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Departamento de Engenharia Elétrica

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**Modeling, Simulation and Performance
Analysis of Dispatch Policy for Open Pit
Mines**

Flávio Henrique Batista de Souza

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**MODELING, SIMULATION AND PERFORMANCE ANALYSIS OF
DISPATCH POLICY FOR OPEN PIT MINES**

FLÁVIO HENRIQUE BATISTA DE SOUZA

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Orientador: Prof. Rodney Rezende Saldanha

Coorientador: Carlos Andrey Maia

Coorientador: Adriano Chaves Lisboa

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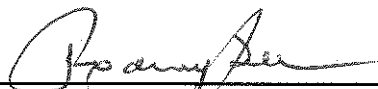
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Aprovada em 26 de setembro de 2019.

Por:



Prof. Dr. Rodney Rezende Saldanha
DEE (UFMG) - Orientador



Dr. Adriano Chaves Lisboa
Diretor Técnico (GAIA - BHTEC) - Coorientador



Prof. Dr. Carlos Andrey Maia
DEE (UFMG) - Coorientador



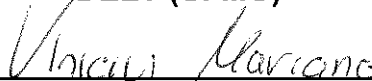
Prof. Dr. Rafael Santos Mendes
FEEC-DCA (UNICAMP)



Dr. Douglas Alexandre Gomes Vieira
Diretor Técnico (ENACOM)



Prof. Dr. Antônio de Pádua Braga
DELT (UFMG)



Prof. Vinícius Mariano Gonçalves
DEE (EEUFMG)

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Abstract

A structured and robust methodology of modeling and simulation can be available through modular stochastic timed Petri nets, including experiments that allow designers to simulate the processes involved in ore production on well-founded estimates. The research represents a relevant industrial production process optimization through a computational simulation structure, and a modeling of complex stochastic systems, constructed from real data of the process (extraction of knowledge based on data). This prerogative guides an experimental research based on real data from an Brazilian open pit mine operation. This research presents a continuity and assertion of experiments already performed with modular Petri nets, which presented significant and better results than tools already available in the industry (SIMAN). Firstly, we present an experimental design optimization methodology, focusing on performance and response quality in the modeling and simulation of the open pit mine truck dispatch process. Then, this research introduces and compares two fast heuristics for dispatch strategies in a mine simulated using Stochastic Timed Petri nets. Issues such as productivity and equipment positioning are evaluated and discussed in order to allow synthesizing sub-optimal dispatch policies. As results of the experiment, we derived a valid simulation structure for the open-pit mining process using Petri nets. It was obtained a behavioral evaluation of the efficiency of the structure according to variations in the probability distribution function. The simulation structure demonstrated a modular, scalable, transparent modeling, besides providing mathematical support, power analysis and computational efficiency.

Keywords: Dispatch Process, Experiments Design, Open Pit Mine, Simulation to Discrete Events, Stochastic Timed Petri Nets, Generalized Stochastic Petri nets.

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Introduction

Open pit mining operations involve the extraction of minerals from the earth's surface, as opposed to underground mining. The operations are primarily governed by the truck cycle, in which the ore is loaded by loaders at the extraction site and transported to the crusher for processing. A computationally efficient simulation of the mining model can support experiments involving behavior analysis of the loading and unloading processes, which can guide activities that represent a cost of 50-60% of the total investment in the mining process (evaluated as a complex system due to its dynamic, stochastic and uncertain nature).

There have been many studies that focus on the modeling and simulating open pit mines. Each approach presents a technique with specific characteristics and limitations.

[Burt and Caccetta \(2014\)](#) present a review concerning equipment selection problem for mining. The methods presented use:

- Linear programming: uses analytic models of mines in order to optimize many aspects such as fleet selection problem ([Baxter *et al.*, 2010](#)), preventive maintenance ([Topal and Ramazan, 2010](#)) and energy consumption in open pit coal mines ([Patterson *et al.*, 2015](#)). These models are usually simple and fast, but it is common to be associated to a number of approximations. More detailed models can be developed, improving accuracy but requiring more generic algorithms to optimize them, such as Genetic Algorithms ([Naoum and Haidar, 2000](#)).
- Queuing Theory: the mining process performance is directly connected to the queuing in bottlenecks, such as loader, crusher and maintenance places. It has been applied to model the truck loader system ([May, 2012](#)) in order to select a proper fleet. The models can consider the stochastic system behavior ([Raman *et al.*, 2009](#)). Using queuing theory, [Karshenas \(1989\)](#) has stated that the truck capacity should be about 5 or 7 times the loader capacity in a process of landscaping.
- Fuzzy Logic: the uncertainties in a mine model can be modeled using this technique ([Bitarafan and Ataei, 2004](#)).

- Artificial Neural Networks: used to forecast operational conditions for trucks in a landscaping environment (Marinelli *et al.*, 2014), to forecast load for shovels (Jonak, 2002), or to estimate the reserves in an open pit mine (Kapageridis, 2002).
- Other approaches: several studies with other strands are also presented in the literature, including combinatorial analysis (Bastos *et al.*, 2011), stochastic analysis (Chaowasakoo *et al.*, 2017a), and real-time dispatch optimization (Sgurev *et al.*, 1989). However, those analyses do not focus on experimental design.

A generalized approach can be derived through the discrete event simulation, which enables to represent more details in the mine. However this process requires a substantial simulation computational time as performed by Dahl and Derigs (2011) in a simulation of cooperative transportation and presented by Daaboul *et al.* (2014) in a modeling and simulation for strategic analysis.

In this context, researchs based in Petri nets have demonstrated relevant tools to simulate detailed transportation systems, vehicular mobility and process simulation (Febbraro *et al.*, 2004; List and Mashayekhi, 2016; Wang *et al.*, 2019; Zhang *et al.*, 2018). They have also been applied to model and simulate a coal mine (Konyukh and Davidenko, 1999). The authors presented the operational bottlenecks as a function of the vehicles speed variations.

Brahma (2007) presents a significant study for the modeling of open pit mines. In this model the author uses fusion techniques; which allow specifying a set of identical places that represent a single conceptual place. According to Brahma (2007), Petri nets enable the hierarchical and modular decomposition of mining projects, thus reducing the project complexity. Time uncertainties and cost estimates can be modeled using appropriate probability distributions. A general decomposition can take place for large Petri nets (Ye *et al.*, 2017), but they may lack of physical meaning for the modules.

Stochastic timed Petri nets (STPN) is a very appropriate technique to model stochastic discrete event systems due to its concise representation (with few building blocks required), modularity, transparency and mathematical fundamentals. Those characteristics enable the STPN to model and simulate a complex and uncertain process as the open pit mine exploration providing support to the operational management, evaluation of the production processes in a controlled computer environment, reducing of the time and costs associated to tests that would be performed in the operation.

Literature includes studies on the simulation of discrete event system, which involves

evaluating the number of trucks in operation, and the optimization of ore blend. In addition to this analysis, the studies also evaluated the quality of the simulation responses and the performance of the developed tool. We will also evaluate such concepts in this research.

The modeling and simulation processes in this work are developed using stochastic timed Petri nets, which are based on the concept of simulating discrete events as described by [Blouin *et al.* \(2007\)](#) and [Ribeiro *et al.* \(2018\)](#).

Specifically, [Ribeiro *et al.* \(2018\)](#) presents a hybrid methodology for handling stochastic systems. This methodology uses a graph based on Petri nets to analyze client/server services. Such a methodology aggregates Max-Plus Algebra with Markov Chain to model the load haulage cycle of an open-pit mine. Therefore, the present research focuses on Petri nets as a framework for modeling and simulating stochastic discrete event models.

In this research, the optimization of ore blending is not performed during the dispatch process as performed by [White and Olson \(1986\)](#). The papers evaluated the availability of trucks (but not dynamically) as an option in the studies presented by [Koryagin and Voronov \(2017\)](#) (they presented a dynamic consideration of the availability of trucks).

In terms of statistical analysis, the simulations evaluate the quality of the answers as presented by [Lizotte and Bonates \(1987\)](#). In this work, evaluation is performed by an exploratory evaluation of the number of samples and the quality of the responses obtained during the simulation process. An analysis is also performed to determine any variation in the behavior of the responses according to variations in the cumulative distribution function (CDF) of operation times. We also validate performance as described by [Guimaraes *et al.* \(2007\)](#), where a computational simulation model was used to validate results based on dynamic allocation of trucks in open-pit mines.

While executing the experiments in this research, we used the simulation concept of discrete events and focused on the sample numbers and the quality of the experiment output. Using this simulation, various experiments can be performed with a much lower operating cost compared to tests under real conditions and materials. The number of samples is an important question in the simulation processes. [Mathews \(2010\)](#) demonstrated an evaluation of resource consumption versus the number of samples used in surveys, shown in [Figure 1.1](#), where sample costs become expensive because of wrong decisions. The optimal number of samples minimizes the total cost of the analysis. Analyzing the number of samples can make the simulation process efficient and effective, which helps guide the operations involved in this type of activity. The main objective of this article is to estimate the expected value $J(\theta)$ (where

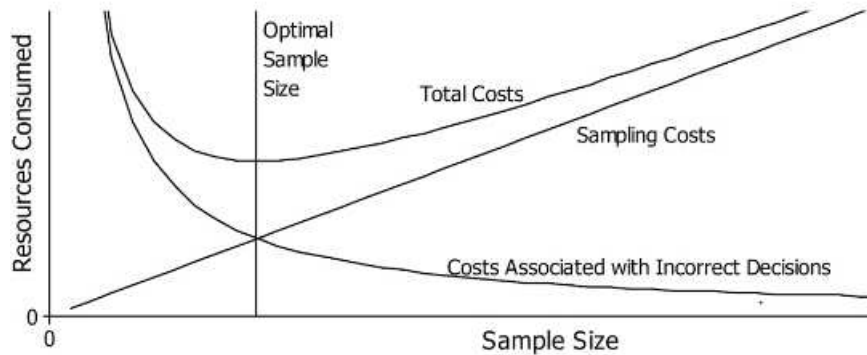


Figure 1.1 Resources versus Sample Size. This reading of the optimal number of sample size behavior is not a trivial deduction. Poorly substantiated analysis may lead to excessive resource consumption or insufficient samples. Source: Mathews (2010)

θ is the mean productivity (in tons of ore per hour) by considering the dispatch of trucks in the simulation process and the sampling variable ω , which encompasses the stochastic character of activity times of the process (Ribeiro *et al.*, 2018).

To perform the experiments, an open pit model is delineated for orientation of the simulation tools.

1.1 Objectives

This work proposes the use of simulation structures based on Petri nets to optimize the process of dispatch. The main objective of this research is to present and evaluate a process of Petri net based on simulation and optimization of dispatch process in an open-pit mining operation.

To accomplish this task, it is necessary to first estimate productivity $J(\theta)$ (in tons of ore per hour) considering the dispatch process in the simulation. Productivity $J(\theta)$, in tons of ore per hour, can be obtained as the mathematical expectation of a performance index L that depends on the activity parameter θ and the sampling variable ω , which encompasses the stochastic character of the activity times of the process (Ribeiro *et al.*, 2018):

$$J(\theta) = E[L(\theta, \omega)] \quad (1.1)$$

A complete productivity process has a range of n conditions to be considered, thereby tending to endless issues. Hence, the exact calculation of $J(\theta)$ is rendered complex, as can be seen from Eq. 1.2.

$$J(\theta) = \lim_{n \rightarrow \infty} \frac{\sum_{i=1}^n L(\theta, \omega_i)}{n} \quad (1.2)$$

Thus, with the concepts of simulation, a finite number of considerations, N , is evaluated.

$$\hat{J}(\theta) = \frac{\sum_{i=1}^N L(\theta, \omega_i)}{N} \quad (1.3)$$

where $\hat{J}(\theta)$ is a random variable. Therefore, for this estimator to be a relevant approximation of $J(\theta)$, two conditions must be satisfied. First, the number of samples N must be sufficiently large and the analysis must employ techniques that evaluate the variance of $\hat{J}(\theta)$. Second, a true random number generator must be used. These considerations must be taken into account because they can directly interfere with the quality of the estimator of $\hat{J}(\theta)$. This is because of the fact that in practice, the size N of the sample is a function of the available computational resources (for systems with reasonable complexity - e.g. with many entities - the computational time to perform the analysis is considerably onerous).

Statistical analyses are necessary for evaluating the quality of the answers presented. It is also necessary to evaluate the performance of the simulator, to ensure efficiency and effectiveness, in simulations involving a low number of executions sufficient for a trustworthy quality response.

So, dispatch optimization techniques for trucks based on specific rules, such as the formation of service queues, productivity of each equipment, and time of each productive cycle, are presented and compared. According to the results of simulation and optimization of dispatch process, a last objective is drawn to verify the behavioral issues of the simulation structure. The aim is to analyze the impact on productivity of the distance imposed by the positioning of equipment (loaders and crushers).

1.2 Relevance

Many papers have good sub-optimal solutions, but with complex mathematical models with difficult abstraction. There are also processing time issues (since heuristics demand computational resources). Another factor to consider is dependence on paid or proprietary tools, which often involve license payments or lack of decision-making power of the developer at the time of abstraction. In addition, the use of Petri nets makes it possible for the solution to be exported to different programming platforms with simplicity of implementation. These questions were extremely relevant in this work.

1.3 Originality

The contributions and originality of the present work are represented by experiments that bring the application of structures based on Petri nets, counting on a behavioral evaluation of distribution functions, number of samples optimization and two new and fast heuristics for truck dispatching to increase the productivity.

1.4 Organization

This work organization is:

- [chapter 2](#) presents the references that supported this research, which include the precepts of open pit mine, truck dispatch process, Petri nets and some of their types, probability distribution functions and statistical analysis;
- in the [chapter 3](#), the methods of experiments that were used are defined, demonstrating tool definitions, models and parameters;
- [chapter 4](#) presents and discuss the obtained results;
- [chapter 5](#) presents the conclusions;
- in [chapter 6](#) the future analyses of the project are presented;

- The published papers are presented in [chapter 7](#).

Theoretical References

2.1 Open Pit Mining

The open pit model, according to [Ribeiro \(2013\)](#) is a surface mine operation in which the ore, or residue, is excavated from the surface of the earth. During the process, a deeper well is formed until the mine operation ends. For [Ribeiro \(2015\)](#), during ore extraction, cargo equipment should be allocated at specific locations (mine fronts), from which material (ore or waste) removed is deposited in trucks suitable for transportation to a crusher, where the ore is processed. In case of waste it is taken to the proper repository of this material.

As already mentioned by [Subtil *et al.* \(2011\)](#), loading and transport operations are the most critical within mining processes. A simplified and theoretical model of the loading and transport process is presented in [Quevedo \(2009\)](#) and referenced in several works ([Ribeiro, 2015, 2013](#)). [Figure 2.1](#) demonstrates the component blocks of the process, while [Figure 2.2](#) demonstrates the operation sequence.

According to [Ribeiro \(2015\)](#), in this model the queues in the crusher and the loader define a restriction of these equipments, since they are occupied by only one truck at a time. The presented model of load and transport is considered a simplified model, considering only one front of mining and consequently does not consider the system of dispatch of trucks for different fronts of mining. The models that consider more than one mining front are known as a problem of mixing or blending. They consist of determining how much ore from each front should be mixed in order to meet production requirements. The vast majority of the time spent in open pit mining processes is stochastic, are typically modeled by probability distributions.

Prior to the simulation, the model of the mine must be created. Such a model should describe the rules that govern the dynamics of operation of each equipment involved in the process. [Figure 2.1](#) and [Figure 2.2](#) demonstrates a model based on ore loading and unloading. The simulation that is studied in this work represents the rules used in this model, in order to advance the research that involves the dispatch process during the transport process between

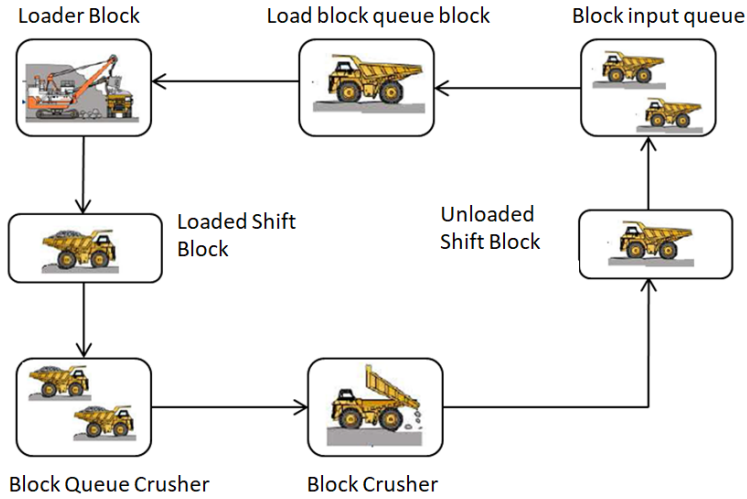


Figure 2.1 Simplified block model. Source: Ribeiro (2015)

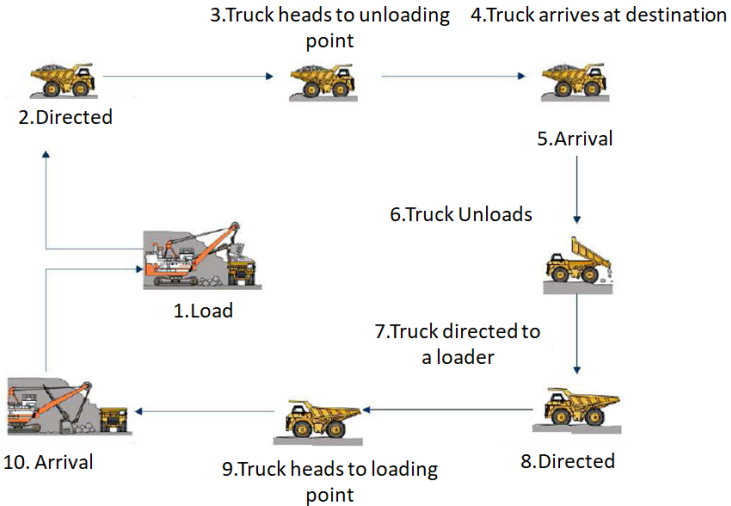


Figure 2.2 Simplified sequence model. Source: Ribeiro (2015)

the ore loading and unloading points.

The investments in simulations for this process can be justified by the various mining operations are highly complex in terms of technological and planning aspects (Ribeiro, 2013). Such operations imply an intensive investment in an environment of many uncertainties. The mining planning phase is very important in any type of mine because it seeks to reduce costs associated with operations, satisfying production plans and meeting quality requirements.

According to Ribeiro (2015) and Ribeiro (2013), issues such as the cycle time of the trucks, the amount of cargo transported, the reliability and availability of the assets, the efficiency of the maintenance units are some of the operational factors that precede the uncertainties that exist in the system and that directly influence the production of a mine.

Subtil *et al.* (2011) states that the efficiency of the transport fleet depends on its size and the distances traveled between the loading and unloading stations of the mine. Insufficient amount of trucks can result in unproductive periods. Already many trucks can increase the length of the waiting queues for use of other resources such as: loaders, maintenance and supply units, etc. For Torkamani and Askari-Nasab (2012), material handling and transportation system (including the treatment of truck routing, focus of this work) are some of the main contributors to such costs.

Several forms of simulation approaches are present in the literature. It may be noted that several techniques can be used on the same model, considering the fact that each technique can bring benefits and limitations. Burt and Caccetta (2014) demonstrates that there are several methods as follows: linear programming, heuristics, artificial intelligence and simulation theory.

2.2 Dispatch in Open Pit Mine

Several works have focused on optimizing the process of dispatch. Analyses in this field, applying a variety of techniques, have been carried out for more than three decades. Maran (1987) demonstrated that the operations of loading and hauling can account for 60% of the total costs incurred in surface mining. A similar observation was made 24 years later by Subtil *et al.* (2011), who noted that optimization and control of these operations can provide substantial reductions in cost. They addressed the following problems: process of allocating trucks to loading equipment, performance evaluation of an existing operation, and performance

prediction of a future system. Their research was guided by the strategies of dynamic programming, integer programming, and heuristic algorithms for truck allocation, and queuing theory for process evaluation.

[Maran \(1987\)](#) proposed an approach based on analytical methods and noted the complexities of this methodology. They compared simulation results with steady-state analytical results of average haulage time during starting conditions, and for a single-cycle truck and shovel system.

[Lizotte and Bonates \(1987\)](#) used a stochastic simulation program to assess the dispatching rule proper to small-scale computerized systems for optimizing productivity, minimizing shovel idle time, maximizing immediate truck use, and assigning trucks to shovels to meet specific production objectives.

Other approaches have been developed over the years, focusing on various aspects of the process of dispatch. [Temeng *et al.* \(1998\)](#) designed a non-preemptive goal programming dispatch model to provide an efficient basis for maximizing production while also maintaining ore quality characteristics within desirable limits. It was observed that employing a linear programming (LP) model only resulted in production maximization, and required re-handling or stockpiling.

[Wang *et al.* \(2006\)](#) demonstrated a real-time dispatching principle for open-pit mine trucks under macroscopic control. The truck flow rates were considered by taking the unloading points as emphasis. The authors noted an advantage in the performance of their proposed principle over that of the dynamic programming method of DISPATCH developed by Modular Mining.

Three years later, [Ercelebi and Bascetin \(2009\)](#), studied shovel and truck operation models, and optimization approaches for the allocation and dispatch of trucks under various operating conditions. They used closed queuing network theory for truck allocation and LP for truck dispatch to shovels. [Samavati *et al.* \(2017\)](#) subsequently considered LP in combination with a few heuristic tools, and used a multi-period precedence-constrained knapsack, in which the decision-maker faces a horizon of several periods. An LP relaxation formulation of the problem was performed, and the solutions were used to generate efficient weights for the sequencing heuristic.

A few researchers, such as [Souza *et al.* \(2010\)](#), applied dynamic truck allocation. The objective was to optimize mineral extraction by minimizing the number of mining trucks used to meet production goals and quality requirements.

Subtil et al. (2011) stated that the efficiency of a transport fleet depends on its size and distances travelled between the loading and unloading stations at the mining site. An insufficient number of trucks can result in unproductive periods. The use of several trucks can increase queue length, i.e., waiting time, for use of other resources, such as loaders, and maintenance and supply units.

Tan et al. (2012) proposed a few procedures to optimize the number of trucks and estimate the maximum mining capacity of an open copper pit. They performed a simulation to demonstrate the creation of a truck dispatching control table to achieve maximum mining capacity. A series of data obtained from a transportation control system with global position system (GPS) was utilized to perform the simulation.

Other researchers focused on stochastic analyses considering the time windows present in the process of dispatch. *Bastos (2010)* applied a stochastic method using time-dependent Markov decision processes (TiMDPs) to the truck dispatching problem using probabilistic density functions. To mitigate the well-known issue of dimensionality that plagues multi-agent problems entailing discrete state models, the system was modeled based on the single-dependent agents introduced. A metaheuristic was designed and presented, and the genetic TiMDP (G-TiMDP) method was applied to the truck dispatching problem.

Some works focused on other equipment involved in the process of dispatch. *Mena et al. (2013)* presented a novel modeling framework for simulation and optimization of system productivity in which equipment availability is a variable in the expected productivity function of the system. The framework was used to allocate trucks by route according to their operating performances in a truck-shovel system of an open-pit mine to maximize overall fleet productivity.

