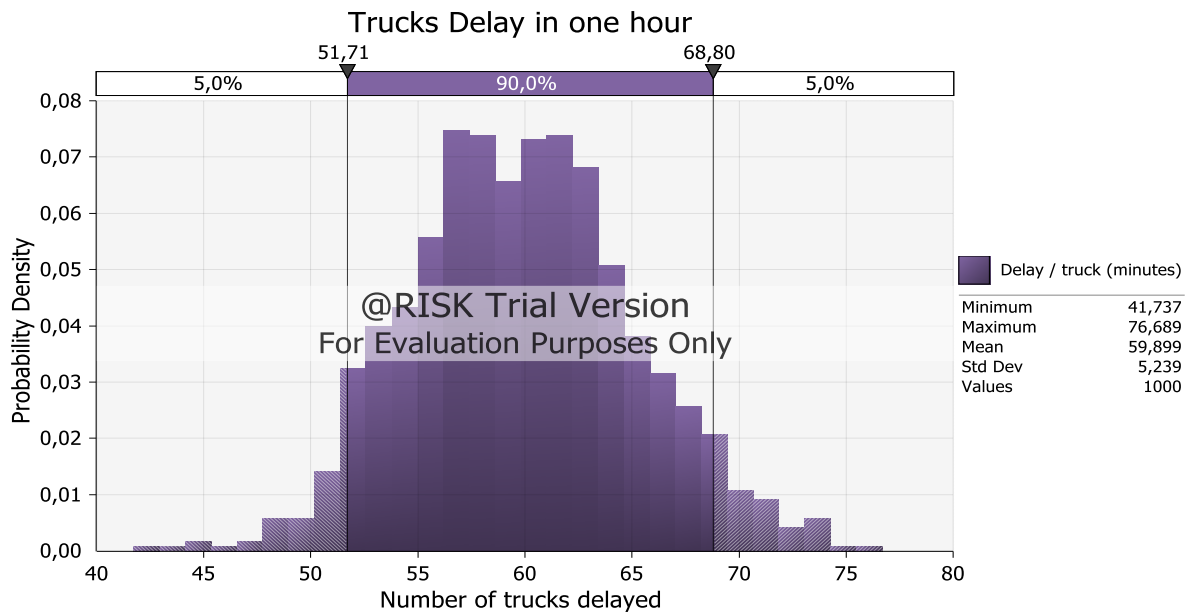


Figure 27. Truck delay per hour for the real case.

