RESOURCE ALLOCATION IN AN IRON ORE MINING PROCESS: A DISCRETE EVENTS SIMULATION AND SCENARIO ANALYSIS APPLICATION

Guilherme Freitas Coelho
Universidade Federal de Minas Gerais – Escola de Engenharia
Av. Antônio Carlos, 6627- Belo Horizonte - MG - 31270-901
coelhoxz@gmail.com

Pedro Henrique Vianna Moreira
Universidade Federal de Minas Gerais – Escola de Engenharia
Av. Antônio Carlos, 6627- Belo Horizonte - MG - 31270-901
pedrovianna90@gmail.com

André Cristiano Silva Melo
Universidade do Estado do Pará
Trav. Enéas Pinheiro, nº 2626 – Belém – PA - 66095-100
acsmelo@yahoo.com.br

RESUMO

Neste artigo, a Simulação de Eventos Discretos é apresentada como uma ferramenta de análise de cenários, ideal para resolver problemas de grande escala, onde toda tomada de decisão demanda grande investimento de capital e está ligada a incertezas que, se não levadas em consideração, podem aumentar custos e variabilidade de processo. Durante o estudo, o processo de extração de minério de ferro no complexo de Carajás, Brasil, foi analisado para identificar variáveis dependentes e independentes, possibilitando a proposição de bons cenários de alocação dos recursos utilizados no sistema. A metodologia consistiu em realizar um diagnóstico do sistema produtivo, avaliar a relação entre todos os processos envolvidos, construir um modelo de simulação a partir dos dados coletados e definição de cenários para medir o resultado das modificações no critério de alocação dos recursos.

PALAVARAS CHAVE. Cadeia de Suprimentos do Minério de Ferro, Simulação de Eventos Discretos, Análise de Cenários.

Área principal: SIM - Simulação

ABSTRACT

Herein the Discrete Event Simulation is presented as a scenario analysis tool, ideal for solving large real application problems, where every decision to be made demands great capital investment and is connected to uncertainties which, if not taken in consideration, may raise costs and process variability. During this study, the iron ore mining process at the Carajas mining complex, Brazil, was analyzed to point out its dependent and independent variables, allowing the proposition of the good resource allocation scenarios, regarding the equipment used within the system. The methodology consists on the production system diagnosis, relationship evaluation between all involved processes, the construction of a simulation model from the collected data and definition of scenarios to assess possible changes on the resource allocation criteria.

KEYWORDS. Iron ore supply chain. Discrete event simulation. Scenario analysis

Main area: SIM - Simulation

1. Introduction

The mining industry worldwide is of great relevance to society. It is a giant in terms of employment generation, financial transactions, among other parameters. Even though the extraction of minerals from the earth is one of the most primary activities of civilization, today, after the Industrial Revolutions, great expansions and intensification of the whole system occurred, and Brazil has a significant role in this new scenario.

Iron ore, the main raw material for steel production, was one of the drivers of technological and productive growth of the greatest countries. Worldwide, according to the British Geological Survey (BGS, 2012) and the United States Geological Survey (USGS, 2013), Brazil ranks third in iron ore production, standing only behind China and Australia.

Following the evolution of processes involved in the iron ore production, the related companies prompted innumerous researches for the optimization of its various stages: extraction, crushing, processing, rail and maritime transport. Research in this type of supply chain has already been conducted as in Beresford et al (2011) and Plambeck and Gibson (2010). Regarding supply chain modeling in general, there are studies as in Byrne and Heavey (2006) or in Jayant et al (2012).

The object of this study is the Carajas mining complex, north of Brazil, responsible according to Departamento Nacional de Produção Mineral (DNPM, 2012) for 90% of all the region's mineral exports in 2011. This research is to develop a model of discrete events simulation to evaluate resources allocation scenarios for the equipment involved (trucks and loaders) in each extraction point, in order to maximize their utilization, reduce Work-In-Process (WIP) and raise the total production.

2. Industry background

According to the BGS (2012) and USGS (2013), Brazil is the third largest producer of iron ore in the world, where production in 2011 was 373 million tons, with approximately 12.68% of the world's total, and its production in 2012 was estimated at 375 million tons. According to Instituto Brasileiro de Mineração (IBRAM, 2012), the country's main producers are: VALE (84.52%), SAMARCO (6.29%), CSN (5.45%), MMX (2.03%) and Usiminas (1.71%). Figure 1 shows the evolution of iron ore production by the main competitors, in millions of tons, corrected for iron content.