Kaboli and Carmichael (2014) proposed that truck dispatch in earthmoving and similar operations are worthy of examination because of potential emission reductions and cost savings gained through the appropriate allocation of trucks to excavators and dump sites. They proposed a methodology wherein truck dispatch is performed on the basis of LP and the effects of truck allocation on unit emission and unit cost are established. The number of trucks, unit cost, and unit emission were all considered.

Zhang and Xia (2015) formulated the truck dispatching problem in an open-pit mine into an integer programming problem to optimally determine the number of truck trips from shovel to dump site.

Koryagin and Voronov (2017) considered the unproductive time of equipment. They

developed a heuristic algorithm for making dispatching decisions under the condition of dynamic allocation of trucks to reduce the idle time of mining trucks and shovels in an open-pit coal mine.

A work of literature can be verified, in this case, [Blouin et al. \(2007\)](#). It focuses on the dispatching problem of an oil sand excavation process subject to production objectives and specifications. It cast the truck dispatching task in a decision-making framework for determining solutions and helping a dispatcher to make decisions and apply the discrete-event formalism to investigate the dispatching of a large truck fleet. [Blouin et al. \(2007\)](#) examines the capabilities and limitations of two distinct theories: discrete-event system (DES) and vector discrete-event system (VDES). Despite their differences, both theories can be used to model the logical structure of the dispatching process. These theories also had provided techniques for implementing specifications and representing solutions in a compact manner.

For consolidation, the tables 2.1-2.8 show comparative summaries of the respective approaches in this research.

Concept: Positioning evaluation		
Proposal	Method and Findings	Reference
A low-cost GPS/INS integrated navigation system is an ideal positioning component for an open-pit truck monitoring and dispatching system The model was based on the ECEF (Earth-Centered Earth-Fixed) frame and was suitable to implement the in-motion alignment with GPS aid.	The sensitivity of low-cost GPS/INS was not sufficient for the initial alignment in a static base before navigation	Zhang et al. (2013)
Comparative: A proposal of productivity analysis by positioning of equipment is presented.		

Table 2.1 Comparative by positioning evaluation

2.3 Simulation

According to [Robinson \(2014\)](#), the simulation is considered as an experiment with a simplified imitation of an operations system that works over time, for a better understanding

Concept: Availability of trucks		
Proposal	Method and Findings	Reference
Procedures to obtain an optimized number of trucks and to estimate the maximum mining capacity at an open copper pit.	A series of data obtained by a transportation control system with GPS technology was utilized to perform the simulation.	<i>Tan et al. (2012)</i>
A novel system productivity simulation and optimization modeling framework in which equipment availability is a variable in the expected productivity function of the system.	A framework was developed for allocating trucks by route according to their operating performances in a truck–shovel system of an open-pit mine, so as to maximize the overall productivity of the fleet.	<i>Mena et al. (2013)</i>
Optimize a LP dispatching, based on minimizing truck numbers and unit costs, accordingly impacts the environment the least in terms of emissions.	Truck dispatching through linear programming (LP) and the effect of truck allocation on unit emissions and unit costs.established	<i>Kaboli and Carmichael (2014)</i>
Reduce idle times of mining trucks and shovels in an open-pit coal mine.	A heuristic algorithm for making dispatching decisions in conditions of dynamic allocation of trucks.	<i>Koryagin and Voronov (2017)</i>
Comparative: The present work carried out experiments that consider this concept, but not dynamically.		

Table 2.2 Comparative by availability of trucks

Concept: Optimization of the cargo mix		
Proposal	Method and Findings	Reference
Minimize the costs considering the mining rate, the quality of the mixture, the feed rate of ore to the beneficiation plant and the handling of materials.	An algorithm that is the basis for the dispatch system, which operates in many mines around the world (LP Based).	<i>White and Olson (1986)</i>
Comparative: The ore mix complexity is not considered in this work.		

Table 2.3 Comparative by optimization of the cargo mix

Concept: Heuristics and Metaheuristics		
Proposal	Method and Findings	Reference
An algorithm is proposed to make real-time dispatch decisions in open pit mines based on discrete position information	New heuristic rules are presented using current local data collected by peer-to-peer (P2P) communication systems and vehicle position estimates to select the ideal destination for the travel plan for each vehicle.	<i>Arelovich et al. (2010)</i>
A methodology based on linear and dynamic programming, as well as a heuristics-based methodology, was implemented for truck dispatch simulation.	A simulation model was developed to reproduce the behavior of mining operations in order to evaluate the impact of dispatch decisions in each of the methodologies studied.	<i>Rodrigues and Pinto (2012)</i>
A multiobjective genetic algorithm for dynamic truck dispatching in open pit mining.	The proposed algorithm implemented a heuristic for generating the initial solutions set that uses local search operators for scanning the neighborhood of non-feasible solutions set and for exploring the neighborhood of feasible solutions set.	<i>Mendes et al. (2016)</i>
A approach based on differences in the match factor.	A simulation study provided evidences that the match factor can be used to determine ranges for numbers of different types of trucks in an optimal fleet	<i>Chaowasakoo et al. (2017c)</i>
Comparative: Heuristic for truck dispatching were used to optimize the productivity.		

Table 2.4 Comparative by Heuristics and Metaheuristics

Concept: Quality of the answers		
Proposal	Method and Findings	Reference
Issues concerning simulation software, statistical support software, processing times and implementation costs.	SLAM II and FITPLUS for simulating and statistically analyzing mining models.	Castillo and Cochran (1987)
A stochastic simulation program used to assess several dispatching rules applicable to small scale computerized systems for optimizing truck/shovel productivity.	The simulation program was structured on an advance clock approach which enables the insertion of dispatching rules at various points in the haulage network.	Lizotte and Bonates (1987)
Comparative: Analysis of response quality ($\hat{J}(\theta)$ estimative) is one of the research objectives.		

Table 2.5 Comparative by quality of the answers

Concept: Stochastic analysis		
Proposal	Method and Findings	Reference
Through SMART MINE system, a stochastic optimization technique was applied, using the genetic algorithm with parallel processing.	Basically, the problem is to indicate the best tilt or load point and the trajectory for the movement, when there is a choice situation to be made. The author pointed to productivity gains of 5-15%.	Alvarenga (1997)
Illustrate the differences between the strategies by conducting a stochastic simulation study based on the data gathered from an actual mine in operation.	A comparison of several stochastic methods is demonstrated and the findings underline the importance of the global vision in dispatching decisions.	Chaowasakoo <i>et al.</i> (2017b)
Comparative: The use of stochastic Petri nets was used precisely because of the problem characteristic.		

Table 2.6 Comparative by stochastic analysis

Concept: Constraints and Uncertainties		
Proposal	Method and Findings	Reference
The treatment of truck dispatch as combinatorial problem of assigning trucks to blades in order to optimize a specific objective, taking into account various constraints and uncertainties.	The stochastic question is considered as in real world. The dispatch of trucks in open pit mines is subject to uncertain behavior, such as variations in fuel consumption, unexpected equipment stops (failures, flat tires, emergencies, etc.) and lasting actions.	<i>Bastos et al. (2011)</i>
The truck is not only the carrier of transport material, but also act as the bridges and linkages between the loading sites and the unloading sites.	A model to calculate the production measurement of the transport, loading, unloading, material respectively, as well as with any calculation in combination of more than one factor as needed.	<i>Sun et al. (2016)</i>
Comparative: This research considers uncertainties and constraints that occur in the real process.		

Table 2.7 Comparative by constraints and uncertainties

Concept: Performance validation		
Proposal	Method and Findings	Reference
A computational simulation model to validate the results obtained by the application of a mathematical programming model to determine the mining rate in open pit mines. A optimizing performance process is evaluated.	LINGO solver, version 7.0, was used to optimize the problem and ARENA, version 7.0, simulated the solver solution.	<i>Guimaraes et al. (2007)</i>
Comparative: A sample number optimization process is carried out in Chapter 4.1		

Table 2.8 Comparative by performance validation

or improvement of such system. It is a computerized process and it is justified by the need to understand the real systems, which present elements of variability, interconnectivity and complexity.

The simulations have the following advantages (Robinson, 2014):

- Considering real systems: cost, time, control of experimental conditions and can be used when the real system does not yet exist;
- Considering other modeling approaches: model variability, transparency, and involves restrictive elements;
- The management perspective: creativity, creation of knowledge and understanding, visualization and communication, consensus building;

However, the simulation has disadvantages when characteristics that deconstruct the advantages obtained. This occurs when after modeling, the simulation is characterized face on financial issues and time, requires expertise or becomes confidential. One of the focuses of simulation approach that is presented by Robinson (2014) is the modeling systems in queues. The simulations have as key methods the simulation to discrete events, Monte Carlo, dynamic systems and simulation based on agents.

In the present work, we will focus on the simulation method oriented to discrete events.

2.3.1 Discrete Event Systems

During the research, the concepts of discrete event systems were used. For this, an analysis of the concepts of System, Events and the interaction between them will be carried out.

According Cassandras and Lafortune (2008) the concept of system can be defined as an aggregation or assemblage of things so combined by nature or man as to form an integral or complex whole (as in Encyclopedia Americana), a regularly interacting or interdependent group of items forming an unified whole (as in Webster's Dictionary), or a combination of components that act together to perform a function not possible with any of the individual parts (IEEE Standard Dictionary of Electrical and Electronic Terms).

Still according to Cassandras and Lafortune (2008), there are two salient features in these definitions. First, a system consists of interacting "components", and second a system is

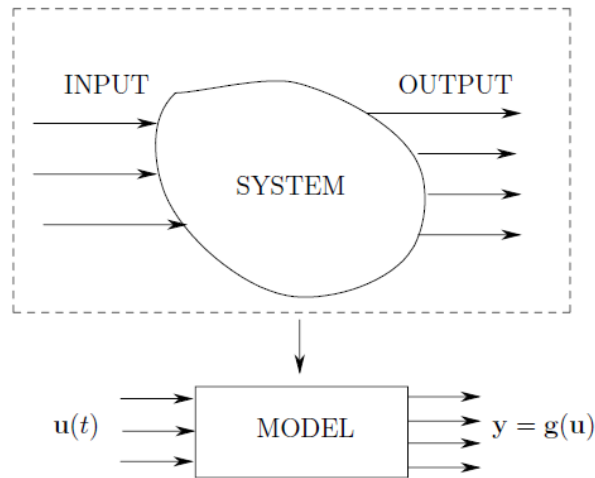


Figure 2.3 Simple Modeling Process

associated with a "function" it is presumably intended to perform. It is also worth pointing out that a system should not always be associated with physical objects and natural laws.

The systems have several types. For a brief analysis, [Figure 2.3](#) will first be taken as a reference ([Cassandras and Lafortune, 2008](#)):

- **Static and Dynamic Systems:** [Figure 2.3](#) reveals one of the major ways to classify systems, where the set input-system-output can describe all input–output functional relationships we can construct. They are simply described by algebraic equations. [Cassandras and Lafortune \(2008\)](#) define a static system to be one where the output $y(t)$ is independent of past values of the input $u(\tau)$, $\tau < t$ for all t . A dynamic system is one where the output generally depends on past values of the input.
- **Continuous-State and Discrete-State Systems:** In continuous-state models the state space X is a continuum consisting of all n -dimensional vectors of real (or sometimes complex) numbers. Normally, X is finite-dimensional, although there are some exceptions where X is infinite-dimensional. This normally leads to differential equations and associated techniques for analysis. In discrete-state models the state space is a discrete set, where a typical sample path is a piecewise constant function, since state variables are only permitted to jump at discrete points in time from one discrete state value to another. There are many situations in which a hybrid model may be appropriate, that is, some state variables are discrete and some are continuous.

- **Deterministic and Stochastic Systems:** [Cassandras and Lafortune \(2008\)](#) define a system to be stochastic if at least one of its output variables is a random variable (otherwise, the system is deterministic). In general, the state of a stochastic dynamic system defines a random process, whose behavior can be described only probabilistically. Thus, in a deterministic system with the input $u(t)$ given for all $t \geq t_0$, the state $x(t)$ can be evaluated. In a stochastic system, the state at time t is a random vector, and it is only its probability distribution function that can be evaluated.
- **Time-Varying and Time-Invariant Dynamic Systems:** According [Figure 2.3](#), using the reference input-model-output, note that we have assumed $g(\cdot)$ to be independent of time. However, a more general representation would be $y = g(u, t)$ where allow $g(\cdot)$ to explicitly depend on the time variable t . When this is not the case, it is obtained the class of systems which are called time-invariant, as opposed to time-varying, or sometimes stationary systems. A system is said to be time-invariant if it has the following property: if an $u(t)$ (as a input) results in an $y(t)$ (as a output), then the $u(t - \tau)$ results in the $y(t - \tau)$, for any τ . In other words, if the input function is applied to the system τ units of time later than t , the resulting output function is identical to that obtained at t , translated by τ ([Cassandras and Lafortune, 2008](#)).

Several experiments in this work will contemplate this type of definition.

In order to use the concept of Event, according [Cassandras and Lafortune \(2008\)](#), it is a primitive concept. An "Event" should be thought of as occurring instantaneously and causing transitions from a state value to another (e.g., somebody presses a button).

According [Cassandras and Lafortune \(2008\)](#), it may be viewed as a spontaneous occurrence dictated by nature or it may be the result of several conditions which are suddenly all met. The symbol e can denote an event. When considering a system affected by different types of events, it is possible define an event set E whose elements are all these events, where E is a discrete set.

Systems may have characteristics that classify them as *Time-Driven* and *Discrete-State* Systems ([Cassandras and Lafortune, 2008](#)):

- **Time-Driven Systems:** In continuous-state systems the state generally changes as time changes (evident in discrete-time models: The "clock" is what drives a typical sample path). With every "clock tick" the state is expected to change, since continuous state variables continuously change with time. It is because of this property that defines such

systems as time-driven systems. In this case, the time variable (t in continuous time or k in discrete time) is a natural independent variable which appears as the argument of all input, state, and output functions.

- **Discrete-State Systems:** In discrete-state systems, the state changes only at certain points in time through instantaneous transitions (with each such transition, it is possible associate an event).

For a single analysis, taking a clock as reference to measure time, there are two possibilities (Cassandras and Lafortune, 2008):

- At every clock tick an event e is to be selected from the event set E . If no event takes place, it is a "null event" as being a member of E , whose property is that it causes no state change.
- At various time instants (not necessarily known in advance and not necessarily coinciding with clock ticks), some event e "announces" that it is occurring.

The distinction between first and second points gives rise to the terms time-driven and event-driven systems respectively.

The continuous-state systems are by their nature time driven. However, in discrete-state systems this depends on whether state transitions are.

According the characteristic properties of Discrete Event Systems, those systems, satisfy the following two properties:

- The state space is a discrete set.
- The state transition mechanism is event-driven.

Finally, the definition of a Discrete Event System (DES) is: a DES is a discrete-state, event-driven system, that is, its state evolution depends entirely on the occurrence of asynchronous discrete events over time.

According to Robinson (2014) discrete event simulation is used for modeling queuing systems. A system is represented as a flow of activities performed by performing entities, which present a time delay to each activity. Activities are separated by queues, which are generated by

the fact that the entity's arrival is faster than the processing capability that frees up the next task. Many systems can be conceptualized as queuing systems, with people, data or other elements being considered entities that circulate through the system.

2.3.2 Petri Nets

According to Mathews (2010) and Murata (1989), the Petri nets are a quintuple (P, T, A, w, x) , where:

- P is a set of places,
- T is a set of transitions,
- A is a set of arcs,
- w is a set of weights,
- $x_0 = \{x_1, x_2, \dots, x_m\}$ is an initial marking.

The graphical representations of a Petri net comprise a graph composed of nodes connected by oriented segments called arcs A . This graph has two types of nodes called places P (circles) and transitions T (bars). Each arc is directed and terminated by an arrow. Arcs link a place p to a transition t or a transition t to a place p and are assigned weight w , which determines the number of tokens to be consumed or assigned to p after the firing of t . The number of places and transitions is finite and not zero. This structure considers the marking x , which generates a quintuple (P, T, A, w, x) . Figure 2.4 presents an example of a Petri net, with places $P = \{p_1, p_2\}$ connected to the transition t_1 , where $T = \{t_1\}$.

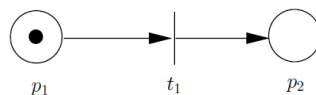


Figure 2.4 An example of Petri net with two places ($P = \{p_1, p_2\}$), one transition ($T = \{t_1\}$), two arcs $A = \{(p_1, t_1), (t_1, p_2)\}$ and a marking vector $x = (1, 0)$

The link between those places and transition t_1 is indicated by the arcs $A = \{(p_1, t_1), (t_1, p_2)\}$, which are assigned weights $w_{(p_1, t_1)} = w_{(t_1, p_2)} = 1$. This Petri net has the marking vector

$x = (1, 0)$, that is, it has two tokens in p_1 and zero tokens in p_2 . The firing sequence is performed based on a criteria presented by Murata (1989), where a transition t can fire when the resource demand (tokens) is satisfied by the composition of places in P and arcs in A that precede such a transition t . If places preceding t have enough tokens to meet the arc demands, then firing of t is permitted.

The connection between arcs and places (or transitions) is represented through the incidence matrix $W = W^+ - W^-$, where its elements are defined by:

$$W_{p,t}^+ = \begin{cases} w_a, & a = (t, p) \in A \\ 0, & \text{otherwise} \end{cases} \in \mathbb{N}^{|P| \times |T|} \quad (2.1)$$

$$W_{p,t}^- = \begin{cases} w_a, & a = (p, t) \in A \\ 0, & \text{otherwise} \end{cases} \in \mathbb{N}^{|P| \times |T|} \quad (2.2)$$

where w_a is the weight w of arc a .

Through the association between the incidence matrix W and the marking vector x , the process of updating the state of the Petri net is obtained by:

$$x_{k+1} = x_k + W^+ e_t - W^- e_t \quad (2.3)$$

where k is the state number, e_t is a vector with zeros except in the position t , which is unitary, and t is the enabled transition with the earliest firing time. The matrix W^+ defines the added tokens to each place of P and W^- defines the removed tokens from each place of P . This update is simple and provides elegance for Petri nets.

2.3.2.1 Timed Petri Nets

Petri nets are constructed by adopting a functioning concept that obeys a temporal issue. This concept allows the transitions t_j , where $t_j \in T$, can fire with a time delay, or a delay. For this, it should be noted that in the set T of transitions, there exists a distinction between the set of transitions T_0 (immediate firing) and the transitions T_D (temporal delays in the firing process called timed transitions, indicated by an empty rectangle), where $T = T_0 \cup T_D$. There exists a clock structure (or timing structure) associated with the set of timed transitions T_D , where $T_D \subseteq T$ defined by a set $V = \{v_j : t_j \in T_D\}$ with duration time sequences $v_j = \{v_{j,1}, v_{j,2}, \dots, v_{j,k}\}$, $t_j \in T_D, v_{j,k} \in \mathbb{R}^+$ where $k = 1, 2, \dots, K$. In other words, every transition of T_D has a holding time

$v_{j,k}$ for its k -th firing, $k \in K$ (Mathews, 2010; Murata, 1989).

The timed Petri net is six-fold (P, T, A, w, x, V) , where $V = \{v_j : t_j \in T_D\}$ denotes the clock structure. The state equations of the Petri net will generate firing sequences of the transitions $\tau_{j,k}$, where $\tau_{j,k} = \{\tau_{j,1}, \tau_{j,2}, \dots\}$, and $j = \{1, 2, \dots, m\}$. $\tau_{j,k}$ presents the instant of occurrence of the k -th firing of the transition t_j , where $k = \{1, 2, 3, \dots\}$ (Murata, 1989). Fig. 2.5 illustrates a timed Petri net. This analysis is based on the arrangement of the transitions $t_j \in T$, where $T = \{a, s, d\}$ and composed by $T_0 = \{s\}$ and $T_D = \{a, d\}$. The clock is $V = \{v_a, v_d\}$. According to this structure, it is also necessary to analyze the time in which places p_i , where $p_i \in P$, receive their tokens. A transition t can fire when the resource demand (tokens) and time

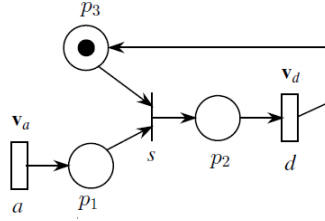


Figure 2.5 An example of timed Petri nets. Transitions a and d received a delay time v_a and v_d to be respected before their firing events.

requirements are satisfied by the composition of places in P and arcs in A that precede such a transition t , considering the associated time delay (Cassandras and Lafortune, 2008).

2.3.2.2 Generalized Stochastic Petri Nets

The Generalized Stochastic Petri net (GSPNs), are extended Petri nets, where the firing transitions are based in a probabilistic delay determined by a random variable following an exponential distribution. This kind of structure has a large number members, forming a GSPN family, each one featuring different time specifications. The GSPNs were proposed in the performance evaluation field, focused in the design phase of projects (modelling, which contains simulation models and analytical models)(Marsan, 1988).

According to Marsan (1988), the GSPN was introduced in the 1980s as an extension of the basic graphical Petri net, to model a system for performance evaluation. The probabilistic approach may provide sufficient accuracy, while yielding more general results, and it may allow

the study of sensitivity to parameter variations.

The basic GSPN model is a member of this family of structure. According to Marsan (1988) and Murata (1989), a transition t can fire obeying a time delay based in distribution function and is a tuple $GSPN=(P, T, A, w, x, \Lambda)$, where:

- P is a set of places,
- T is a set of transitions,
- A is a set of arcs,
- w is a set of weights,
- $x_0 = \{x_{0,1}, x_{0,2}, \dots, x_{0,m}\}$ is a an initial marking,
- $\Lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$ is an array of (possibly marking dependent) firing rates associated with transitions (associated to a exponential distribution).

Such as in the timed Petri nets, a firing delay is associated with each transition. This firing delay is a random variable with negative exponential pdf in the GSPN case. The parameter of the pdf associated with transition t_i is the firing rate associated with t_i ; λ_i . This firing rate may be marking-dependent, so that it should be written $\lambda_i(M_j)$. The average firing delay of transition t_i in marking M_j is $[\lambda_i(M_j)]^{-1}$. The possibly very large number of reachable markings is the most critical aspect of GSPN models.

2.3.2.3 Stochastic Timed Petri Nets

Stochastic Timed Petri nets (STPN) are Petri nets in which stochastic (not following necessarily exponential distributions) firing times are associated with transitions. The STPN automatically generates a stochastic process that governs system behavior (Wang, 1998).

An execution sequence comprises the initial condition for the timed execution of a Petri net P_n :

- an initial marking x_0 is the first execution of the simulation;
- the transitions t_i and t_{i+1} correspond to ordered times τ_i and τ_{i+1} , where $\tau_i \leq \tau_{i+1}$;

- the time intervals between consecutive epochs, where $[\tau_i, \tau_{i+1})$, indicates the periods in which the net awaits temporally to update the marking $x(i)$;
- a history of a Petri net up to the k -th time τ_k is denoted by $Z(k)$.

According those concepts, Wang (1998) describes, in a probabilistic sense, the future behavior i of a system using the knowledge of the past history v .