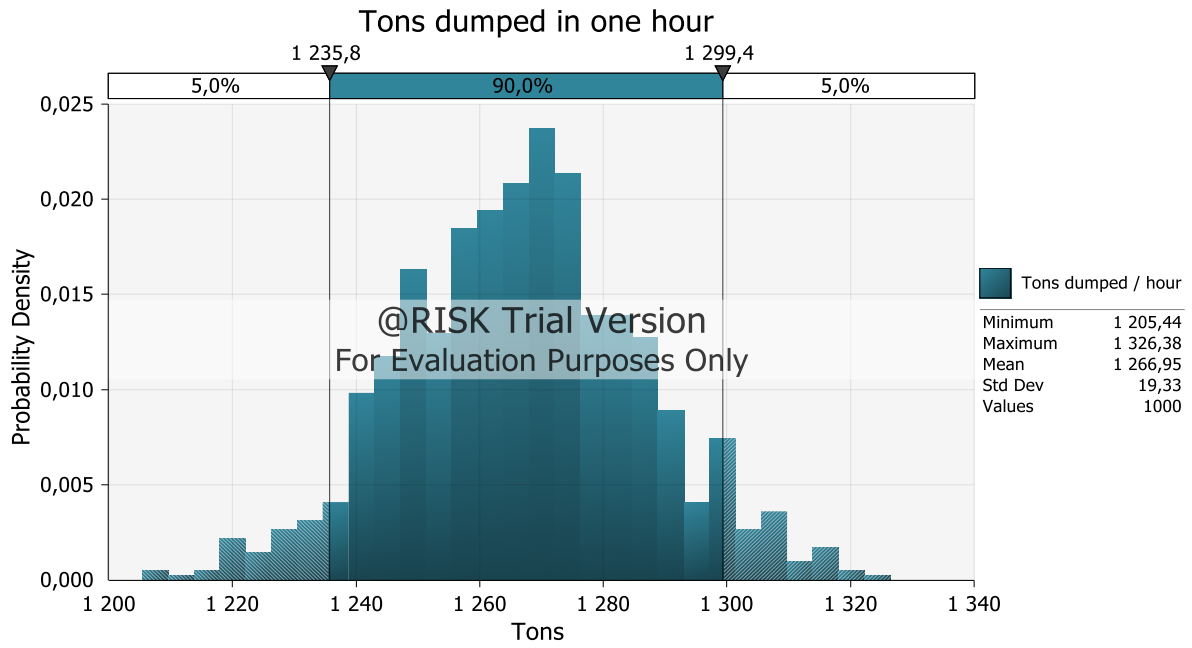


Figure 28. Tons dumped per hour for the worst case.

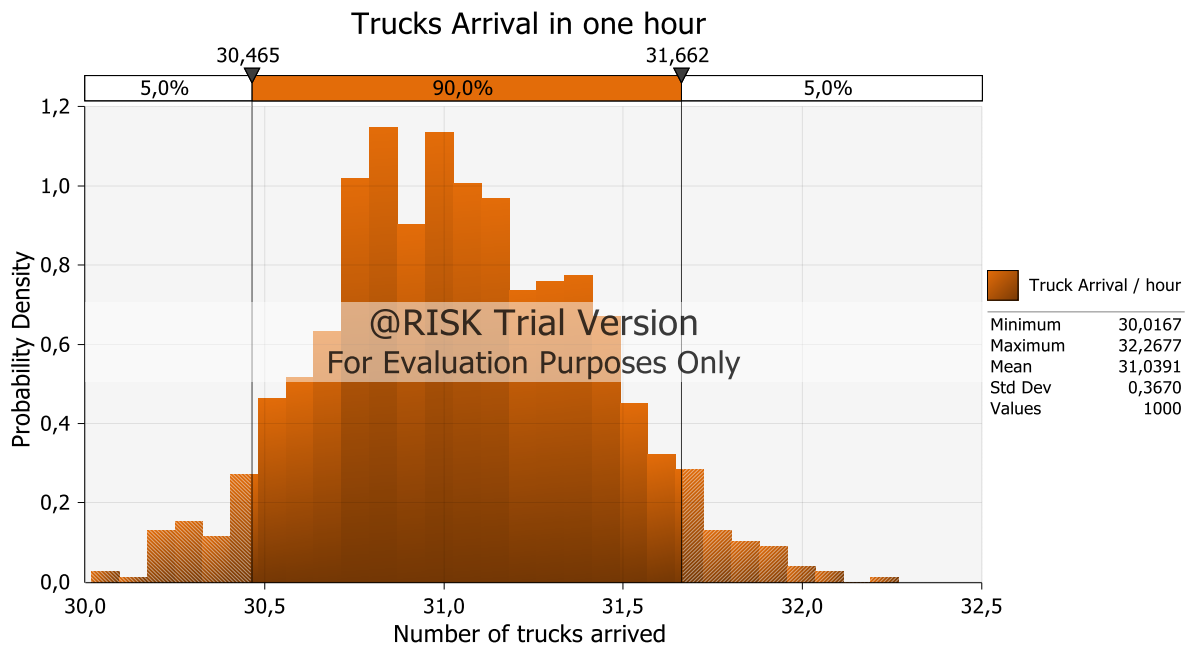


Figure 29. Truck arrival per hour for the worst case.