Therefore, the Petri net recognizes two concepts as references: history of the Petri net up to the k -th firing time and $x = x(k)$ (indicating the firing transition $t_{(k)}$). For all k , Z , and x , the following distribution functions can be determined as follows Wang (1998):

$$F(i, v|x, Z) = P_n\{t_i \text{ fires}, d_f \leq v|x, Z\} \quad (2.4)$$

where the random variable d_f denotes the time elapsed from entering x up to the next transition time. According to Wang (1998), x is known from Z , and there exists the dependence on x . This is the only element that influences the distribution function. Such a distribution must be defined for all transitions t_i . The distribution of the time spent in marking x before the next time is expressed as Wang (1998):

$$F(v|x, Z) = \sum_{t_i \in E(x)} F(i, v|x, Z) \quad (2.5)$$

where E must represent the enabled transitions in T , considering the marking x .

Therefore, using the definition presented it is possible to assume that STPN's can be used in projects involving distributions that are not necessarily exponential as in the design of this paper.

2.4 Distribution Functions

During the experiments, three types of distributions were analyzed to evaluate the behaviors that a simulation could present: Normal, Exponential and Uniform.

2.4.1 Normal Distribution

Montgomery (2008) cites that often is possible to determine the probability distribution of a particular statistic if we know the probability distribution of the population from which the sample was drawn. The probability distribution of a statistic is called a sampling distribution. According to Montgomery (2008), one of the most important sampling distributions is the **Normal** distribution. If y is a normal random variable, the probability distribution of y is:

$$f(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\frac{y-\mu}{\sigma}} \quad -\infty < y < \infty \quad (2.6)$$

Where $-\infty < y < \infty$ is the mean of the distribution and $\sigma^2 > 0$ is the variance. The normal distribution is shown in Figure 2.6. Because sample runs that differ as a result of experimental error often are well described by the normal distribution, the normal plays a central role in the analysis of data from designed experiments. Many important sampling distributions may also be defined in terms of normal random variables. The notation $y \sim N(\mu, \sigma^2)$ denote that y is distributed normally with mean μ and variance σ^2 .

An important special case of the normal distribution is the standard normal distribution; that is, $\mu = 0$ and $\sigma^2 = 1$. If $y \sim N(\mu, \sigma^2)$, the random variable follows the standard normal distribution, denoted $z \sim N(0, 1)$. The operation demonstrated in equation $z = \frac{y-\mu}{\sigma}$ is often called standardizing the normal random variable y . Many statistical techniques assume that the involved random variables are normally distributed.

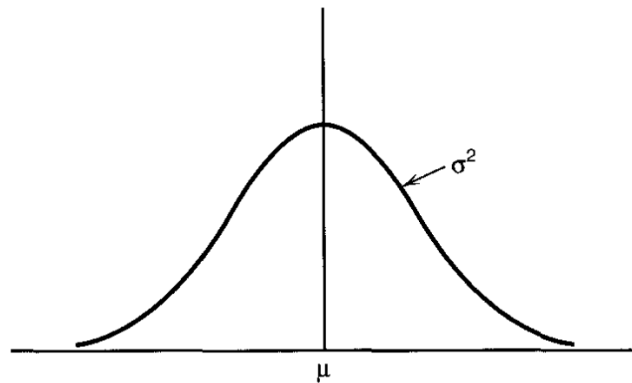


Figure 2.6 Normal distribution density. Source: Montgomery (2008)

2.4.2 Exponential Distribution

The exponential distribution is a type of continuous probability distribution (Walpole *et al.*, 1993), represented by a parameter λ . The graph of the figure 2.7 shows an example of graphical behavior that can be obtained by this type of distribution.

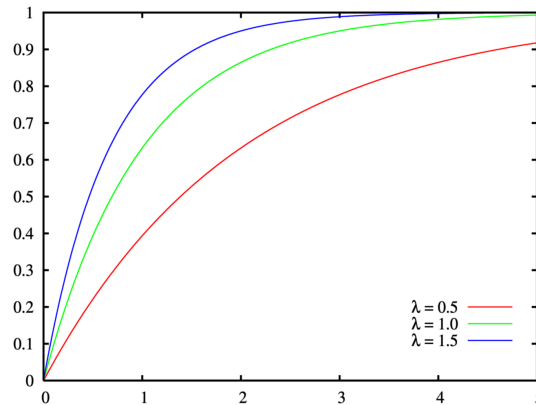


Figure 2.7 Exponential Distribution. Source: Montgomery (2008)

Its density function can be expressed as:

$$f(x; \lambda) = \begin{cases} \lambda e^{-\lambda x} & , x \geq 0; \\ 0 & , x < 0. \end{cases} \quad (2.7)$$

Where the probability of the random variable X assuming any nonnegative value in the infinitesimal interval $[x^*, x^* + dx]$ is $\lambda e^{-\lambda x}$. The probability of the random variable X assuming a negative value is zero. There is a family of exponential distributions, each with a λ different (λ parameter).

And its accumulated function is:

$$F(x; \lambda) = \begin{cases} 1 - e^{-\lambda x} & , x \geq 0; \\ 0 & , x < 0. \end{cases} \quad (2.8)$$

The probability of the random variable X assuming a value less than or equal to a certain value x^* is $1 - e^{-\lambda x}$, if x^* is non-negative, and 0, otherwise. The value of λ is denoted by the equation 2.9. Walpole *et al.* (1993) assumes it is also common among statisticians to refer to this mean as the mathematical expectation, or the expected value of the random variable X , and denote it

as $E(X)$. The equation 2.9 can denote the value of λ :

$$E[X] = \frac{1}{\lambda} \Rightarrow \lambda = \frac{1}{E[X]} \quad (2.9)$$

2.4.3 Erlang Distribution

The Erlang distribution has a relationship to the exponential distribution. We can consider that the Erlang distribution behaves as a sum of series exponential k -phases as shown in Figure 2.8, where k identical phases are connected in series, each with exponentially distributed time (Bolch *et al.*, 2006).



Figure 2.8 A random variable with E_k distribution (Adapted). Source: Bolch *et al.* (2006)

If the interarrival times of some arrival process like our bus stops are identical exponentially distributed, it follows that the time between the first arrival and the $(k + 1)$ -th arrival is Erlang- k distributed.

The Erlang pdf is (Bolch *et al.*, 2006):

$$f(x) = \frac{k\mu(kx\mu)^{k-1}}{(k-1)!} e^{-kx\mu}, x > 0, k = 1, 2, \dots \quad (2.10)$$

and cdf:

$$F(x) = 1 - e^{-kx\mu} \sum_{j=0}^{k-1} \frac{(kx\mu)^j}{j!}, x \geq 0, k = 1, 2, \dots \quad (2.11)$$

2.4.4 Uniform Distribution

By definition, according Carmona (2013), to the uniform distribution, the probability density function is described by Equation 2.12 and its CDF (Cumulative distribution function)

by Equation 2.13.

$$f(x) = \begin{cases} \frac{1}{(b-a)}, & \text{for } a \leq x \leq b \\ 0, & \text{for } x < a \text{ or } x > b \end{cases} \quad (2.12)$$

$$F(x) = \begin{cases} 0, & \text{for } x < a \\ \frac{x-a}{(b-a)}, & \text{for } a \leq x \leq b \\ 1, & \text{for } x > b \end{cases} \quad (2.13)$$

The graphical presentation is shown in Figure 2.9.

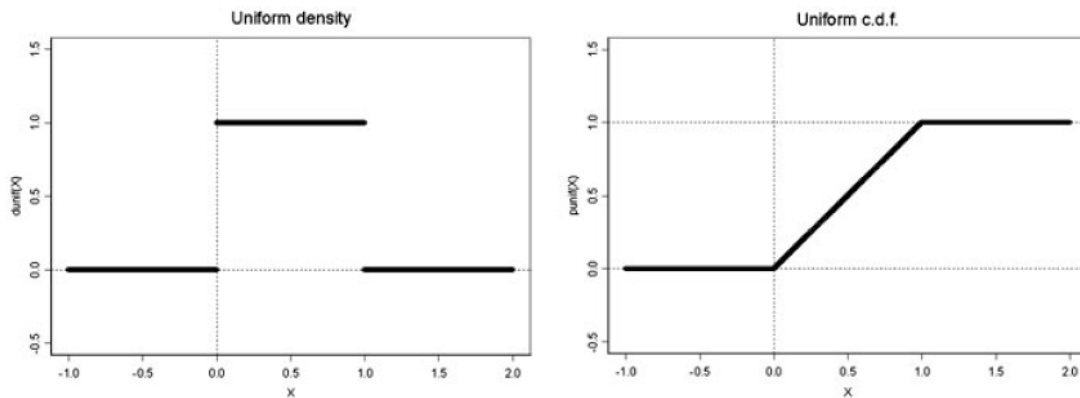


Figure 2.9 Uniform Function. Source: [Montgomery \(2008\)](#)

2.5 Statistical Analysis

According to [Gelman and Hill \(2006\)](#), prior to data collection, it may be useful to estimate the sample size needed to achieve a certain accuracy. [Montgomery \(2008\)](#) states that selecting an appropriate number of samples is one of the most important aspects of any experiment planning problem. [Mathews \(2010\)](#) in the chart in [Figure 1.1](#) demonstrates an estimate of resource consumption versus the number of samples used in surveys, where sample costs become expensive with wrong decisions about their quantity.

The optimal number of samples minimizes the total cost of an analysis.

[Gelman and Hill \(2006\)](#) cites that the goal of delimiting the quantity of samples is usu-

ally defined in one of two ways:

- Specifying the standard error of a parameter or quantity to be evaluated;
- Specifying the probability that a particular estimate will be "statistically significant".

According to [Gelman and Hill \(2006\)](#), in both cases, the calculation of sample size requires some assumptions, which cannot normally be tested until the data are collected.

It may be stated that the sample size calculations are inherent to the hypothesis. According to [Montgomery \(2008\)](#), statistical hypothesis can be considered as an analysis on parameters of a distribution of a probability or parameters of a model. They are taken as references, two possibilities:

- A null hypothesis H_0 that denotes that there is no significant variation on a given affirmative;
- An alternative hypothesis H_1 that denotes that there is a significant variation on a given affirmative;

Presenting the following conjuncture:

$$\begin{aligned} H_0 : \mu &= m \\ H_1 : \mu &\neq m \end{aligned} \tag{2.14}$$

If the alternative H_0 is true, the mean μ is equivalent to a stipulated value m (then $\mu = m$). The alternative (alternative hypothesis) can be considered two-sided, if $\mu > m$ or $\mu < m$.

According to [Montgomery \(2008\)](#), to test the hypotheses, a procedure must be done, considering an appropriate statistical test, that can or can not reject the null hypothesis H_0 . Part of this procedure is based on specifying a set of values that lead to the rejection of H_0 , which would be the **critical region** or **rejection region** values. This region is determined by α (shown in the notation analyses in (2.15)) shown in [Figure 2.10](#).

Also according to [Montgomery \(2008\)](#), two types of errors must be analyzed when such hypotheses are tested. When the null hypothesis is rejected when it is true, an error type I occurs. If the null hypothesis is not rejected when it is false, an error type II occurs, where:

$$\begin{aligned} \alpha &= P(\text{Error Type I}) = P(\text{reject } H_0 | H_0 \text{ is True}) \\ \beta &= P(\text{Error Type II}) = P(\text{fail in reject } H_0 | H_0 \text{ is False}) \end{aligned} \tag{2.15}$$

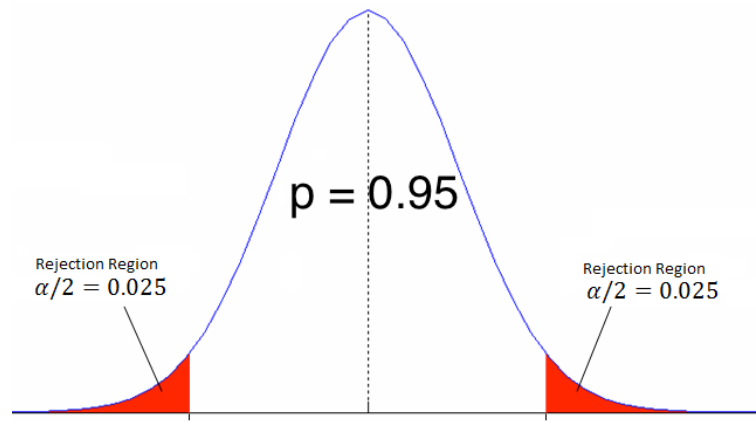


Figure 2.10 Rejection Region. Source: [Montgomery \(2008\)](#)

However, for the structure proposed (will be used in [chapter 4](#)), where the samples show normality (and without anomalies), a sufficiently large sample number for analysis ($n = 100$, with n chosen according to the experiments described in [chapter 4](#) of the document), independence between (based on the concepts of the Central Limit Theorem - CLT), a method based on **Confidence Interval** was proposed.

The process that can be used is focused on the confidence interval that a sample can obtain having a valid CLT (based on the characteristics of the problem mentioned above: under certain conditions, the arithmetic mean of a sufficiently large number of independent random variable iterations, each with a well-defined finite expected value and finite variance, will be approximately normally distributed, regardless of the underlying distribution)([Fischer, 2010](#)). Thus, the process used relies on a study of the normal and t-Student distributions, with an analysis of which of the two best meets the demands of the problem.

2.5.1 Z-test and t-Student

According to [Mathews \(2010\)](#), the t-test, or the t-Student test, can be used to:

- Perform a comparison of a sample with a population;
- Perform a comparison of two paired samples;
- Perform a comparison of two independent samples;

Similar to the t-Student test, there is the z-test analysis, where both are Hypothesis

Tests can be used for the same purpose, which is to test if there is a difference between the average of a sample (random) and the population mean. This is due to the fact that whenever a sample is selected, there is a difference between the mean of this sample and the population mean, which generates the **standard error of the mean** or **sample error**.

For the use of the z distribution, reference is made to the assumptions that a random sample \bar{X} is being analyzed and that the mean μ_X and the standard deviation σ_X (both of the analyzed population) are known. Thus, as presented by [Montgomery \(2008\)](#), a *standard normal distribution*, which can be represented by the formulation given in (2.16), is presented.

$$z = \frac{\bar{X} - \mu_X}{\sigma_X} \quad (2.16)$$

However, when we do not know σ_X , we use t (or t -Student) distribution and, instead of the calculation of σ_X , we make the estimation based on the sample value of S_x , as shown in (2.17)([Montgomery, 2008](#)):

$$t = \frac{\bar{X} - \mu_X}{S_X} = \frac{\bar{X} - \mu_X}{\frac{S}{\sqrt{n}}} \quad (2.17)$$

[Montgomery \(2008\)](#) states that the distribution t is similar to z , since it is symmetric, with an average equal to 0 and with dispersion (which is determined by "degrees of freedom" - so much so that the form of distribution depends on degrees of freedom). The degrees of freedom represent the number of observations that are completely free to vary, where for a single sample, $d = n - 1$.

Another information that should be taken as a reference is the Confidence Interval that will be further detailed later.

2.5.2 Confidence Interval

According to [Gravetter and Wallnau \(2007\)](#) the statistic t is used to test hypotheses about an unknown mean μ of a population, which (evaluating an average m of a sample) is equivalent to when the value of σ (standard error, standard deviation) is unknown:

$$t = \frac{m - \mu}{\sqrt{\sigma^2/n}} \quad (2.18)$$

In a parallel with (2.17), one can assume that the mean m is equal to \bar{X} , the population mean, μ represents μ_X and σ represents the estimated S .

For the simulator structure, it is possible to make estimates that make feasible a statistical analysis of t .

For the mean μ an estimate was made based on the simulations that present a response x (in tons of ore) for each complete cycle. Taking n as the total number of cycles of simulations performed and x_1, \dots, x_n the responses of each cycle during the entire course of n simulations, we generate a reference mean μ and a variance σ^2 (hence a standard deviation σ) estimated by:

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i \quad (2.19)$$

$$\sigma^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \quad (2.20)$$

Before the distribution t , one must assume that there is the element of degree of freedom d which describes the counting of samples that are independent and free to vary. Due to the fact that the mean m configures a restriction to the value of a count in the sample, there is $n - 1$ degrees of freedom for the sample (Gravetter and Wallnau, 2007).

Thus, the t distribution with $n - 1$ degrees of freedom is the sampling distribution of the t value when the samples consist of independent observations identically distributed from a normally distributed population. According to Mathews (2010), for an estimate of the confidence interval is given by:

$$\delta = t_{\alpha/2} \frac{\sigma_x}{\sqrt{n}} \quad (2.21)$$

where δ is the confidence interval analyzed (interval between a minimum and maximum value, which the designer can afford as error or difference in a simulation performed), t is a distribution with a degree of freedom $d = n - 1$ (where n is 100 samples taken by reference) and σ_x the standard deviation of the sample (where the commented estimate was used).

It should be noted that δ , in relation to (2.18), it represents the range of differences between a minimum error e_{min} and maximum e_{max} relative to the mean μ calculated in (2.19).

For the proposed experiments, a condition derived from the previous equation was used:

$$\delta = t_{\alpha/2} \frac{\sigma_x}{\sqrt{n}} \Rightarrow \delta = t_{\alpha/2} \frac{\sigma_x}{\sqrt{n}} \Rightarrow \delta^2 = (t_{\alpha/2} \frac{\sigma_x}{\sqrt{n}})^2 \Rightarrow n = (\frac{t_{\alpha/2} \sigma_x}{\delta})^2 \quad (2.22)$$

where n is the number of samples given δ which will be assumed during a proposed search process. The n obtained must be the smallest integer number considering $t_{\alpha/2}$.

CHAPTER 3

Methods

Two experimental processes were performed during the research. The first one, based on modular Petri nets (initially developed by [Ribeiro \(2015\)](#)), where modeling and simulation process was developed, focusing on the definition and optimization of the simulator structure and performance (section [3.1](#)).

According to the results and knowledge acquired in the first process, a research focused on modeling, simulation and optimizing the dispatch process through heuristics and positioning evaluation (section [3.2](#)) was performed.

3.1 Modeling and Simulation Design

In this approach, three questions have guided the experimentation methods:

- How is the production process to be modeled and simulated?
- What kind of Petri net structure would be used in the simulation?
- What would be the statistical methods that could optimize the number of simulation samples?

These guiding questions were answered in the subsections [3.1.1](#), [3.1.2](#) and [3.1.3](#).

The results of those experimental methods in this first process are described and analyzed in the section [4.1](#)

3.1.1 Production Process

Our model is based on an open-pit mining operation, in which ore exploration occurs on the earth's surface. This model includes trucks that transport the collected ore and crushers that

receive the ore. The mine used for the analysis is a mine in the state of Minas Gerais, Brazil.

The simulation logic relies on the evaluation of the sequence of occurrences described in Figure 3.1, which presents the sequences of ore loading and unloading (a summary of the operations (Phillips, 2016)). The simulation includes four possible states: 1. truck is loaded by a loader, 2. truck hauls the load, 3. truck unloads load in crusher, 4. unloaded truck in haulage. The complete scenario in the proposed model considers the following possible events: corrective maintenance (fail), preventive maintenance (check), fuel supply (fuel), and shift change (shift). The sequence of activities is modeled according to the structure of Petri nets and is expressed as a closed production cycle. The availability of loaders and crushers is denoted by the presence (or absence) of tokens in places P , which will represent such equipment. The transitions T indicate the attendance of the truck in each step described and are timed according to the times of each activity (according to the distribution function).

The abstraction performed to indicate the analyzed process (seen in Figure 3.1) is a necessary method for solving the problem. This is because of the complexity that is implicit in such a process, where the tendency of infinite possibilities and varying conditions of the process implies an abstraction of the calculation of $J(\theta)$ into an estimation of $\hat{J}(\theta)$, with delimited abstractions (as seen in equation 1.3).

Using the referenced model (and the tool set to develop the simulator), it was possible to evaluate scenario hypotheses, enabling the estimation of the production $\hat{J}(\theta)$ (in tons) to be obtained during the loading and unloading processes (with a given confidence interval).

For this purpose, we evaluated the availability of equipment, number of simulations performed, total simulation time and quality of responses because of variations in the activity distribution function.

3.1.2 Modular Structure Design

The open pit mine model shown in this paper represents the truck fundamental cycle in the mine, composed by 5 steps: loading, loaded haulage, unloading, unloaded haulage, and stops. A module always starts in places and ends in transitions, which define the interface between modules. Furthermore, the modules are splitted so that they have physical meaning. In the case of an open pit mine, the model has two fundamental building modules: machine and haulage, which are explained in the next sections. Those modules are basic and can be inserted and removed as demanded. Furthermore, these modules can increase or decrease in

Open Pit Mine - Complete Description

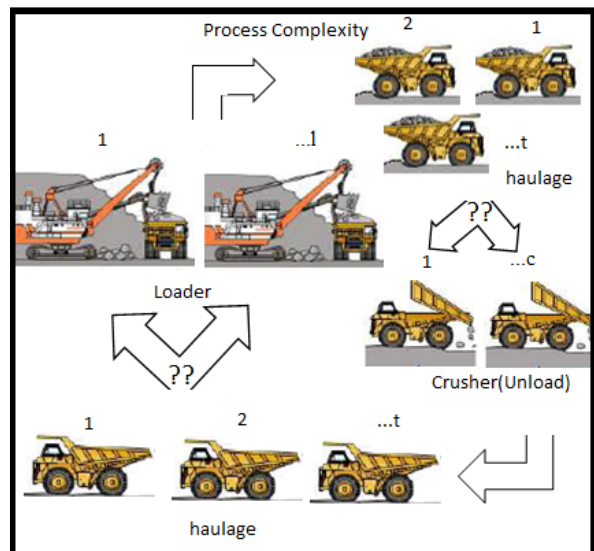
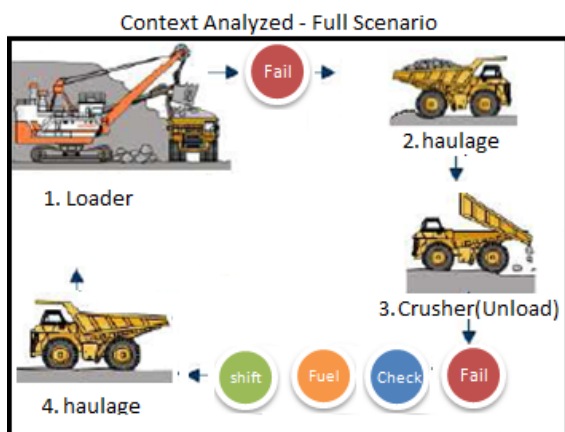
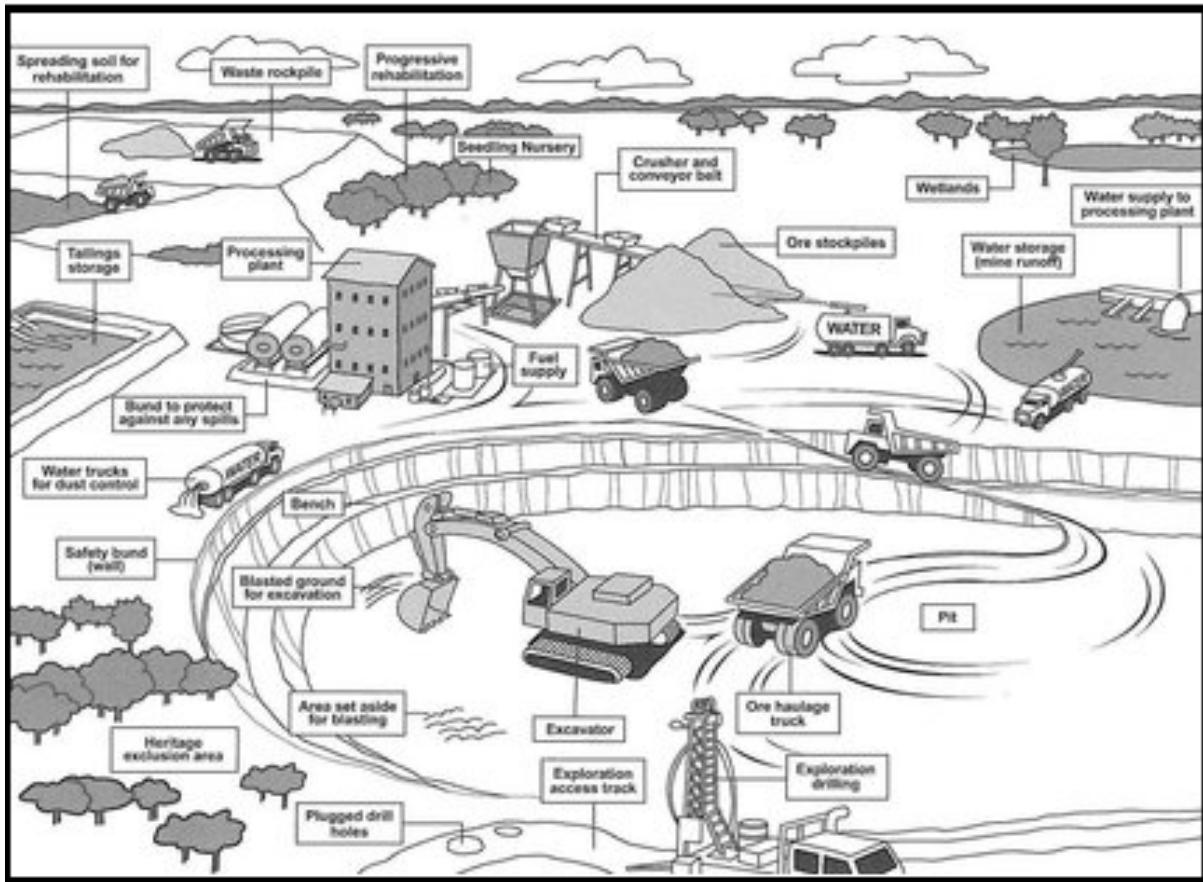


Figure 3.1 Conceptual modeling highlighting the main features that must be considered.

scale according to a specific logic.

A **machine module** can represent a loader, a crusher or a waste pile. It counts the number of trucks that have been served, controls the queue and serving time, as demonstrated in Figure 3.2. A token in place p_5 and in place p_1 enables transition t_1 , which fires immediately. Then transition t_2 fires after the serving time has passed. Place p_4 receives a token every time transition t_2 fires, indicating the number of finished services. There is one fundamental block for each pair of truck and machine, so that individual data logs can be properly assembled during simulation. Trucks sharing resources share the machine availability indicator (e.g. p_5 in Figure 3.2).

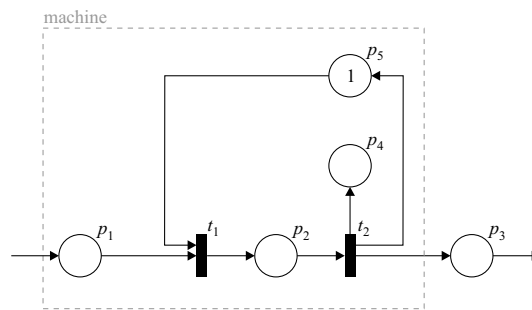


Figure 3.2 A basic machine block (i.e. loader, crusher or waste pile). A token in place p_5 indicates that the machine has a free position to receive a truck. The number of token in place p_4 indicates how many trucks have passed by the machine. Each token in place p_1 indicates a truck waiting for a free position in the machine. Each token in place p_2 indicates a truck in a position in the machine. Transition t_1 controls the number of trucks in the machine and transition t_2 controls the timing for the machine to finish one truck.

A **haulage module** represents any route between loaders and crushers or waste piles. It routes trucks to the correct destination and individually controls the haulage time for each possible route, as depicted in Figure 3.3. This block maps all combinations to go from n to m places, so that the haulage time can be properly measured. The routing rule is to send trucks to destination with less associated trucks. Despite being simple, this rule leads to results very close to a maximum productivity mining. A column of dummy places and transitions so that the block ends with single connected transitions. The haulage time is indirectly obtained by truck speed and travel distance. This model allows a truck overtaking other trucks in its route.

The **stop module** represents time between stop events (e.g. maintenances, truck refueling, shift change) and stop duration time. It is composed of a place and a transition, as represented by Figure 3.4. The place models a location subject to stops. The transition controls the time between stop events (providing null firing times during this period) and duration

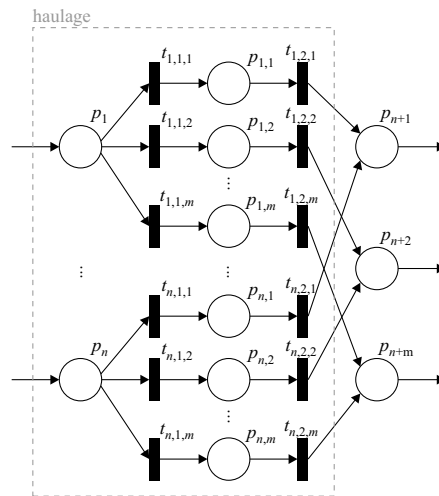


Figure 3.3 A basic haulage module used to route n places (e.g. loaders) to m places (e.g. crushers). Tokens in places $p_1 - p_n$ indicate trucks to be routed. Tokens in places $p_{1,1} - p_{n,m}$ indicate trucks during haulage. Transitions $t_{1,1,1} - t_{n,1,m}$ route the trucks and transitions $t_{1,2,1} - t_{n,2,m}$ control the haulage time.

time (providing a non-null stop time). Without lack of generality, the haulage time to a stop is considered in the stop duration time.

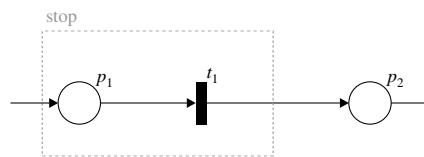


Figure 3.4 A basic stop module used to model maintenances, refueling or shift changes. Tokens in place p_1 indicate trucks in stop position. Transition t_1 controls stop time, which can be null if the time is between stop events.

The human effort to scale and add modules to the model is practically null, since the modules are parameterized by the quantity of equipment, and removing and adding modules is automatized: it is analogous to adding and removing blocks from a drawing. The model of simulation is presented in section 4.1.

3.1.3 Output Data Analysis of Simulation Process

Supposing that the data X_1, X_2, \dots, X_M are used to define a measure of collected ore per hour, where the performance of interest is $L(X_1, \dots, X_M)$. The performance evaluation of ore

collection over M unloading processes can be expressed as (Cassandras and Lafortune, 2008):

$$L(X_1, X_2, \dots, X_M) = \frac{1}{M} \sum_{i=1}^M X_i \quad (3.1)$$

To collect n sample values for estimating the mean $\hat{\theta}$, a given number of sampling values n , must be defined to analyze each performance L_i in the simulation process as expressed by:

$$\hat{\theta}_n = \frac{1}{n} \sum_{j=1}^n L_j \quad (3.2)$$

In this case, $\hat{\theta}$ denotes the estimation expressed in (1.3). The complexity of the process makes it infeasible to obtain the θ presented in equation 1.1.

The primary challenge in estimating steady-state parameters (such as $\hat{\theta}$ in (3.2)) involves obtaining an infinitely long sequence of data X_1, X_2, \dots , because the system better represents its steady-state behavior as n increases.

It is reasonable to execute and discard the first part of data collecting, during the simulation process of a finite m . So must be performed and excluded for some r simulations, where $r < m$. The evaluations must concentrate on the remaining data $X_{r+1}, X_{r+2}, \dots, X_m$, which can better approximate the steady state Cassandras and Lafortune (2008).

This method includes an initial data deletion and *warming up* process for the simulation. The objective is to eliminate the effect of the transient part of the system's behavior by discarding as few samples (computer power loss) as possible. By assuming an acceptable *warming up* interval length r and a total simulation run length m , we estimate a steady-state performance measure such as the mean θ of a stationary CDF $F(x)$ based on independent replications. The only difference is that the sample mean obtained from the j th replication is based on equation 3.2. Therefore, the j -th sample function is now in the form $L_j = \{X_{r+1}, \dots, X_m\}$, which is usually the sample mean:

$$L_j = \frac{1}{m-r} \sum_{i=r+1}^m X_{i,j} \quad (3.3)$$

where $\{X_{r+1,j}, \dots, X_{r+m,j}\}$ is the data sequence obtained in the j -th sample.

3.1.3.1 Warming up Evaluation

The process of warming up (symbolized by the excluded cycles r in the equation 3.3) indicates computational processing costs (associated with the permanent state of simulation). There are several ways of estimating the best value for this process, including: analysis using graphical methods; techniques based on heuristic approaches; statistical methods; initialization bias tests; hybrid methods (graphical or heuristic approaches); statistical process control (SPC) for constructing a control chart (Robinson, 2007).

In this research, we used a method that would maintain the quality of the analyzed answers, and we aim to ensure that the method incurs the least computational cost to simulate the r ore collects to be discarded.

3.1.4 Statistical Experiment Design

The statistical analysis considered sampling conditions such as normality (without anomalies); a sufficiently large sample number for analysis; and independence (based in the Central Limit Theorem). They were based on the following characteristics of the problem: under certain conditions; the arithmetic mean of a sufficiently large number of independent random variable iterations; each with a well-defined finite expected value and finite variance, will be approximately normally distributed, regardless of the underlying distribution Mathews (2010). However, as the variance σ_n^2 is unknown, we used t -Student and Tests z to estimate the variance, based on a sample value of S_x^2 , where:

$$\hat{\sigma}^2(\theta_n) = \frac{S_n^2}{n} = \frac{1}{n(n-1)} \sum_{i=1}^n (L_i - \hat{\theta}_n)^2 \quad (3.4)$$

The distribution t is similar to z , because it is symmetric, with an average value of 0, including dispersion (determined by degrees of freedom, where $d = n - 1$).

Actually, since we are dealing with a stochastic experiment, in equation 3.2 and 3.3, we have assumed $M = m$ and $N = n$, where M is a random variable that denotes the number of ore unloading events and N denotes the number of simulation samples (where $N \in \mathbb{N}$). So the purpose of more rigorous experiment is determined by minimizing the number N of samples:

$$\text{Minimize } N \quad (3.5)$$

s.t.

$$L_j = \frac{1}{M} \sum_{i=r+1}^M X_{i,j} \quad (3.6)$$

$$\hat{\theta}_N = \frac{1}{N} \sum_{j=1}^N L_j \quad (3.7)$$

$$\text{Var}[\hat{\theta}_N] = \frac{1}{N} \text{Var}[L_j] \quad j \in \{1, 2, \dots, N\} \quad (3.8)$$

$$\text{Var}[L_j] = \frac{1}{N-1} \sum_{j=1}^N (\hat{\theta}_N - L_j)^2 \quad j \in \{1, 2, \dots, N\} \quad (3.9)$$

$$t_{N-1, \alpha/2} \sqrt{\text{Var}\hat{\theta}_N} \leq \delta \hat{\theta}_N \quad (3.10)$$

$$t_{\alpha/2}(N-1) \sqrt{\frac{\text{Var}[L_j]}{N}} \leq \delta \hat{\theta}_N \quad j \in \{1, 2, \dots, N\} \quad (3.11)$$

$$t_{\alpha/2}^2(N-1) \frac{\text{Var}[L_j]}{N} \leq \delta^2 \hat{\theta}_N^2 \quad j \in \{1, 2, \dots, N\} \quad (3.12)$$

$$t_{\alpha/2}^2(N-1) \Rightarrow (N-1) \text{degrees of freedom} \quad (3.13)$$

$$N-1 > 0 \quad (3.14)$$

The model presents constraints as:

- the average unloading processes (equation 3.6),
- the estimated sample mean (equation 3.7),
- the estimated variances (equation 3.8, equation 3.9),
- evaluating the term where the variation is added to $\hat{\theta}_n$ (equation 3.10),
- interval limits can be evaluated according to equation 3.11,
- evaluation of δ in equation 3.12.
- the degree of freedom (equation 3.14),

The expected value, obtained by $E[M \times N]$ is extremely complex. The stochastic characteristics of the problem and the behavior distribution functions make such a task difficult. A proper modeling requires precision of the results.

In theory, a large number of E samples would be necessary for a good quality of the productivity demonstration, however this demands a high number of simulations, which increases the computational cost without a relevant increase of the response quality.

In a "divide and conquer" approach, so let us see what we can do by considering $M = m$ fixed and $\text{Var}[\hat{\theta}_n]$ approximately constant.

An estimate of the mean μ was obtained based on the simulations that include a response x (in tons of ore per times unit) for each complete cycle. Denoting n as the total number of cycles of simulations performed and L_1, \dots, L_n as the responses of each cycle during the entire course of n simulations, we generate a reference mean μ and estimated a variance $\hat{\sigma}^2$. Estimating the sample confidence interval requires calculating the half-width of the confidence interval:

$$\delta = t_{n-1, \alpha/2} \frac{\sigma_x}{\sqrt{n}} \quad (3.15)$$

where δ is the half-width of the confidence interval analyzed and t is a normal distribution with a degree of freedom d . For the proposed experiments, a condition derived from the equation 4.1 was used to estimate n :

$$\delta = t_{n-1, \alpha/2} \frac{\sigma_x}{\sqrt{n}} \Rightarrow \delta^2 = (t_{n-1, 0.025} \frac{\sigma_x}{\sqrt{n}})^2 \Rightarrow n = \text{ceil}(\frac{t_{n-1, 0.025}^2 \sigma_x^2}{\delta^2})^2 \quad (3.16)$$

where n indicates a sampling of n values of a sample space (as n is integer, it is considered $\text{ceil}(n)$), given a δ value that will be assumed during a proposed search process. There is a need to perform independent replications to estimate the confidence interval and ensure that the estimative respects the t -Student distribution.

So this problem considers the confidence interval analysis, as described in equation 3.17, which represents the target interval of $[\hat{\theta}_n \pm \delta \hat{\theta}_n]$.

$$[\hat{\theta}_n - t_{n-1, \alpha/2} \sqrt{\text{Var} \hat{\theta}_n}, \quad \hat{\theta}_n + t_{n-1, \alpha/2} \sqrt{\text{Var} \hat{\theta}_n}] \quad (3.17)$$

Therefore, as the value of n increases, the value of $t_{\alpha/2}^2(n-1)$ decreases. The $t_{\alpha/2}^2(n-1)$ range varies for each experiment performed, adding complexity to the simulation process.

3.2 Dispatch Process Optimization Design

After assimilating the characteristics, capacities and optimizations obtained through the methods proposed in section 3.1 (with the results shown in 4.1), the following questions were defined:

- How would new proposals for the organization of cargo dispatch behave in this simulator?
- What would new proposals for organizing freight forwarding look like and behave if implemented in this simulator?
- Can a strategy based on changing equipment positions improve productivity?

For this experimental process, the assumptions of how dispatch rules would be modeled and simulated (subsection 3.2.1) and the proposed new rules for driving the trucks involved were defined (subsection 3.2.2). The results were presented in section 4.2.

3.2.1 Dispatch rules

The methodology used in the experiments is based on two types of abstraction: first, the definition of the rules of modeling and simulation of the dispatch processes involved; and subsequently, the definition of an optimization strategy for truck dispatch.

3.2.1.1 Dispatch Modeling and Simulation Definitions

As mentioned, in this process, the dispatch in a real open-pit mine in operation in Minas Gerais, Brazil, is described. During the cycle, a truck is stocked in a loader, transports ore to a crusher, and returns to the point of collection in the loader. When this cycle occurs, the truck can be subjected to preventive and corrective maintenance, which can influence its travel time and consequently, its productivity. This process is the basis of the model based on discrete event systems and stochastic Petri nets. The dispatch process has some implicit complexities:

- multiple visiting nodes, each with a defined role, service time and productivity;
- availability of loading and unloading equipment;

- service times that have distributions that are not necessarily exponential;
- decision making of which route is most advantageous, in terms of time, distance and generation of queues;
- the model has multiple nodes and the transitions firing time obeys generalized probability distributions, not necessarily exponential.

Figure 3.5 shows the model for the analysis of one truck in the process of dispatch. Table 3.1 shows the reference parameters pertaining to truck speed, production (in tons), and loading and unloading times. When a truck is empty, it should be directed to a loader to collect ore. As

Table 3.1 Mean values used in simulations

	Scale
Cargo (ton)	239
Unloaded speed (km/h)	29,6
Loaded speed (km/h)	23,8
Maneuver time for load (s)	65,4
Loading time (s)	156
Unloading time (s)	58,2
Loaded haulage time (s)	151.52 (Loader 1)/1515.3 (Loader 2)
Unloaded haulage time (s)	121.62 (Loader 1)/1216.2 (Loader 2)

there may be more than one loader, the target loader must be determined. This process is called dispatch and has significant implications for mine productivity.

3.2.2 Truck dispatch strategies

3.2.2.1 By association with loaders (Queue dispatch)

This is the simplest dispatch rule. The truck is dispatched to the loader with the least number of associated trucks. Once dispatched to a loader, this truck becomes associated with that loader and thereafter can only return to the crusher.

3.2.2.2 By filling more productive cycles

The time T of a cycle is the sum of the time spent by the truck in each stage (empty transport time t_h , maneuver time for load t_m , loading time t_l , time of full transport t_f , and time

of discharge t_c):

$$T = t_h + t_m + t_l + t_f + t_c \quad (3.18)$$

In a uniform truck fleet, the bottleneck time t_b is given by the generating step of queues with longer service life, and is mathematically expressed as:

$$t_b = \max\{t_m + t_l, t_c\} \quad (3.19)$$

Thus, the number of trucks needed to fill a cycle, i.e., the number beyond which the insertion of more trucks does not increase mine productivity, is obtained from:

$$n_t = \frac{T}{t_b} \quad (3.20)$$

The idea of filling more productive cycles is to dispatch trucks to a more productive cycle until it is filled with trucks. Thereafter, the next most productive cycle takes precedence.

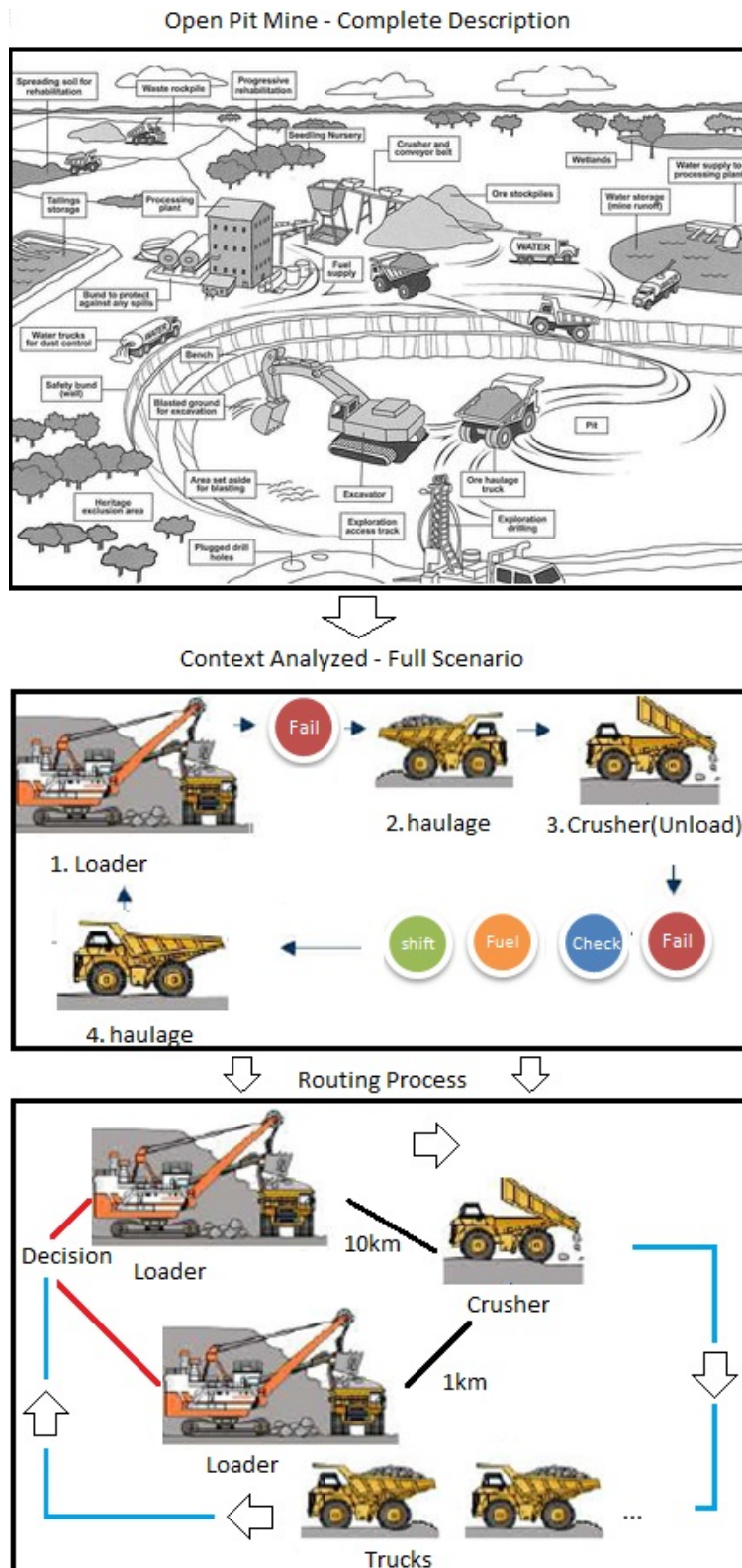


Figure 3.5 Dispatch Process

CHAPTER 4

Results

The results of this research were divided into two main ways. The first focuses on the experiments resulting from the modeling proposed in 3.1, with a sample size optimization process, experiments with different CDFs and evaluation of the computational time spent in the process. The second kind of the results, following the methodology proposed in 3.2, optimize the dispatch process of trucks using two fast heuristics and evaluate possible productivity gains with equipment positioning evaluation.

4.1 Modeling and Simulation Process

4.1.1 Simulation Model

Figure 4.1 shows the full model using the two building blocks to compose the four cycle steps.

Note that there is an additional pair of place and transition in the loader to model the maneuver time. Figure 4.2 shows a complete model containing stop modules (e.g. preventive maintenance, corrective maintenance, refueling and shift change). It shows the importance of a modular approach, where each module still has a physical meaning and they easily scale.