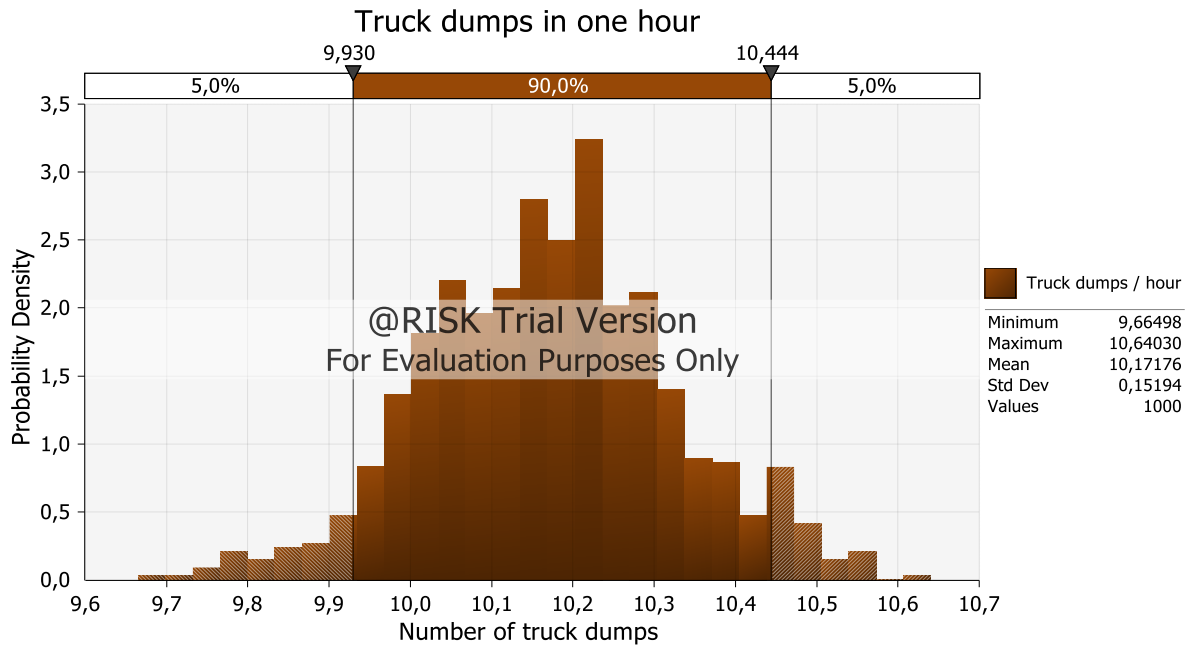


Figure 30. Truck dumps per hour for the worst case.