4.1.2 Optimizing Sampling Size and Evaluation Time

The first approach evaluates only the load and unload processes (the events fail, check, fuel and shift were not considered) to estimate an efficient sample size. Therefore, we employed a simulator based on Petri nets (Figure 4.1 occulting the four events mentioned), with time delay as a normal distribution. A confidence interval of 95% and a δ value (in %) were proposed to demonstrate variations in the sample size, which can be detrimental to the error assumed. The

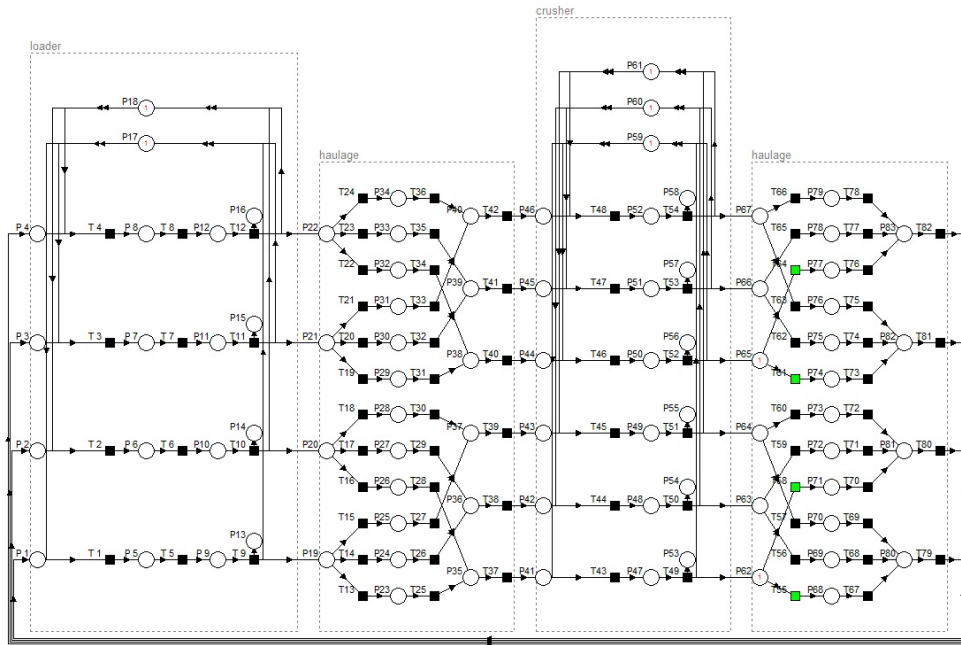


Figure 4.1 Simulation structure with two trucks and the presence of the processes: loading (with two loaders available), transport (haulage between the two loaders and three shredders) and unloading (with three available crushers).

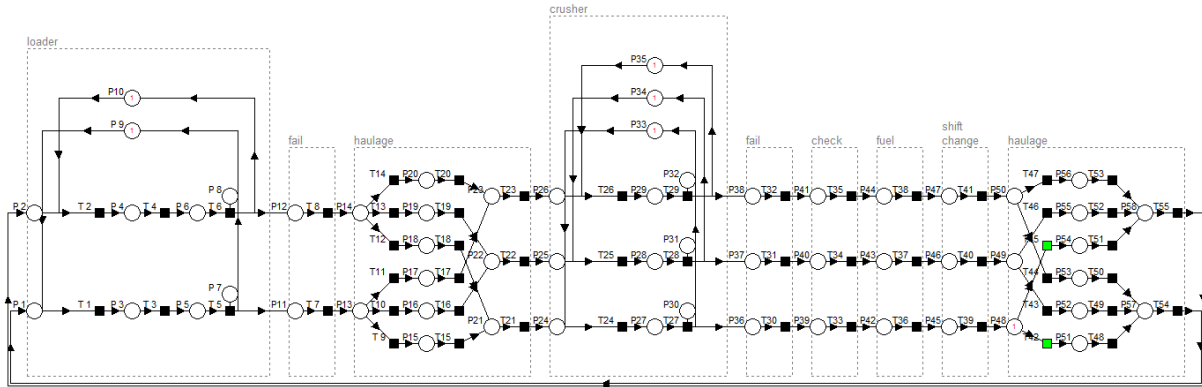


Figure 4.2 Simulation structure with one truck and the presence of the processes: loading (with two loaders available), transport (haulage between the two loaders and three shredders) and unloading (with three available crushers). However, the following processes are also evaluated: fail, check, fuel and shift change

experiments were performed using the *z*-tests and *t*-Student. The result presents a comparison between the values used in the confidence interval and the time savings (statistically reliable).

It was estimated a sample size and analyzed time savings. To obtain the number of

samples n in the process to be presented is the execution of the optimization process provided in (3.5) is executed, minimizing N to evaluate the expected value $E[N \times M]$.

Before initiating the simulation process, an adaptation of the warming up process was performed with ten preliminary simulations of periods of productivity on 1 day, 1 week, 1 month and 1 year. First, using graphical analysis, it was observed that there exists a maximum variation of 15% of productivity in the first 10 ore collections of the 1-day simulation, after which the process exhibits variations of less than 5%.

This effect propagates to other proposed periods. A heuristic rule was used with the following premise: considering $\Delta X = X_{i+1} - X_i$, where $i \geq 0$ and $i \in M$. The number of collections r is obtained when ΔX is less than 15%, with $r_{\max} = 10$. Therefore, even with a change in the distribution function used in the simulation, there is no demand for a graphical analysis of each function evaluated. In addition, prior assurance of the quality of the response is presented, where responses already begin with at least 15% of stability.

The first simulation sequence was performed for productivity estimation. Ten samples were collected by simulation, considering the estimated average production $\hat{\theta}_n$ (in tons per hour) as a reference and by considering the periods of 1 week, 1 month, 6 months and 1 year. The results are presented in Table 4.1 (with a confidence interval of 95%). Table 4.1 demon-

Period	$\hat{\theta}_n$ (ton/h)	$\hat{\sigma}_n$	time (seconds)	r
1 week	568.2726	3.8801	96.0031	4
1 month	570.5019	2.5710	420.5108	4
3 month	570.1539	0.5579	1.3068e+03	4
6 months	569.8156	0.4718	2.9515e+03	4
1 year	570.0440	0.4184	7.8610e+03	4

Table 4.1 Preliminary Simulation illustrating the gain in reducing the sample size while almost preserving the standard variation

strates that the $\hat{\theta}_n$ varies less than 2 ton/h (less than 0.5%) with the period increasing. However, the estimated standard deviation $\hat{\sigma}_n$ decreases during this process. It must be noted that the simulation time exceeded the mark of 96 seconds using the proposed periods, with an almost linear increase in simulation time. An almost constant increase in the simulation processing time can be observed (e.g. 1 week (7 days) to 1 month (30 days): an increasing of 4 times in each period). The time spent in each experiment is considered a very high computational cost. Assuming those experiments as reference to the next analyses, a projection of two days will be considered.

n	$\hat{\sigma}_n$	time (seconds)
100	5.3711	976.68
500	4.7618	4.78263×10^3
1000	4.6857	9.6939×10^3

Table 4.2 Number of Samples

4.1.2.1 Number of Replications

An initial sample value was not determined according to a statistical analysis, and so a set of n simulations were performed, where $n \in N$ and $N = \{100, 500, 1000\}$. The values in N are relatively high, which ensures security in the initial analysis.

The first analysis criterion of each n was the estimation of the standard deviation $\hat{\sigma}_n$ and each time T_n of execution. A large enough n value must be chosen for representation, which ensures time saving. Table 4.2 illustrates, in detail, how variations in the number of samples n has a considerable impact on the processing time in T_n , with costs increasing proportionally to the increasing number of samples n . However, the estimation of standard deviation $\hat{\sigma}_n$ was not changed during the process (because of the same period of analysis - two days - opposing the behaviour in Table 4.1). The times of $T_N = \{976.68, 4.78263 \times 10^3, 9.6939 \times 10^3\}$ were obtained (in seconds). The estimated standard deviation, where $\hat{\sigma}_N = \{5.3711, 4.7618, 4.6857\}$ demonstrates that there is no significant difference. However as $\hat{\sigma}_N$ decreases n increases. The estimated mean production is $\hat{\theta}_n = 570$ tons/h. A saving of $n = 100$ is notorious: almost 10 times faster than $n = 1000$, without significant loss in the quality of the response. It has been noted that, as in Table 4.1, the time increase is almost linear and proportional to increases in n (e.g. by increasing n from 100 to 500 - an increment of five times - the processing time increased practically 5 times, as in the case of the simulations with the periods presented in Table 4.1). Therefore, based on such results, the reference value n for other calculations was $n = 100$. The following experiments seek to further optimize this value.

4.1.2.2 Sample Size Savings

A $n = 100$ samples were used to estimate the standard deviation $\hat{\sigma}_x$ (considering a normal distribution). A comparative analysis was performed between the confidence level variations δ of the sample numbers proposed as ideal for the experiments. This comparison and its results are shown in Figure 4.3.

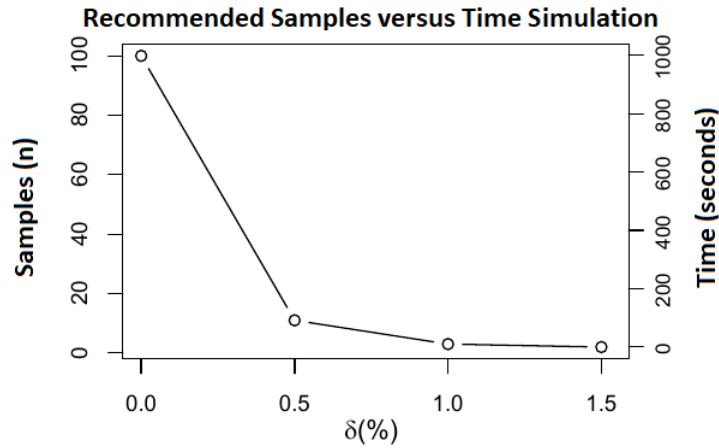


Figure 4.3 Number of Recommended Samples versus Time Simulation

In a variation of δ (ranging from 0 to 1.5%), the number of samples recommended was 11 ($\delta = 0.5\%$). The number decays as δ increases (achieving 2 samples in $\delta = 1.5\%$). The value $n \geq 2$ was maintained so that at least 1 degree of freedom is achieved.

4.1.2.3 Time Simulation Savings

Figure 4.3 illustrates variations in the execution time of the simulation process by considering the variation in δ (presented in obtaining n). The simulation time decreases by approximately 800 seconds when $\delta = 0.5\%$.

The simulation time falls drastically as the interval increases. In $\delta = 1\%$ (the second analysis) the simulation time is approximately 28.37 seconds. In $\delta = 1.5\%$, the simulation time is approximately 18.79 seconds. Assuming the execution time of the simulation as $n = 100$ (976.68 sec.), the savings range from approximately 89.45% ($\delta = 0.5\%$) to 98.07% ($\delta = 1.5\%$). Table 4.3 presents this effect on the data collected in table 4.1.

Period	$\hat{\theta}_n$ (ton/h)	time(sec.) $n = 10$	time(sec.) $n = 2$
1 week	568.2726	96.0031	21.5115($\delta \leq 1\%$)
1 month	570.5019	420.5108	95.2944($\delta \leq 0.2\%$)
3 months	570.1539	1.3068e+03	263.1934($\delta \leq 0.2\%$)
6 months	569.8156	2.9515e+03	594.6787($\delta \leq 0.2\%$)
1 year	570.0440	7.8610e+03	1.533e+03($\delta \leq 0.2\%$)

Table 4.3 Sample Estimation

4.1.2.4 Distribution Function Evaluation

The structure was tested using an exponential distribution function. This process is based on the fact that exponential, uniform, and Erlang distribution are simple to generate and can be used to approximate more complex distributions. The time distributions were obtained by assuming as references the operating times of the open pit mine activities analyzed and the distribution function evaluated.

First, with a degree of freedom $d = 1$ ($n = 2$). The exponential functions averaged in $\hat{\theta}_n = 548.73$ tons/hour (4.2% less than the normal distribution - no significant difference was obtained) and a time simulation of 18.2912 seconds.

For comparison with a deterministic function, a value of $\hat{\theta}_n = 572.24$ tons/hour was obtained from a simulation time of 5.75 seconds for the two samples, which results in a difference of only 0.35% compared to the reference experiment ($\hat{\theta}_n = 570$). In an analysis of the coefficient of variance cv (where $cv = \sigma/\mu$), which varies between $0 < cv \leq 1$, by assuming the value obtained in the exponential function as a reference, $cv_{exp} = 1$, the constant distribution $cv_{const} = 0.0099$ and normal distribution with $cv_{norm} = 0.0138$ (approximately constant).

4.1.3 Complete Scenario Simulation

Firstly, a simulation structure based on Petri nets is presented in Figure 4.2, where we have a number of trucks $n_t = 1$, with the number of loaders $n_l = 2$ and the number of crushers $n_c = 3$. During the simulation, n_c and n_l were kept constant. The places p_{33} , p_{34} and p_{35} in figure 4.2 denote the available crushers, p_9 and p_{10} represents the available loaders. Such a structure was used when the experiments were performed. This study contemplates the complete process described in Figure 4.2, where preventive maintenances (check), corrective maintenances (fail), truck refueling (fuel) and shift (shift-change - may occur between operators) were considered.

The time delay is modeled by some probability distribution functions (constant, exponential, uniform and Erlang). Additional questions have been presented in this research, including processing time and confidence interval. The confidence intervals are analyzed, besides a presentation of bottleneck scenarios and evaluations pertinent to the events.

During the experiments, it was stipulated that the number n would be $n = 10$, where the degree of freedom $d = 9$. The degree of confidence remains at 95%. For productivity

analysis, it was assumed a period of two days. The number of trucks n_t was also varied in $n_t \in \{1, 2, \dots, 10\}$ during the process. Variations in the number of trucks implies variations in the presented structure.

4.1.3.1 Experiment I - Productivity per truck versus number of trucks

Productivity variations according to an n_t evaluation are presented in Figure 4.4. Five effects can be observed. First, during the variation of n_t , the distribution with constant values remained approximately constant until $n_t = 6$. We then observe the beginning of a decrease in output that accentuates up to $n_t = 10$. The exponential distribution already exhibits a noticeable decrease in productivity from $n_t = 2$, which decays to the last option of n_t . The behavior of the uniform function accompanies what was presented by the exponential function, with the only difference that includes a variation of results that is less abrupt than the second function. It must be noted that the estimated productivity $\hat{\theta}_n$ presented in this analysis exhibits decreased productivity considering the full scenario, but not more than 5%.

The second effect was the simulation time variation according to the number of available trucks n_t .

The third is a bottleneck effect in processing time and in production. This problem is due to unavailability of loaders and crushers that should attend a truck in the process of loading and unloading the ore.

The fourth effect was the increasing simulation time and the decreased production, due to the simulation of fail, shift, fuel, and check events.

The fifth effect was the production variation in each n - simulated sample (for each n_t). In the constant and uniform distributions, we observe variations with little distortion (less than 5%) in relation to the average $\hat{\theta}_{n_t}$ that each set of n samples present for each option of n_t . The exponential function (as Erlang) exhibits a variation of approximately 15% per sample in relation to $\hat{\theta}_{n_t}$ (keeping in mind that the comparison is performed between samples with the same option of n_t). Despite this internal variation of samples n , the exponential function can maintain a $\hat{\theta}_n$ mean, which is similar to those that are presented by the function constant. This effect demonstrates that despite of less strict behavior, the exponential function presents average values of $\hat{\theta}_n$ that is consistent with the other functions.

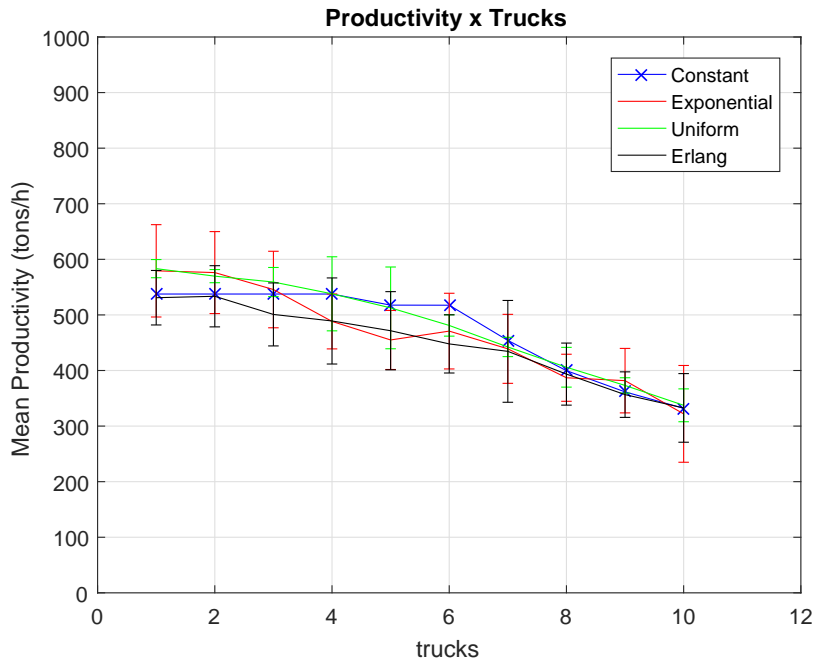


Figure 4.4 A productivity analysis per truck based on the variation of distribution function. The productivity per truck variation is shown by the number of trucks in the process.

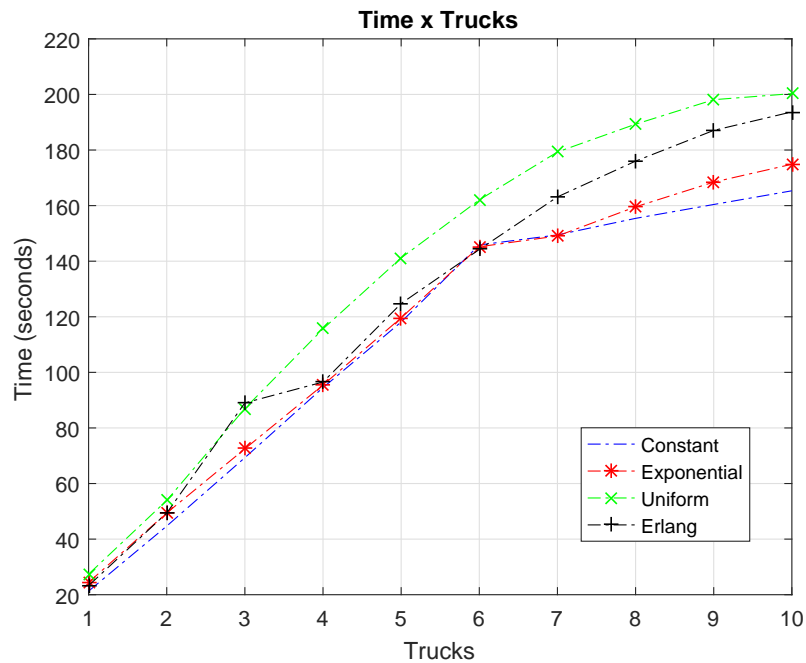


Figure 4.5 Simulation time due to the number of trucks used in the production process.

4.1.3.2 Experiment II - Evaluating the distribution function influence

This analysis individually considers each of the routines and subroutines that are implemented in the simulator. The analyzed simulator exhibits great robustness and considerable deal of checking of values and consistencies. However, these routines can interpose with the simulation time. As shown in Figure 4.5, the constant function is the fastest in terms of simulation time, followed by the exponential function and then the uniform function. However, the justification for this fact lies in the conferences and dynamic elements that the simulator presents to verify the functions, configuring information associated with the verification of consistencies directed to the simulator.

An experiment was performed to demonstrate this evaluation, in this case, using 10 trucks, 3 crushers and 2 loaders. The total simulation time of an uniform distribution is 1.645 seconds. The inverse function of the uniform CDF exhibits a simulation time of 0.134 seconds. The remaining times denote conferences and dynamic elements of the implemented class, with error and inconsistency checks.

The exponential distribution exhibits a total simulation time of 1.525 seconds (faster than the uniform). The function (the inverse function of the exponential CDF) exhibits a simulation time of 0.186 seconds (confirming the fact that the analysis in uniform distribution is faster than that of the exponential distribution). A sample with the same parameters was used in the constant function. The delay function exhibits time spent of 0.107 seconds. Therefore, the simulation times presented in the experiments, when considering only the generating function (structures without the overhead), are 0.107 (constant), 0.134 (uniform) and 0.186 (exponential). A robust framework of the complete scenario may exhibit variations in processing time due to information from headers and possible increases of states passed during the simulation.

4.2 Dispatch Process Optimization

Figure 4.6 shows the model for the analysis of one truck in the process of production (accessing two loaders and one crusher), and Fig. 4.7 demonstrates the model for the analysis of 25 trucks (a demonstration of scalability). The functions and firing times used are based on the production information of the real open-pit mine, which leads to an analysis based on real data. Table 3.1 shows the reference parameters pertaining to truck speed, production (in tons), and loading and unloading times. Two types of experiments were conducted according to the

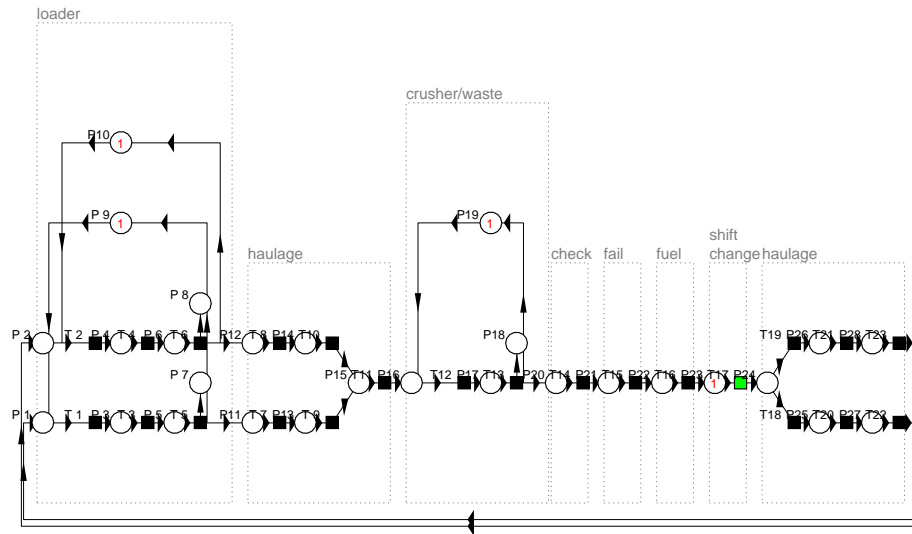


Figure 4.6 Simulation structure in Petri nets for one truck

methodology proposed.

4.2.1 Experiment I: Simulations and comparisons

This first sequence of experiments is a process of comparison between three methods: an analysis of production, and Petri-net based simulations employing two dispatch rules, one based on queue dispatch and the other on optimal dispatch using cycle time. The analytical estimation provides an upper bound for productivity.

The analysis based on Petri Nets used 10 sample simulations by fleet size n_t , in which $n_t = 1, \dots, 25$ totaling 250 samples for each dispatch rule (i.e., 500 samples in total for two dispatch rules). "Warming up" was defined as four cycles of each sample for each analysis of n_t , the rationale being that variation in productivity is less than 2% in the case of four cycles.

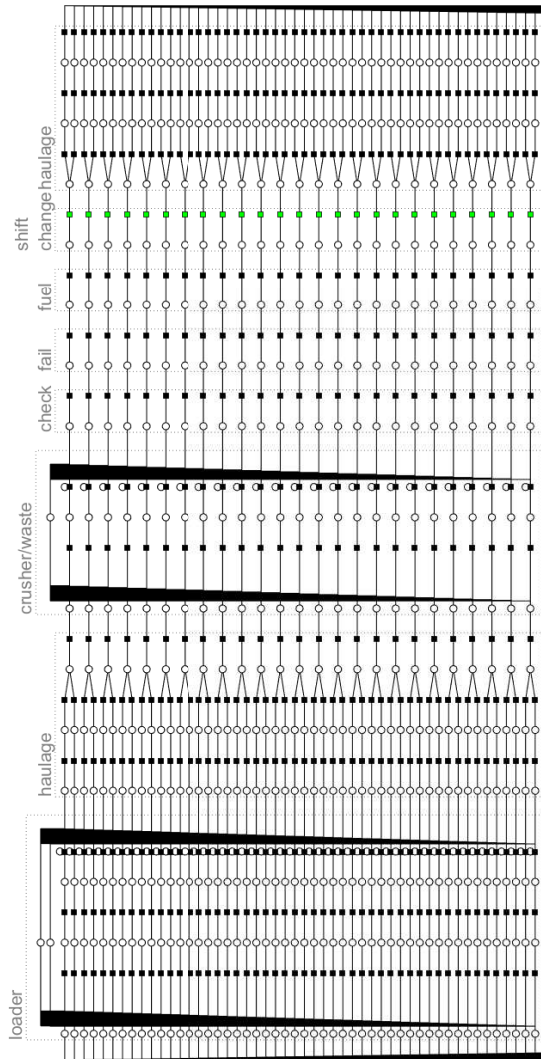


Figure 4.7 Simulation structure in Petri nets for 25 trucks

4.2.1.1 Experiment I: Results

Figures 4.8 and 4.9 show a comparison between the simulated results of productivity attained as functions of the number of trucks for several rules of dispatch and the maximum possible values determined analytically. The model considers identical trucks and identical

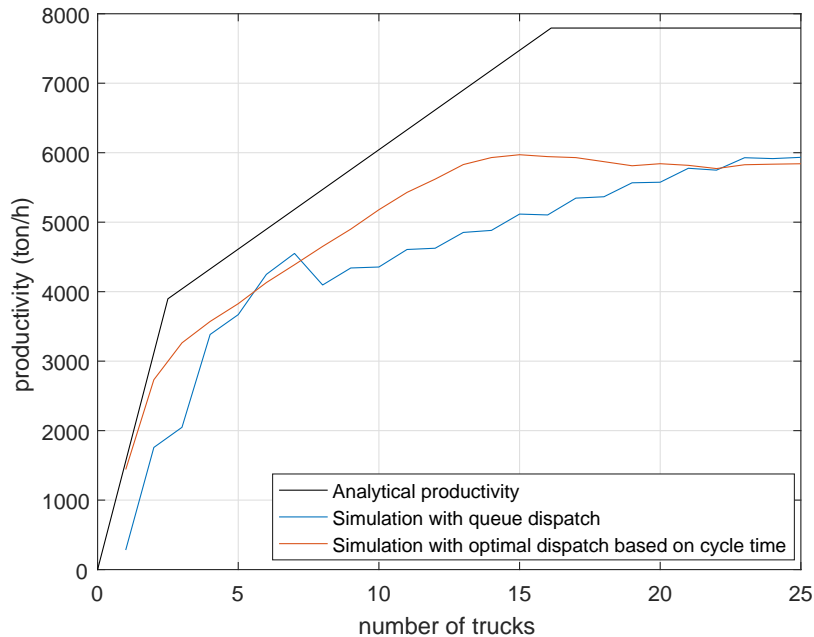


Figure 4.8 Simple structure evaluation

loaders with equal times of loading and unloading. One loader was placed 1 km from the crusher and another was 10 km from the crusher. As already mentioned, the values used in the simulation are given in Table 3.1.

Based on analytical calculations, 2.5 trucks are filled in the fastest cycle (with the loader placed 1 km away) and 13.6 trucks in the slowest cycle. It is noteworthy that in Figures 4.8 and 4.9, until the fastest cycle is filled, dispatches based on time to pass through the loader as well as on filling more productive cycles have practically equal efficiencies, which are greater than that of dispatch based on division of trucks between the loaders. One can visualize there is no significant difference in terms of productivity between the two structures evaluated (simple and complete). A structure is considered complete when it entails all the steps described in figures 4.6 and 4.7. A simple structure does not entail analysis of the stages of check, fail, fuel, and shift change, but has a runtime that is 20% to 30% faster than that of the complete structure (a modular analysis).

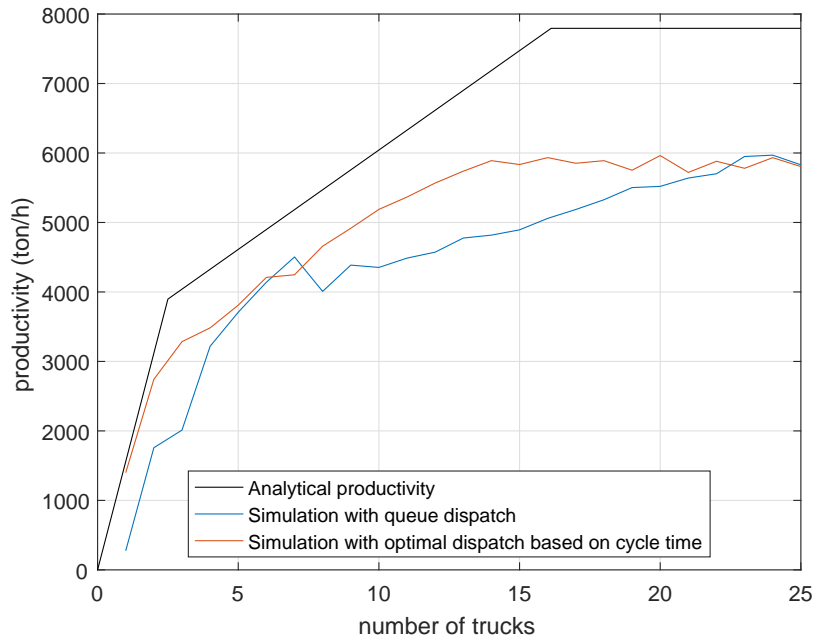


Figure 4.9 Complete structure evaluation

The simple and complete analysis (figures 4.8 and 4.9) demonstrate the modular analysis power of the simulator based on GSPN. The scalability of the analysis was demonstrated through the developed simulator, during the variation of the number of trucks during the service demand.

Thereafter, productivity in the case of dispatch based in queues is lower than that obtained in the case of dispatch by productive cycles. This is because in the former, the more productive cycle becomes saturated with trucks, but trucks continue to be sent to the nearest loader in this cycle, because the nearer loader can be reached faster than the one further away. It is also noteworthy that the maximum value of analytical productivity is higher than the numerical value as the crusher operation was disregarded between cycles. The idea of designing dispatch based on the filling of more productive cycles seems very promising.

4.2.2 Experiment II: Positioning evaluation

In the second experimental sequence, the impact of loader displacement on productivity is verified. The objective is to analyze how a positioning strategy can influence the strategies already presented. The model considers identical trucks and identical loaders with equal times

for loading and unloading.

One loader was placed 1 km from the crusher and the other 10 km away. This is referred to as the 1x10 km positioning option.

In this research, the simulation and production behaviors according to variation in positioning are verified, as shown in Table 4.4.

Table 4.4 Positioning Options

Positioning Option	Distance (km)
1	1x10
2	10x10

4.2.2.1 Experiment II: Results

As shown in Table 4.4, equipment positions were varied to evaluate their influence on the process of dispatch optimization. Each dispatch technique was analyzed individually, with standards and reference values identical to those of Experiment II.

A preliminary evaluation is pertinent. In Fig. 4.10, it can be seen that the saturation point of productivity was not reached when the new options of equipment positions were employed, hence, an experiment with $n_t = 40$ was performed to evaluate the saturation point in the 10x10 km positioning option.

As shown in Figs. 4.11 and 4.12, the productivity of each option presented in Table 4.4 was evaluated with $n_t = 25$ and a focus on experiments with the Petri nets model.

The maximum and minimum productivities were described according to the positioning option and weighted by the number of trucks and type of dispatch rule. A few results from the experiment are listed below:

- Productivity can be completely affected by the position of equipment, as can be seen in Figs. 4.11 and 4.12.
- Equipment positioning affected the maximum and minimum production values obtained using the two simulation-based dispatch techniques, as can be seen in Figs. 4.11 and 4.12.

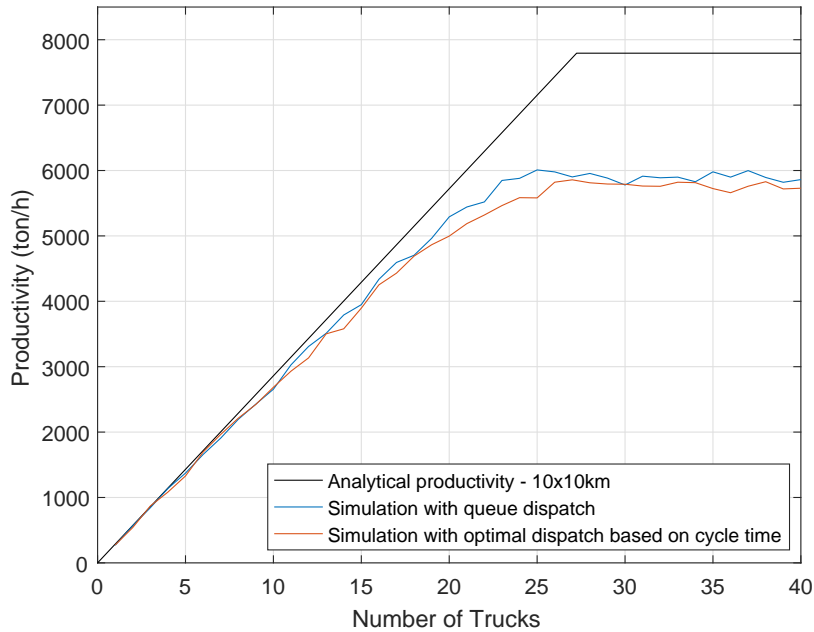


Figure 4.10 Evaluation of 10x10 km positioning option with 40 trucks

- Depending on the number of trucks and position of equipment (loaders and crushers), the difference between maximum and minimum production can be a few hundred tons (as can be seen in Figs. 4.11 and 4.12, where the number of trucks $n_t = 25$) or as high as 1,000 tons. In some cases, the difference may reach almost 2,000 tons (as seen when $n_t = 2$ in Fig. 4.12).
- Depending on the positioning option adopted, the process can suffer great loss of productivity. This loss of productivity can be seen by comparing the positioning options evaluated analytically or relative to the results obtained from the simulation methods.

4.2.3 Experiment III: Performance Analysis

On the last experiment, in search for performance gains in the simulation, a statistical analysis was performed, based on hypothesis inference, on the number of simulations required for the experiments.

This experiment has its importance linked to the fact that the execution time is a cost that the simulation process tends to charge the designer. If well estimated, an effective and efficient

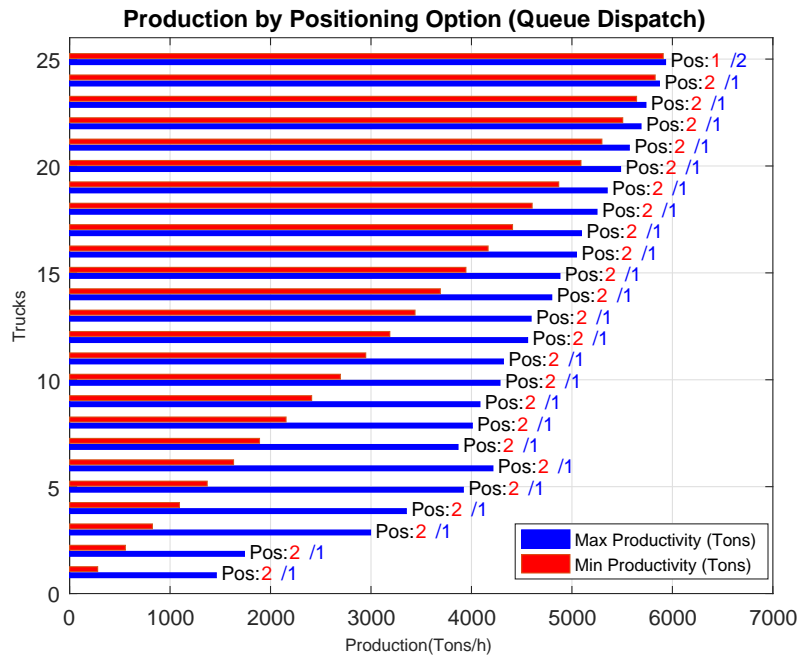


Figure 4.11 Production by queue-based positioning option

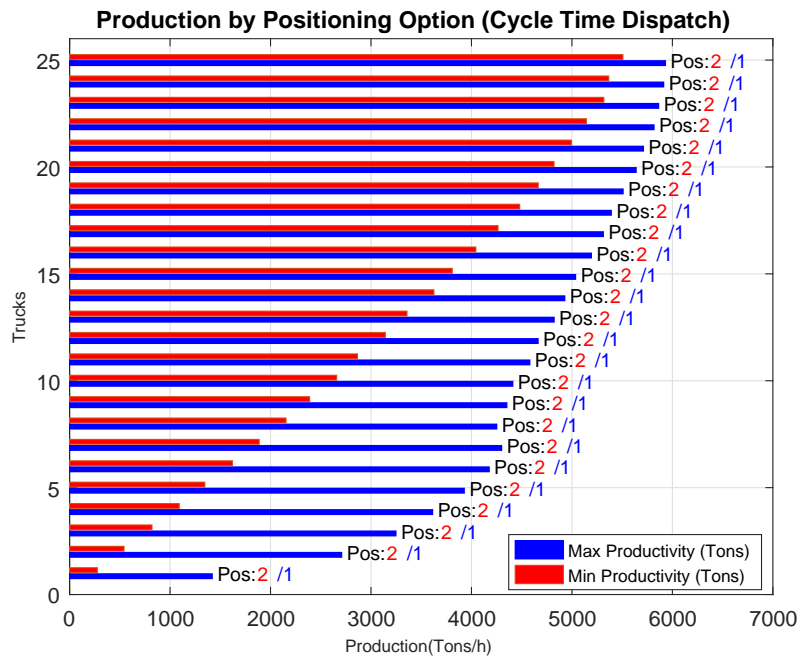


Figure 4.12 Production by cycle time-based positioning option

simulation process can serve the process. For a conscious use of the simulation process, an experiment was proposed to guide the number of samples required

The statistical analysis considered sampling conditions such as normality (without anomalies); a sufficiently large sample number for analysis; and independence (based in the central limit theorem).

They were based on the following characteristics of the problem: under certain conditions; the arithmetic mean of a sufficiently large number of independent random variable iterations; each with a well-defined finite expected value and finite variance, will be approximately normally distributed, regardless of the underlying distribution (Mathews, 2010). However, σ_x is not known. t-Student and Tests z were used to estimate it, basing on the sample value of S_x . The distribution t is similar to z, since it is symmetric, with an average equal to 0 and with dispersion (which is determined by degrees of freedom, where $d = n - 1$).

For the mean μ an estimate was made based on the simulations that present a response x (in tons of ore) for each complete cycle. Taking n as the total number of cycles of simulations performed and x_1, \dots, x_n the responses of each cycle during the entire course of n simulations, we generate a reference mean μ and a variance σ^2 (hence a standard deviation *sigma*).

An estimate of the confidence interval is given by:

$$\delta = t_{\alpha/2} \frac{\sigma_x}{\sqrt{n}} \quad (4.1)$$

Where δ is the confidence interval analyzed and t is a distribution with a degree of freedom d . Such an analysis is performed to compare the computational time between different dispatch rules.

4.2.3.1 Experiment III:Results

The results presented in Experiments I and II, consider the average productivity obtained, through a number n simulation samples, where $n = 10$, for each number of trucks n_t , where $n_t = \{1, \dots, 25\}$, evaluated.

Following the concepts of Experiment I, the first approach of this evaluation focuses on completing the load and unload processes (the events Fail, Check, Fuel and Shift were restored to simulation process). Considering the structure of the complete dispatch process, with the same sample rate, where $n = 10$, no behavioral changes were observed in the productivity

responses and the simulation times showed some differences (below 1 second).

Thus, taking the complete process as a reference, a process was proposed to evaluate the number of samples n needed for the simulation process in order to optimize the efficiency of the developed structure.

This process was used to estimate an efficient sample size. It was proposed a confidence interval of 95% and a δ (in %) to demonstrate the variation of the number of samples to the detriment of the error assumed. The experiments were executed with the z-tests and t-Student. The result is a comparison between the values used in the confidence interval and the time savings (statistically reliable). A sample size estimating and a savings analysis were obtained.

An initial sample value was not determined according to a statistical analysis, so a battery of n simulations was performed, where $n = \{100\}$ to each n_t , where $n_t = \{1, \dots, 25\}$. The value in n is relatively high, which can provide security for an initial analysis to each n_t . The results of time and production are in Figures 4.13-4.16.

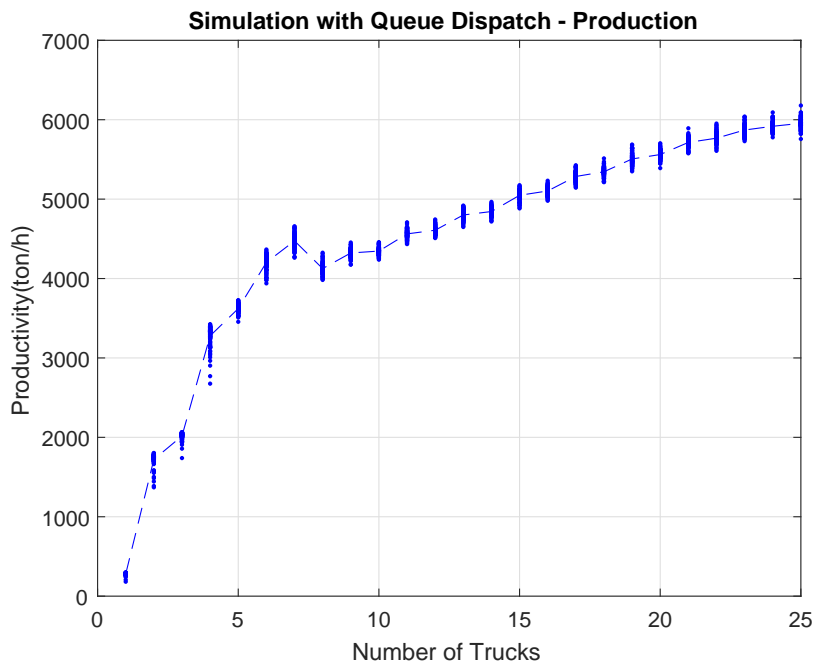


Figure 4.13 Complete Structure - Queue Based (Production) - 100 Samples

The first analysis criterion of each n was the verification of the standard deviation σ_n and each time T_n of execution. The choice of the n considers a n big enough for representation, respecting a time saving. It was analyzed standard deviation, which shows that there was no significant difference to each mean production m (tons). The initial sample size fixed in

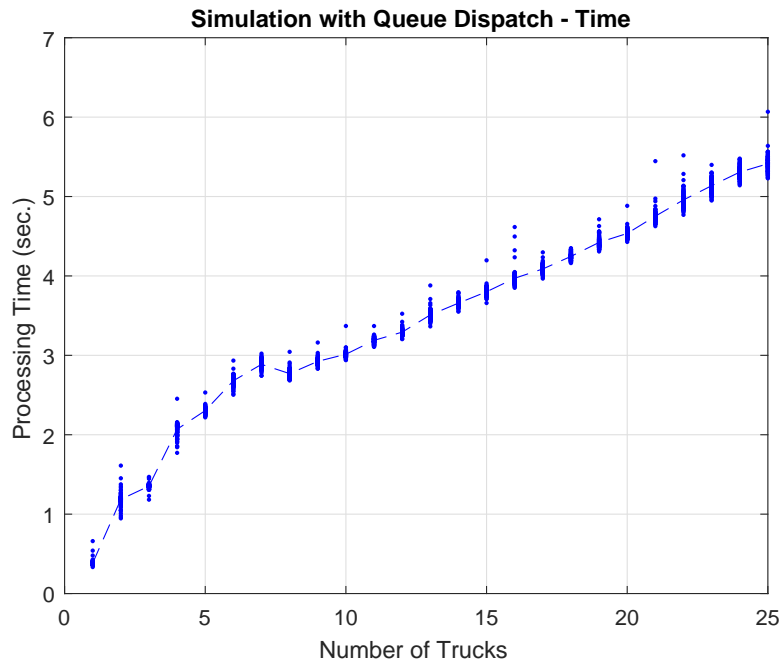


Figure 4.14 Complete Structure - Queue Based (Time) - 100 Samples

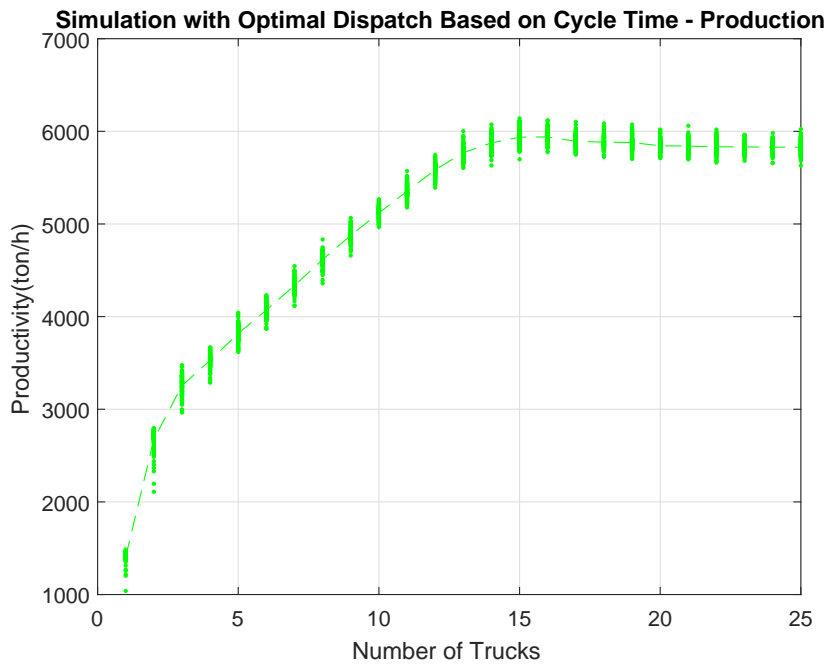


Figure 4.15 Complete Structure - Cycle Time Based (Production) - 100 Samples

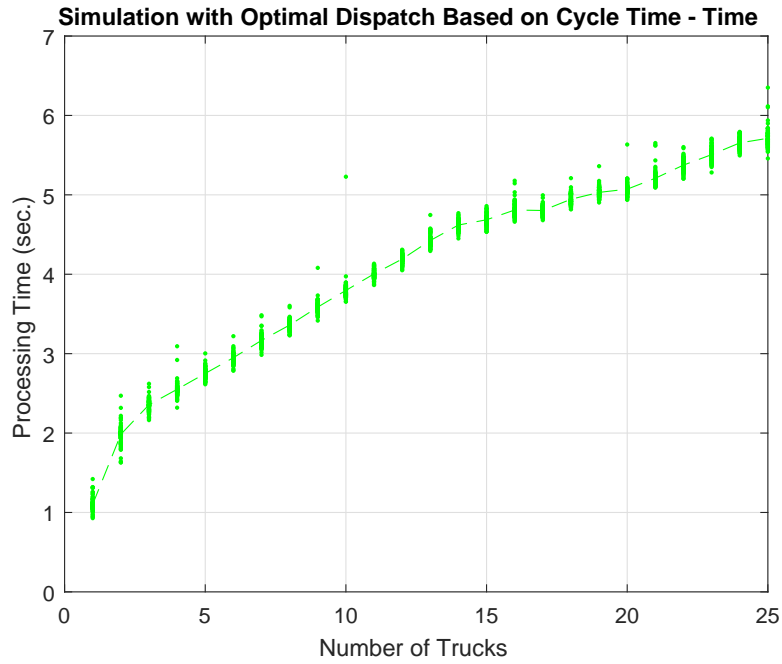


Figure 4.16 Complete Structure - Cycle Time Based (Time) - 100 Samples

$n = 100$. This comparison and its results are demonstrated in Figures 4.17-4.20.