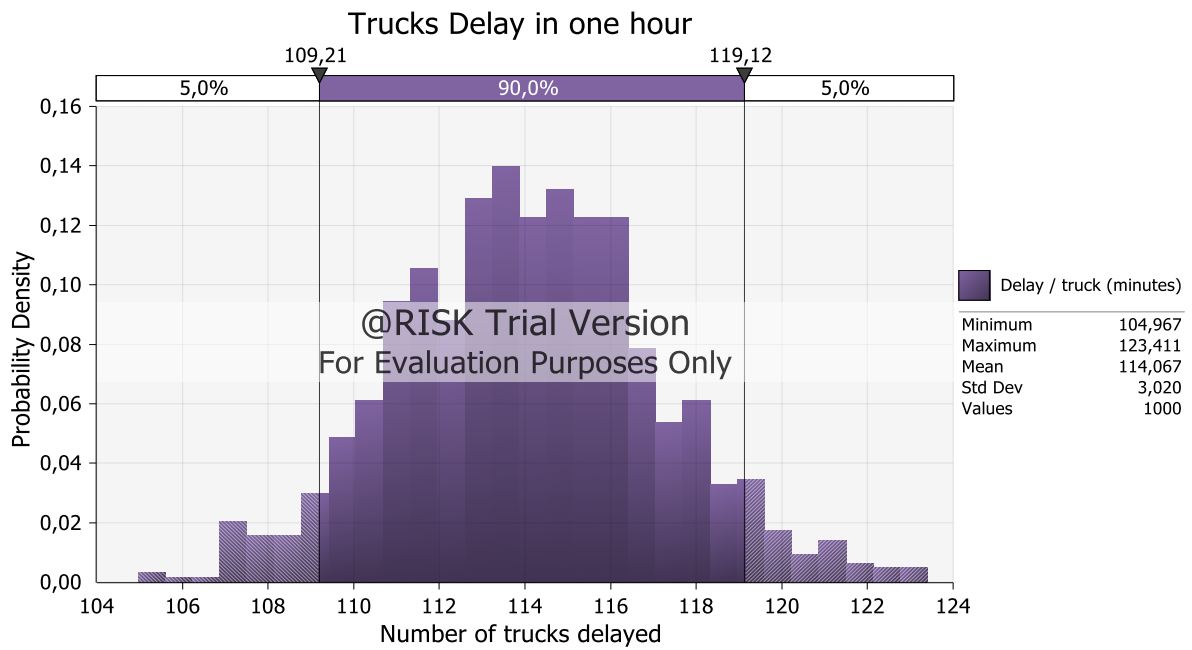


Figure 31. Truck delay per hour for the worst case.

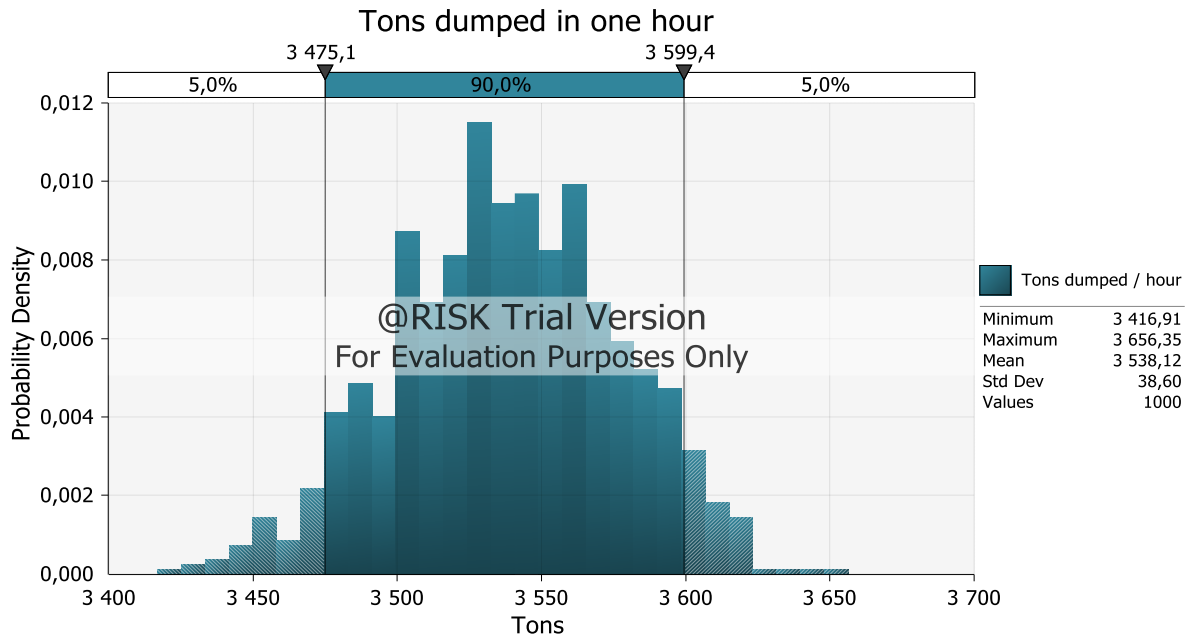


Figure 32. Tons dumped per hour for the best case.