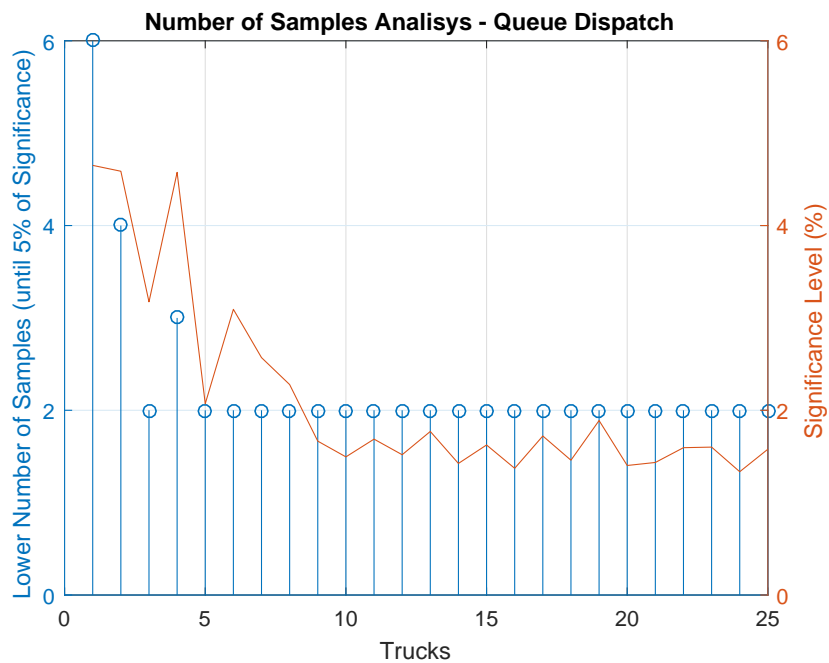


Figure 4.17 Queue Based - Number of Samples

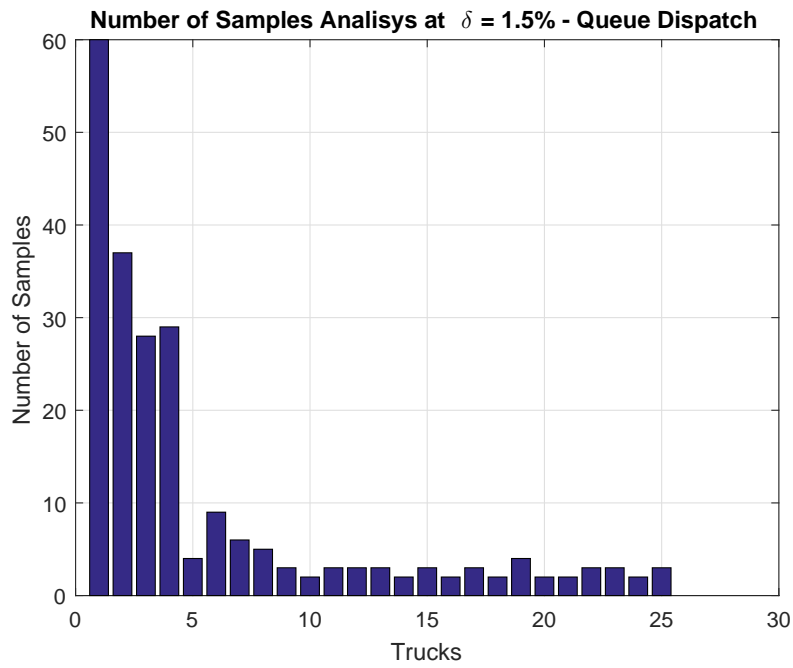


Figure 4.18 Queue Based - Number of Samples $\delta = 1.5$

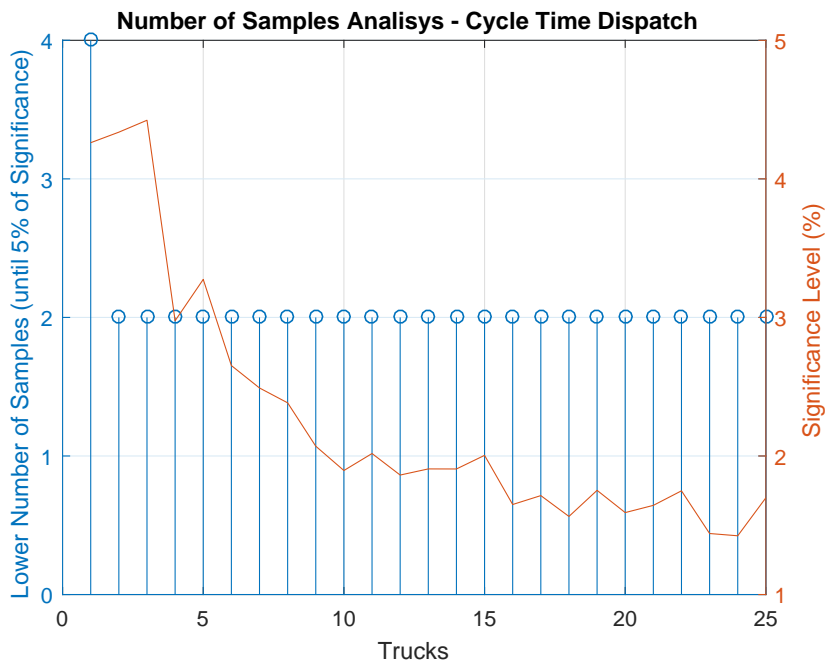


Figure 4.19 Cycle Time - Number of Samples

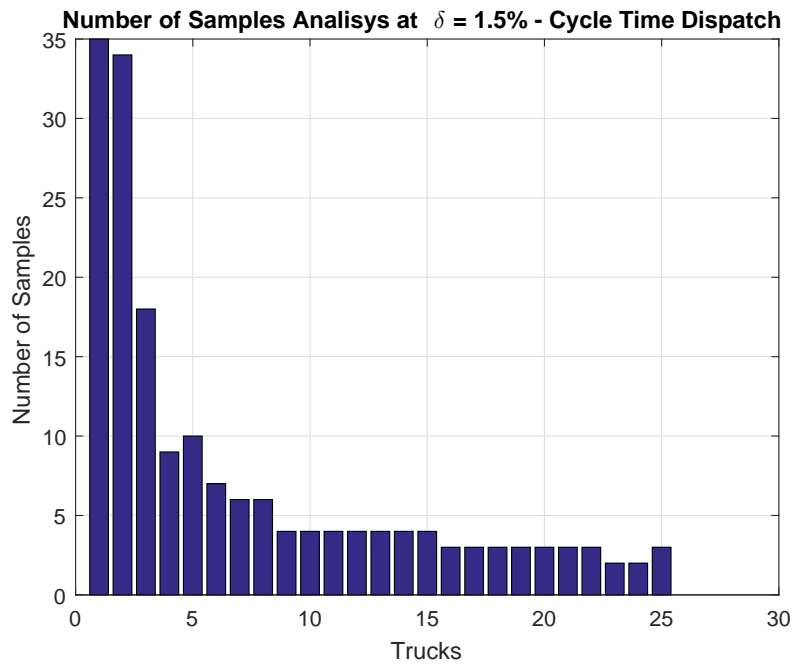


Figure 4.20 Cycle Time - Number of Samples $\delta = 1.5$

We can see two aspects in these results:

- The first one demonstrates the smallest number n of samples allowed, with a significance level of 5% and the level of significance guaranteed for the recommended (example: in Figure 4.17, with $n_t = \{15\}$, the significance reaches in 1.62%, for the rule based on Queue);
- The second demonstrates the number of samples recommended, with a significance level of 1.5% (example: in Figure 4.18, with $n_t = 15$, the number of samples required is $n = 2$, for the rule based on queues - which represents an economy of 80%, compared to experiments where $n = 10$).

All those results with 95% confidence and the estimated standard deviation σ . A $n > 1$ have been maintained so that at least 1 degree of freedom is maintained.

CHAPTER 5

Conclusion

The research has involved the development of a modeling and simulation methodology capable of abstracting a real mining process, as well as optimizing the dispatching process, presenting relevant productivity gains.

During the simulation process it was possible to visualize the capacity of stochastic Petri nets of representing the analyzed process. The structure was capable of denoting the activities and availability of resources, and the structure enables the designer to insert the behavioral demonstration of events, even if such events obey different probability distributions (normal, uniform, exponential or constant).

It was also possible to demonstrate statistically well-founded methodologies that guarantee the efficiency of the developed simulator. With an optimal number of simulation samples, it was possible to satisfy the response quality needs by comparing to measured results that come from a real open pit mine in operation. There is a considerable positive impact of the computational time reduction (simulation time savings ranging from 900 to 6000 seconds according to the analyzed period), without performance loss, where the quality of the responses was preserved and the optimization of the simulation system was achieved.

It was possible to model and optimize the process of dispatch of operational trucks in an open-pit mine using two fast dispatch heuristics. The simulator was able to assimilate the complexities in assigning new dispatch ways to trucks (including variations in the total number of trucks), availability of loaders and crushers during the process, and the process of choosing the best route according to the analysis of queues and most productive cycle time. The cycle time-based dispatch rule is a very promising alternative.

Additionally, it was possible to obtain control over the degree of abstraction to be simulated. A more simplified model can be evaluated and compared with the complete model. Simplifications of model abstractions may not bring about significant changes in the simulation but may represent computational time savings during experiments.

Finally, productivity was affected by equipment positioning strategy. A difference of

more than 50% in productivity was visualized depending on the number of trucks and positioning of equipment. The maximum and minimum productivities could be simulated to guide operational planning based on the structure proposed.

Future Analyses

6.1 Research Proposals

6.1.1 Proposal I - Real-Time Dispatch Simulation

Real-time dispatch management is an option to be explored. Current searches consider the real-time assessment of resource availability during the dispatch in open pit mines, such as [Chaowasakoo *et al.* \(2017c\)](#) and [Chaowasakoo *et al.* \(2017b\)](#). In these works an optimization model based on the heuristic truck dispatching is applied for three heterogeneous fleet types. It should be emphasized that in these works, the authors used heuristics and evaluations on each particular moment of the dispatch process, considering the shovels of the operant equipment and the trucks involved in the process, minimizing the shovel waiting time (an empty truck (large/small) is randomly assigned to a shovel that is expected to be idle first), the truck cycle time (an empty truck (large/small) with minimal cycle time (arrival time + return time) is assigned to a shovel that is expected to have the shortest loading service), the truck waiting time (an empty truck (large/small) is randomly assigned to a shovel in which the loading operation starts first) and shovel saturation and coverage (an empty truck (large/small) with minimal cycle time (arrival time + return time) is assigned to a shovel at equal time intervals to keep shovels busy).

Real-time analytics can not only operate on the availability of resources, but also provide a dynamic heuristic analysis on the best route at the time of analysis, in real time. The heuristic can be fed by distance information and weighting proposed routes according to the behavior of the real-time scenario, providing real-time updates.

Both the [Chaowasakoo *et al.* \(2017c\)](#) and [Chaowasakoo *et al.* \(2017b\)](#) considered the uncertainties that the mine could present. Thus a process that evaluates a real condition must delimit the uncertainties with which it can or cannot deal.

In short this first proposal aims to carry out a research on a simulation methodology

that can provide a real-time routing optimization for the dispatch process of trucks operating in open pit mines.

6.1.2 Proposal II - Real-time Combinatorial Analysis

Combinatorial analysis will be evaluated, focusing on truck dispatch. Some related works already address the theme, such as Alvarez *et al.* (2011) that presents the mathematical framework for the open pit mine planning problem, based on continuous functional analysis.

In this proposal, a combinatorial analysis will be evaluated for the recommendation of real-time dispatch during the production process.

6.1.3 Proposal III - Parallel Computing

In the experiments, the issues of execution time savings were considered, which directly influence the performance of the algorithms. Response times and good solutions presented themselves as two important and complex goals. In section 4.1 was seen how a structure, which covers a complete scenario, can be influenced.

In this proposal, the use of parallel computing in the already evaluated structures will be evaluated. The objective is to evaluate the parallel processing behavior in the already evaluated questions and structures, in order to verify if the parallelism can increase, even more, the performance of the structures developed.

Ercan and Oğuz (2005) experiments the parallelism of processing in heuristics and meta-heuristics, as well, Cecilia *et al.* (2013) uses the parallel processing in GPUs (towards the traveling salesman problem). In its paper, Cecilia *et al.* (2013) cites several approaches where parallelism can contribute to processing time without compromising the quality of the response.

In Manju and Nigam (2014), there is an analysis of several algorithms that use parallelism-based processing, with several structures based on pattern recognition, such as artificial neural networks (ANN) and support vector machines (SVM) and Metaheuristics (Ant Colony Optimization and Genetic Algorithm) are used with parallel processing.

Thus, it is possible to assume that in the literature, the parallel division of processing is a valid tactic to optimize the performance of computational structures and such improvements will be implemented in order to assist the tool developed to deal with the dispatch in open pit

mines.

6.1.4 Proposal IV - Improvement of experimental analysis

The optimal number of simulations and simulation time can be further explored as it varies from experiment to experiment.

The complexity of the stochastic behavior of each sample still allows better explorations, such as: analysis and optimization of the warming up process, evaluation of lower and upper limits of the times of each activity to increase accuracy.

This process to be studied represents a continuation of the optimization of the productivity estimation process, focused on variation from experiment to experiment.

Appendix

7.1 Publications

The research featured two published papers. The most recent and most impactful was approved in the IEEE Access journal, with the research synthesis, focused on the optimization of the simulation process. The second was carried out at the beginning of the research, where two heuristics were proposed to optimize paths for visiting trucks in production:

- **Journal IEEE Access.** Accepted in 4 August 2019. **Title:** On Modelling and Simulating Open Pit Mine Through Stochastic Timed Petri Nets. **DOI:** 10.1109/ACCESS.2019.2934718. **Co-Authors:** Adriano C. Lisboa, César M. Ribeiro, Carlos A. Maia, Rodney R. Saldanha, Felipe L. B. Castro, and Douglas A. G. Vieira. **Pages:** 15.
- **SBPO 2017. XLIX Simpósio Brasileiro de Pesquisa Operacional.** **Title:** Randomization Control in Heuristics and Metaheuristics Applied to the Optimal Path Search in Open Pit Mines. **Synopsis:** Heuristics and Metaheuristics to optimize the visitation process of delivery points in open pit mines. **Co-Authors:** Adriano Chaves Lisboa, Carlos Andrey Maia, Rodney Rezende Saldanha. *Proceedings of the Brazilian Symposium on Operations Research.* **City:** Blumenau. **Pages:** 12.

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Digital Object Identifier 10.1109/ACCESS.2019.2934718

On Modelling and Simulating Open Pit Mine Through Stochastic Timed Petri Nets

ADRIANO C. LISBOA¹, FLÁVIO H. B. DE SOUZA¹, CÉSAR M. RIBEIRO², CARLOS A. MAIA², RODNEY R. SALDANHA², FELIPE L. B. CASTRO², AND DOUGLAS A. G. VIEIRA³

¹Gaia, Belo Horizonte 31310-260, Brazil

²Programa de Pós-Graduação em Engenharia Elétrica, Universidade Federal de Minas Gerais, Belo Horizonte 31270-901, Brazil

³ENACOM Handcrafted Technologies, Belo Horizonte 31310-260, Brazil

Corresponding author: Adriano C. Lisboa (adriano.lisboa@gaiasd.com)

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ABSTRACT A structured and robust methodology of modeling and simulation can be available through modular stochastic timed Petri nets, including experiments that allow designers to simulate the processes involved in ore production on well-founded estimates. This prerogative guides an experimental research based on real data from an Brazilian open pit mine operation. Three basic simple modules allows to achieve complex models for a real mine. The difference between simulated and measured average productivities are small when compared to an analytic model for the bottleneck and a model implemented in discrete event system language SIMAN, which also validates the simple truck dispatch rule proposed in this paper. As results of the experiment, we derived a valid simulation structure for the open-pit mining process using Petri nets. It was obtained a behavioral evaluation of the efficiency of the structure according to variations in the probability distribution function.

INDEX TERMS Design techniques, open pit mines, stochastic experiments, stochastic timed petri nets.

I. INTRODUCTION

Open pit mining operations involve the extraction of minerals from the earth's surface, as opposed to underground mining. The operations are primarily governed by the truck cycle, in which the ore is loaded by loaders at the extraction site and transported to the crusher for processing. A computationally efficient simulation of the mining model can support experiments involving behavior analysis of the loading and unloading processes, which can guide activities that represent a cost of 50-60% of the total investment in the mining process (evaluated as a complex system due to its dynamic, stochastic and uncertain nature).

There have been many studies that focus on the modeling and simulating open pit mines. Each approach presents a technique with specific characteristics and limitations. [1] present a review concerning equipment selection problem for mining. The methods presented use:

The associate editor coordinating the review of this article and approving it for publication was Shouguang Wang.

- Linear programming: uses analytic models of mines in order to optimize many aspects such as fleet selection problem [2], preventive maintenance [3], and energy consumption in open pit coal mines [4]. This model usually are simple and fast, but it is common to be associate to a number of approximations. More detailed models can be developed, improving accuracy but requiring more generic algorithms to optimize them, such as Genetic Algorithms [5].
- Queuing Theory: the mining process performance is directly connected to the queuing in bottlenecks, such as loader, crusher and maintenance places. It has been applied to model the system truck-loader [6] in order to select a proper fleet. The models can consider the stochastic system behavior [7]. Using queuing theory, [8] has stated that the truck capacity should be about 5 or 7 times the loader capacity in a process of landscaping.
- Fuzzy Logic: the uncertainties in a mine model can be modeled [9].



Randomization Control in Heuristics and Metaheuristics Applied to the Optimal Path Search in Open Pit Mines

Flávio Henrique Batista de Souza

Programa de Pós-Graduação em Engenharia Elétrica - Universidade Federal de Minas Gerais -
UFMG
Av. Antônio Carlos 6627, 31270-901, Belo Horizonte, MG, Brazil
flabasouza@yahoo.com.br

Adriano Chaves Lisboa

Gaia, solutions on demand
Rua Professor José Vieira de Mendonça 770, 31310-260, Belo Horizonte, MG, Brasil
adriano.lisboa@enacom.com.br

Carlos Andrey Maia

Programa de Pós-Graduação em Engenharia Elétrica - Universidade Federal de Minas Gerais -
UFMG
Av. Antônio Carlos 6627, 31270-901, Belo Horizonte, MG, Brazil
maia@cpdee.ufmg.br

Rodney Rezende Saldanha

Programa de Pós-Graduação em Engenharia Elétrica - Universidade Federal de Minas Gerais -
UFMG
Av. Antônio Carlos 6627, 31270-901, Belo Horizonte, MG, Brazil
rodney@cpdee.ufmg.br

ABSTRACT

The main contribution of the article is the presentation of a control of randomness on the Nearest Neighbour heuristic and the GRASP metaheuristic, in order to explore the capacity of local minimums found in their search processes. These structures have been analysed, readjusted, and verified for a database containing the location of several mines located in the territory of the United Kingdom. New algorithms are compared in terms of results based on reference datasets.

KEYWORDS. Nearest Neighbour. GRASP. Open Pit Mine.

Introduction, Methodology, Results, Conclusion, References

7.2 Extra works

For a better understanding of the tool other works were developed in partnership with students from the Centro Universitário de Belo Horizonte (UNIBH) in order to analyze practical situations with Petri nets:

- ENEGEP 2018 - XXXVIII Encontro Nacional de Engenharia de Produção. **Title:** Discrete Events Systems for Controlling The Production Process in a Dairy Industry. **Synopsis:** Use of Petri nets for modeling, simulation and optimization of the dairy manufacturing process of a Minas Gerais countryside industry. **Co-Authors:** Thamara Reis; Jéssica Daryane. **City:** Maceió. **Pages:** 12.
- CNMAC 2019.a XXXIX Congresso Nacional de Matemática Aplicada e Computacional. **Title:** Redes de Petri Estocasticamente Temporizadas Para Identificação e Classificação de Afundamento de Tensão. **Synopsis:** STPNs for modeling and simulation of voltage sags effects. - **Co-Authors:** Jessica dos Santos Ferreira; Alexandre Alves Costa. **City:** Uberlândia. **Pages:** 2.
- CNMAC 2019.b XXXIX Congresso Nacional de Matemática Aplicada e Computacional. **Title:** Redes de Petri para Modelagem e Simulação de Manobras e Falhas da Subestação Barreiro 1. **Synopsis:** STPNs for modeling and simulation substations operations. - **Co-Authors:** Eric Brian dos Santos Pereira; Guilherme Lelis Fonseca Nascimento. **City:** Uberlândia. **Pages:** 2.
- ENEGEP 2019 - XXXIX Encontro Nacional de Engenharia de Produção. **Title:** Ferramenta Baseada em Eventos Discretos Para Gestão de Estoque em uma Pequena Empresa do Ramo Farmacêutico. **Synopsis:** A tool for stock simulation in a pharmacy. **Co-Authors:** Nayara Nunes Silva; Pedro Henrique Navarro de Faria e Novaes. **City:** Santos. **Pages:** 19
- RESTCONF 2020.a X International Conference on Research in Engineering, Science and Technology. **Title:** Air Modal Perishable Cargo Dispatch: Case Study of a Sustainable Proposal Assisted by Process Modeling and Simulation. **Synopsis:** STPNs for dispatching perishable cargo. **Co-Authors:** Lucas Magno Resende Coelho, Reubert Fernandes Rodrigues Barbosa, Ramon Cleiton Teodoro Silva, Luiz Melk de Carvalho. **City:** Roma . **Pages:** 1.