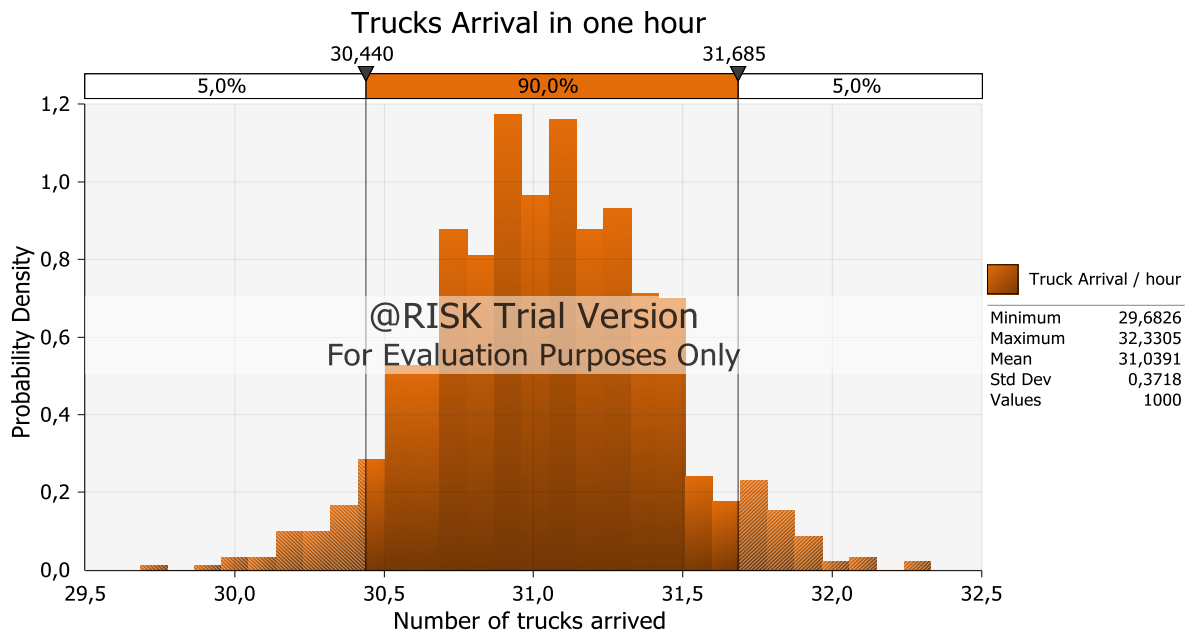


Figure 33. Truck arrival per hour for the best case.

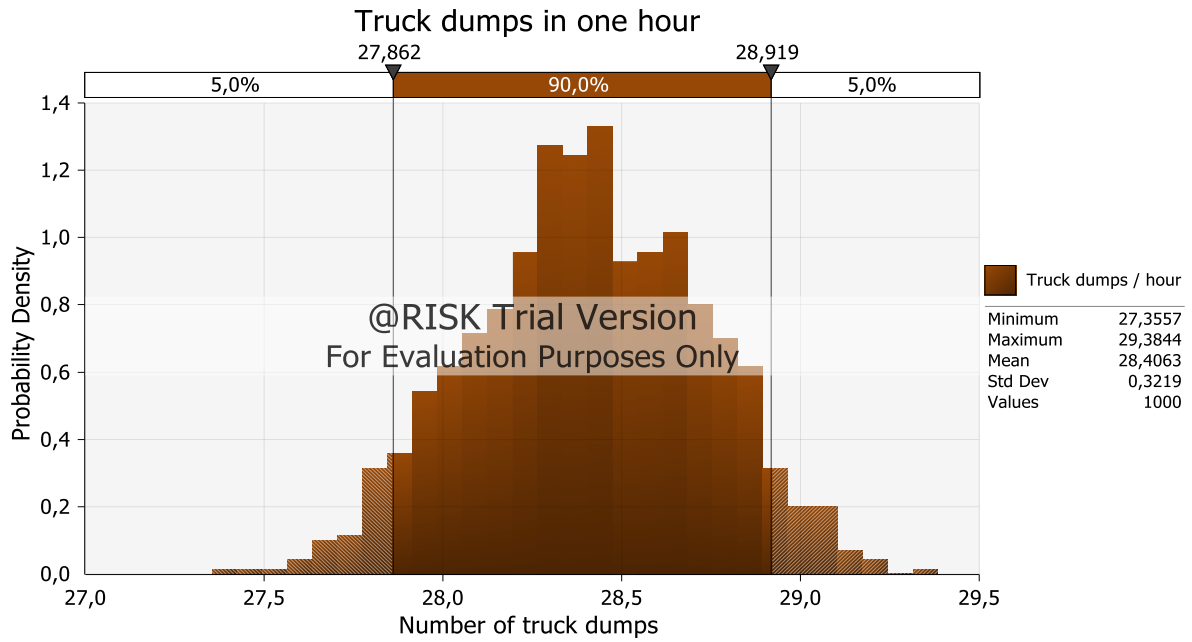


Figure 34. Truck dumps per hour for the best case.

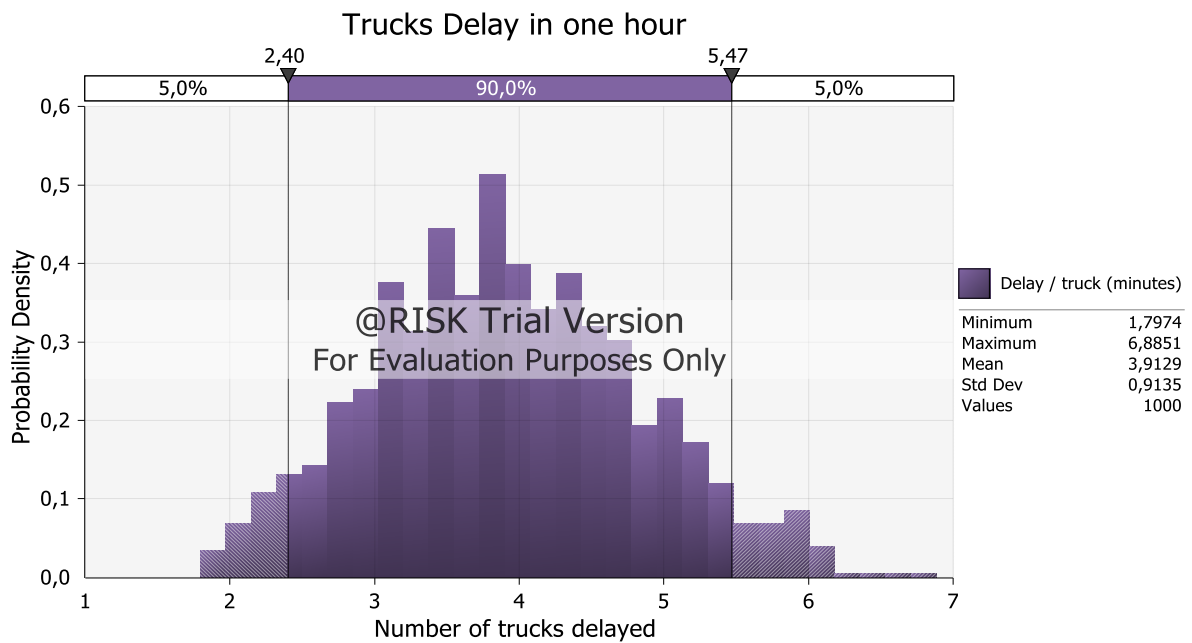


Figure 35. Truck delay per hour for the best case.