- RESTCONF 2020.b X International Conference on Research in Engineering, Science and Technology. **Title:** Mobile Applications and Discrete Event Systems: Low Cost Technology to Assist Stock Management in an Orthopedic Clinic. **Synopsis:** STPNs for modeling and simulation in an Orthopedic Clinic. **Co-Authors:** Daniela Trindade Batista, Thiago Augusto Santos Ferreira, Renata Duarte Mellim, Luiz Melk de Carvalho, Vladimir Alexei Rodrigues Rocha. **City:** Roma. **Pages:** 1

In addition to the articles cited, experiments with other heuristics were developed, generating one more publication. These were focused on the process of moving a vehicle with delivery points based on the exploration of local minimums to optimize the response presented. It is a optimization of the paper in SBPO 2017:

- Revista Produção Online. Accepted in August, 16, 2018. **Title:** Analysis of Random Points as a Strategy for Local Optimal Improvement in a Constructive Heuristic. **Synopsis:** Optimization of the process described in SBPO 2017. **Co-Author:** Hugo Vinicius Freitas Losqui. **Pages:** 29



16 a 19 de Outubro de 2018 • Maceió, Alagoas

XXXVIII ENCONTRO NACIONAL
DE ENGENHARIA DE PRODUÇÃO

CARTA DE ACEITE

É com satisfação que informamos que o trabalho:

DISCRETE EVENTS SYSTEMS FOR CONTROLLING THE PRODUCTION PROCESS IN A DAIRY INDUSTRY

Dos autores:

Thamara Reis, Jéssica Daryane, Flávio Henrique Batista de Souza

foi aceite para ser apresentado no XXXVIII Encontro Nacional de Engenharia de Produção (ENEGEP) que ocorrerá em Maceió, Brasil, nos dias 16 a 19 de Outubro de 2018.

Os membros da Comissão Científica agradecem por sua submissão

Atenciosamente,

Rafael Garcia Barbastefano
Presidente do Comitê Científica

DISCRETE EVENTS SYSTEMS FOR CONTROLLING THE PRODUCTION PROCESS IN A DAIRY INDUSTRY

Thamara Reis

thamarapreis@gmail.com

Jéssica Daryane

jessicadaryane@hotmail.com

Flávio Henrique Batista de Souza

flabasouza@yahoo.com.br



The production process in a dairy industry can be better managed and planned with the application of simulation technologies oriented to discrete events. This article aims to present a description of this market, its demands and needs that can be optimize

Palavras-chave: Petri Nets, dairy, Organizational Tools, Cream Cheese



Carta de Aceite

Parabéns!

Temos o prazer em informar que seu trabalho intitulado

Redes de Petri Estocasticamente Temporizadas Para Identificação e Classificação de Afundamento de Tensão

De autoria de

Jessica dos Santos Ferreira, Alexandre Alves Costa, Flávio Henrique Batista de Souza

foi **aprovado** para ser apresentado no XXXIX Congresso Nacional de Matemática Aplicada e Computacional (CNMAC 2019), que ocorrerá de 16 a 20 de setembro de 2019, na Universidade Federal de Uberlândia - MG.

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Redes de Petri Estocasticamente Temporizadas Para Identificação e Classificação de Afundamento de Tensão

Jessica dos Santos Ferreira¹

Centro Universitário de Belo Horizonte- UNIBH

Alexandre Alves Costa²

Centro Universitário de Belo Horizonte- UNIBH

Flávio Henrique Batista de Souza³

Universidade Federal de Minas Gerais, UFMG

1 Introdução

O Sistema Elétrico de Potência (SEP) deve fornecer com qualidade, energia elétrica aos consumidores, com continuidade e em conformidade com os parâmetros estabelecidos pela ANEEL e descritos nos Procedimentos de Distribuição de Energia Elétrica no Sistema Elétrico Nacional (PRODIST). O SEP é passivo a intercorrências e uma delas é o Afundamento de Tensão (Voltage Sags - VS), um distúrbio apresentado no sistema elétrico e com crescente preocupação desde a década de 90 [1, 2], pois não há um método padronizado rígido para a classificação ou atuação sobre o distúrbio, apesar das normas regulamentadoras sobre a qualidade da energia elétrica. A pesquisa demonstra a modelagem e simulação, baseada em redes de Petri estocasticamente temporizadas, para análise de ocorrências e causas de VS, classificando-as entre instantâneas (entre 0.05 e 0.5 segundos), momentâneas (0.5 e 3 segundos) e temporárias (3 segundos e 1 minuto), oferecendo um suporte ao planejamento de redes elétricas, a um baixo custo computacional.

2 Materiais e Métodos

As redes de Petri estocasticamente temporizadas (STPN) utilizam um tempo estocástico para disparo de transições [3]. Com elas, uma modelagem seguida de experimentos baseados em testes de stress padronizados são realizados, com valores de referência da literatura para cada um dos 3 tipos de VS. Foi visualizado o poder de abstração de tal estrutura para simulação de ocorrências de VS em uma linha de transmissão. Os testes avaliaram comportamentos com tempos constantes e advindos de uma distribuição cumulativa (CDF) para os tempos de disparo. Cada um dos 100 experimentos contou 500 eventos de VS.

¹jessicasantos@outlook.com

²alexandrealves18@yahoo.com.br

³flabasouza@yahoo.com.br

3 Resultados

A estrutura da figura 1 é o modelo desenvolvido e os tempos podem ser alterados pelo usuário e se adaptam ao histórico da linha de transmissão. Durante a simulação a análise A1 identifica as ocorrência de VS, A2 identifica o tipo de VS e A3 identifica os tipos de causas (exemplo: partida de motores). O usuário pode inserir/retirar causas de acordo com a necessidade (e disponibilidade de dados). As causas 1 e 2 tomadas como referência têm a mesma função em qualquer um dos tipos de verificação de VS, com um exemplo de causa particular de um tipo de VS. Durante os experimentos, contataram-se duas funcionalidades

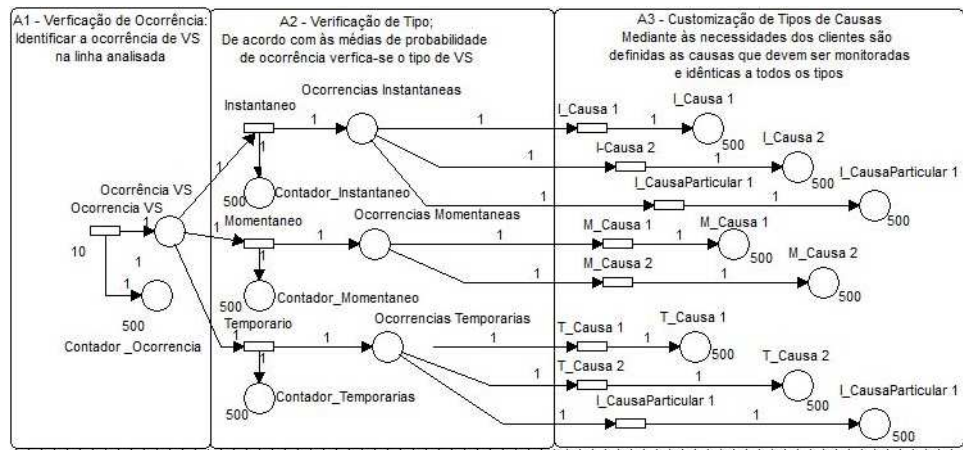


Figura 1: Estrutura de simulação em redes de Petri estocasticamente temporizadas

eficazes para o modelo. O primeiro, o OFFLINE, onde as transições disparariam mediante o histórico (e CDF) das causas avaliadas. O segundo, o ONLINE, onde a comunicação com os equipamentos forneceriam os dados de VS e a estrutura classificaria o evento.

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- [2] T. V. Menezes, *Estratégia para análise de Afundamento de Tensão no planejamento do sistema elétrico*, Dissertação de Mestrado em Engenharia Elétrica, UFMG, (2007).
- [3] J. Wang, *Stochastic timed petri nets and stochastic petri nets*, in *Timed Petri Nets*, Springer, 1:125-153, 1998.



Carta de Aceite

Parabéns!

Temos o prazer em informar que seu trabalho intitulado

Redes de Petri para Modelagem e Simulação de Manobras e Falhas da Subestação Barreiro 1

De autoria de

Eric Brian dos Santos Pereira, Guilherme Lelis Fonseca Nascimento, Flávio Henrique Batista de Souza

foi **aprovado** para ser apresentado no XXXIX Congresso Nacional de Matemática Aplicada e Computacional (CNMAC 2019), que ocorrerá de 16 a 20 de setembro de 2019, na Universidade Federal de Uberlândia - MG.

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Redes de Petri para Modelagem e Simulação de Manobras e Falhas da Subestação Barreiro 1

Eric Brian dos Santos Pereira¹

Centro Universitário de Belo Horizonte- UNIBH

Guilherme Lelis Fonseca Nascimento²

Centro Universitário de Belo Horizonte- UNIBH

Flávio Henrique Batista de Souza³

Universidade Federal de Minas Gerais, UFMG

1 Introdução

O SCADA (*Supervisory Control and Data Acquisition*) é um sistema capaz de registrar eventos de uma subestação como abertura de chaves ou disjuntores, falhas de dispositivos, dentre outros. Seguem a uma normatização, a IEC 61850, que regulamenta o procedimento de comunicação para automação de subestações. Através das redes de Petri, é possível desenvolver uma modelagem capaz de, baseadas nos dados do sistemas SCADA, simular falhas e manobras da subestação[1]. Assim, essa pesquisa demonstra a modelagem e simulação, baseadas em redes de Petri, para avaliação e previsão de ocorrências e manobras da subestação de 345 KV Barreiro 1.

Realizou-se uma análise da subestação Barreiro 1, levantou-se os requisitos de dados, correlações de equipamentos e dispositivos que devam ser apresentados na simulação. Apresentou-se simulações de cenários para validação. Tal experimento se justifica pelo alto impacto que as falhas e quedas proporcionam aos distribuidores de energia, como o advento uma fiscalização entre 11 e 15/06/2012, onde o descumprimento por parte da CEMIG de indicadores individuais e coletivos, que resultou em multa no valor de R\$ 18,6 milhões, conforme despacho N° 2.771, publicado pela ANEEL no Diário oficial da União.

2 Materiais e Métodos

Primeiramente foi feito o fracionamento da rede de atendimento da subestação, baseado no seu diagrama unifilar. Assim, foi modelada a subestação através das redes de Petri, conforme [2], para a demonstração de pontos energizados. Por fim, foi avaliada a coerência da hierarquia dos elementos da rede distribuição e a capacidade de execução do simulador em um computador sem hardwares robustos ou específicos.

¹ericbrian20@gmail.com

²guilherme011l@hotmail.com

³flabasouza@yahoo.com.br

3 Resultados

A estrutura da figura 1 demonstra um fracionamento (no caso o atendimento à região do Taquaril) e sua modelagem correspondente. Durante os experimentos foram simuladas todas as manobras possíveis, de acordo com cada elemento de conexão (disjuntores). A hierarquia se manteve coerente, uma vez que cada conexão hierarquicamente superior define se as conexões inferiores se mantém energizadas (exemplo: se 11P5 não está energizado, 11P4 e toda a sequência depois dele estará desenergizada). Foi constatada a possibilidade de simulações através de tempos em históricos de funcionamento providos do SCADA. Os experimentos foram realizados em um computador com 4 GB de RAM, processador de 2,4 GHz com 4 núcleos e Windows 7.

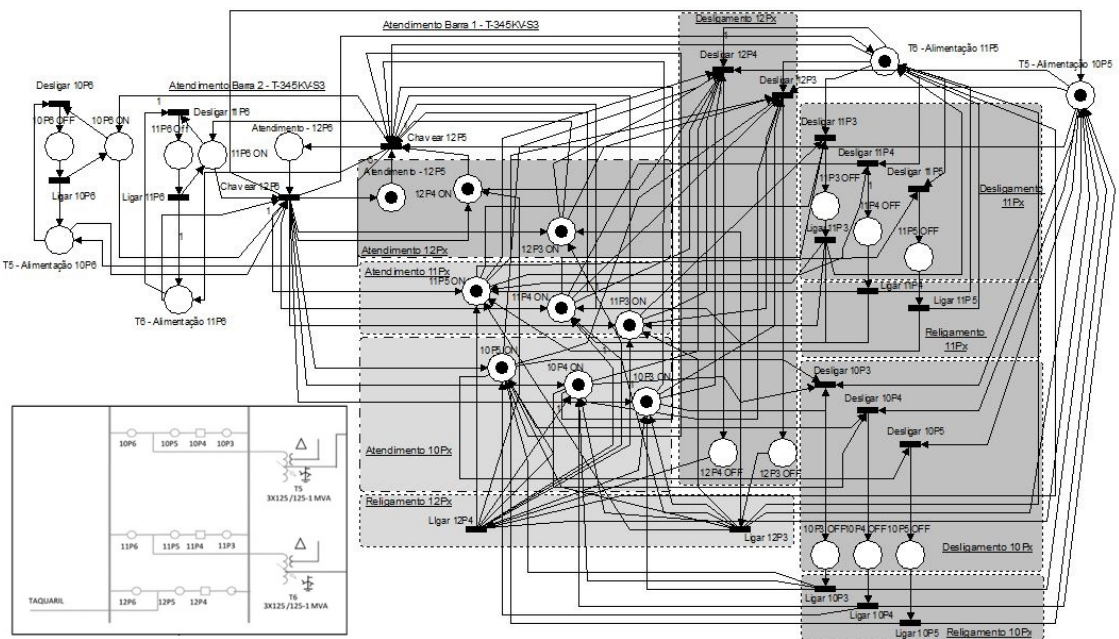


Figura 1: Modelagem para Subestação Barreiro 1 - Taquaril

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- [2] J. Wang, Stochastic timed petri nets and stochastic petri nets, in *Timed Petri Nets*, Springer, 1:125-153, 1998.

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De: secretaria@abepro.org.br

Para: flabasouza@yahoo.com.br

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Prezado(a) **Flávio Henrique Batista de Souza,**

Lhe parabenizamos pela aprovação do(s) artigo(s) abaixo para o **XXXIX Encontro Nacional de Engenharia de Produção - ENEGEP 2019.**

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Atenciosamente,

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1. Introdução

As pequenas empresas comumente decretam falência por ocorrer falta de investimentos em novas tecnologias que proporcionam melhores gerenciamentos estratégicos. Com esses aparatos é possível um maior controle de suas atividades, evitando perdas. Constata-se então que, atualmente, para se manterem no mercado é necessário que essas organizações se modernizem. Uma constatação do setor farmacêutico, que é abordado nessa pesquisa é: *“Com mais de 75 mil drogarias em funcionamento, o Brasil é o país com o maior número de farmácias no mundo, com uma proporção de 3,4 farmácias para cada 10 mil habitantes”* (SEBRAE, 2014).

O objetivo geral deste artigo é demonstrar a eficácia de um modelo, baseado em redes de Petri, para representar o processo de estoque de uma empresa de pequeno porte do setor farmacêutico. Como, objetivos específicos têm-se: delinear o processo de estoque da empresa; modelar, tal processo através das redes de Petri, de forma que consiga contemplar tanto as atividades quanto seus responsáveis; simular cenários de forma a prever tanto o comportamento da empresa com estoque inicial zero e com estoque prévio, para avaliar a quantidade de insumos que permanecem em estoque, depois de um período de vendas (foram avaliadas vendas diárias); verificar a presença e o tempo de duração de rupturas da disponibilidade de produtos.

Essa pesquisa se justifica pelo fato de que as principais geradoras de riqueza no mercado brasileiro, são as Micro e Pequenas Empresas comportando 53,4% do PIB (SEBRAE, 2014). Porém este perfil de empreendimento tem apresentado uma grande demanda por otimização de processos, além de carecer de conhecimentos sobre soluções com teor tecnológico como as que se baseiam nas técnicas de simulação.

As técnicas empregadas para o processo de otimização da empresa, focam na gestão do estoque que, de acordo com Bowersox (2014), consiste em determinar quando e quanto pedir. O gerenciamento de estoques abrange inúmeros tipos de problemas. Supõe-se que as condições do nível de demanda e sua variabilidade, prazos de entrega e respectiva variabilidade, e os custos relacionados aos estoques sejam conhecidos, e que é necessário o melhor trabalho possível de controle de estoques, dadas essas condições (BALLOU, 2006; POZO, 2015).

Tais conceitos são ampliados pela indústria 4.0, que segundo a PwC - Price waterhouse Coopers (2016), digitalizar é integrar processos verticalmente em toda a organização, desde o desenvolvimento e a compra de produtos, até a fabricação, logística e serviços. Uma das técnicas que auxiliam tal conceito é a simulação de processos.

10th International Conference on Research in **ENGINEERING, SCIENCE & TECHNOLOGY**



Rome, Italy
21-23 February 2020

Date: 07-Augusr-2019

Number: 03-13983

Notification of Paper Acceptance

Dear Prof. Flávio Henrique Batista de Souza,

Congratulations! We are pleased to inform you that your paper entitled “Air Modal Perishable Cargo Dispatch: Case Study of a Sustainable Proposal Assisted by Process Modeling and Simulation” has been accepted after double blind peer review by the Scientific Committee of International Conference on Research in Engineering, Science and Technology(restconf)which will be held in Rome, Italy during February 21 – 23 February, 2020 as **Poster** presentation.

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Air Modal Perishable Cargo Dispatch: Case Study of a Sustainable Proposal Assisted by Process Modeling and Simulation

Lucas Magno Resende Coelho¹, Reubert Fernandes Rodrigues Barbosa¹, Ramon Cleiton

Teodoro Silva¹, Luiz Melk de Carvalho¹, Flávio Henrique Batista de Souza¹

¹ Centro Universitário de Belo Horizonte - UNIBH/ Instituto de Engenharia e Tecnologia

ABSTRACT

The importance of perishable transport is clearly observed in research to agile logistic techniques and fragile cargos. This case study evaluate a project that considers a sustainable option for cooling perishable fillers using Polyethylene Terephthalate bottles (PET bottles) cooling elements. The measurement was supported by modeling and simulation technologies based on stochastically timed Petri nets for strategic management of the material supply chain (boxes and PET bottles) for the air modal dispatch process. The optimization process of this straightforward method was submitted to more than 10500 dispatches of perishable cargo in a logistics operator from Minas Gerais (Brazil), and was considered the evaluation of the following parameters during this study: temperature variation, delivery time and compliance with customer requirements. As most prominent results, there is a dispatch methodology that yielded a monthly saving of more than R\$ 36,000 (Brazilian reais) and a tool, open-source, for supply chain simulation. The simulations were able to evaluate the supply of raw material for the process based on PET bottles for a horizon of approximately 2 years, allowing the forecast of unmet demands, and identify which shortages caused the process interruption.

Keywords: Perishable Cargos; Sustainable; Air Modal; Stochastically Timed Petri Nets; Supply Chain.

10th International Conference on Research in **ENGINEERING, SCIENCE & TECHNOLOGY**



Rome, Italy
21-23 February 2020

Date: 07-Augusr-2019

Number: 02-13982

Notification of Paper Acceptance

Dear Prof. Flávio Henrique Batista de Souza,

Congratulations! We are pleased to inform you that your paper entitled "Mobile Applications and Discrete Event Systems: Low Cost Technology to Assist Stock Management in an Orthopedic Clinic" has been accepted after double blind peer review by the Scientific Committee of International Conference on Research in Engineering, Science and Technology(restconf)which will be held in Rome, Italy during February 21 – 23 February, 2020 as **Poster** presentation.

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Mobile Applications and Discrete Event Systems: Low Cost Technology to Assist Stock Management in an Orthopedic Clinic

Daniela Trindade Batista¹, Thiago Augusto Santos Ferreira¹, Renata Duarte Mellim¹, Luiz Melk de Carvalho¹, Flávio Henrique Batista de Souza¹, Vladimir Alexei Rodrigues Rocha²

¹ Centro Universitário de Belo Horizonte - UNIBH/ Instituto de Engenharia e Tecnologia

² Universidade Federal de Minas Gerais – UFMG

ABSTRACT

This paper presents a case study of an inventory management in a medical orthopedic clinic in Belo Horizonte, a 3,000,000 inhabitants city from Brazil. The main objective is to help on the management of supplies to avoid a lack and/or an excess of resources, to eliminate additional costs to the company. The proposed method was based on three steps: firstly, an organizational study of the materials and people involved in the inventory process was made, based on the statistical analysis of material inputs and outputs; secondly, the requirements analysis was executed for the development of a mobile application, responsible for the consolidation and standardization of inventory data; then, a system based on Stochastic Petri Nets (SPN) was developed to simulate scenarios of material availability. As result, the statistical analysis of the scenario of a set of materials commonly used found a lack of inventory data standardization, which justifies the demand for an easy and accessible management tools. Thus, a mobile application for data collection and standardization was developed. The data consolidation is performed through cloud computing, in .csv format, making analysis available in software such as R®, Matlab® and Excel®. Such dataset was used as the reference for SPN transitions firing process. Through SPN it was simulated scenarios for material availability prediction. Several experiments were performed and they predicted the excess and lack of materials such as Xylocaine, Neocain and compresses. Savings of thousands of Brazilian reais were recorded, as well as prevention of stockouts.

Keywords: Health care; Mobile Application; Orthopedic Clinic; Stochastic Petri Nets; Stock Management.

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Professor Flávio Henrique Batista de Souza,

Foi tomada uma decisão sobre o artigo submetido à revista Revista Produção Online,
"Análise de Pontos de Aleatoriedade como Estratégia para Melhoria de Ótimos Locais em uma Heurística Construtiva".

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ANÁLISE DE PONTOS DE ALEATORIEDADE COMO ESTRATÉGIA PARA MELHORIA DE ÓTIMOS LOCAIS EM UMA HEURÍSTICA CONSTRUTIVA ANALYSIS OF RANDOM POINTS AS A STRATEGY FOR LOCAL OPTIMAL IMPROVEMENT IN A CONSTRUCTIVE HEURISTIC

Hugo Vinicius Freitas Losqui* E-mail: hugolosqui@gmail.com

*Centro Universitário de Belo Horizonte – UNIBH, Belo Horizonte, MG

Flávio Henrique Batista de Souza** E-mail: flabasouza@yahoo.com.br

**Universidade Federal de Minas Gerais – UFMG, Belo Horizonte, MG

Resumo: Esse artigo tem como objetivo fazer uma análise sobre o algoritmo NN*. Foi proposto um deslocamento no ponto de aleatoriedade de base por meio de duas propostas, a fim de obter uma otimização em relação ao algoritmo NN*. Após alteração, foram obtidos percentuais de ganhos na margem de até 24% sobre os valores da literatura.

Palavras-chave: Heurística. Problema do Caixeiro Viajante. Nearest Neighbour. Otimização.

Abstract: This article aims to make an analysis about the NN * algorithm. It was proposed a displacement at the point of base randomness by means of two proposals, in order to obtain an optimization with respect to the NN * algorithm. After the change, gains in the margin were obtained from 24% over what was already in the literature.

Keywords: Heuristic. Traveling Salesman Problem. Nearest Neighbor. Optimization

1 INTRODUÇÃO

Durante o experimento de Souza et al. (2017), foi apresentada uma heurística construtiva NN*, a qual faz uma variação do algoritmo vizinho mais próximo (NN – *Nearest Neighbour*), onde o segundo vizinho mais próximo é obtido com a interferência de um ponto de aleatoriedade. Tal algoritmo propõe (e obtém) melhorias nos valores obtidos do caminho ótimo em um processo de visitação, porém é possível que se encontre uma melhor resposta através do deslocamento do ponto de aleatoriedade?

¹ Pesquisa que apresenta uma parte dos estudos envolvidos na Tese de Doutorado de Flavio Henrique Batista de Souza e do trabalho de conclusão de curso de Hugo Vinicius Freitas Losqui.

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