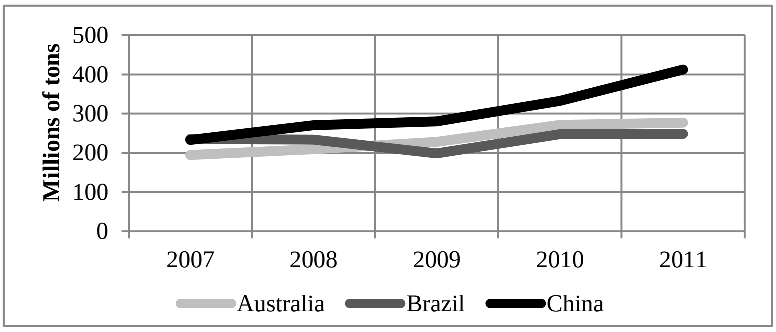

Figure 1 - Largest iron ore producers. Source: USGS (2013)

According to the USGS (2013), estimates point that China has been responsible in 2012 for 60% of the world's imports of iron ore and is currently the main driving force of growth and expansion of iron ore mining. IBRAM (2012) complements that it is expected that up to 2020 China will need to import at least 400 million tons per year. The main buyers of the Brazilian iron ore in 2012 were China (45.78%), Japan (9.71%), South Korea (4.97%), Netherlands (4.56%), Italy (4.09%), Oman (3.06%), Germany (2.95%) and Argentina (2.95%).

The Brazilian mining industry showed remarkable economic growth between the years 2003 and 2008, due to successive increases in metal commodities prices, in which the iron ore is included. In this period, the Brazilian production grew 92%, while global growth was 98%, even though the global financial crisis, which began in late 2008, had a major impact on the country's mineral production, decreasing its production from US$ 29 billion in 2008 to US$ 24 billion in 2009, according to Martins (2011).

Data presented by IBRAM (2012) shows a 30% increase in the value of the Brazilian mineral production from 2010 to 2012, representing a recovery since the economic downturn caused by the global crisis. However, it is estimated that in 2012 there was a slowdown in growth of about 3%. The report also points out that in 2012 there was a trade surplus of US$ 29 billion, demonstrating the mineral sector's relevance in the commercial balance. In addition to the same report, investments announced by mining companies have grown exponentially, so that for the period 2012-2016, announcements reported investments of US$ 75 billion. These values demonstrate the interest of mining companies and the sector's influence in the national economy. Figure 2 shows the projection of the evolution of investments in the sector.

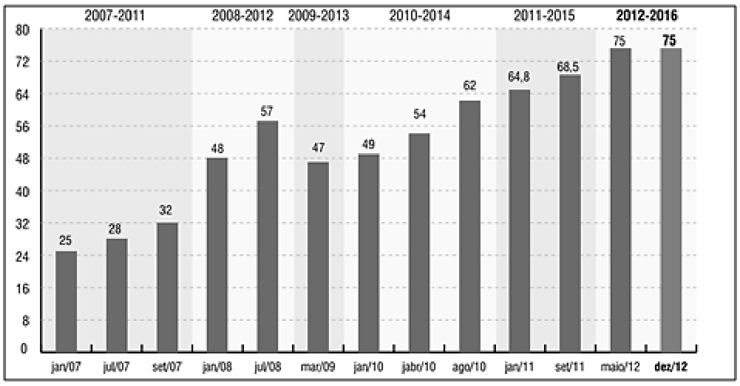

Figure 2 – Announced investments for the mining industry from 2012 to 2016, in billions of dollars. Source: IBRAM (2012).

3. Methodology and Simulation

The mining industry is this paper's object of study due to its importance, as shown above, to Brazilian and the world's economy, to its potential job and income generation, and to its growth perspective. Every company connected to this industry, which deals with commodities, must always seek efficiency improvement and, if possible, optimization of all its resources, e.g., people, equipment, materials, time, and many others.

Therefore, the main objective of this study was to determine based on resource utilization, WIP and the total production, the best scenario for the allocation of resources in an iron ore mining and transportation system. To achieve this goal, a discrete events simulation model was developed with ProModel 7, from ProModel Corporation.

To Harrell et al. (2012), simulation, in current terms, can be defined as an imitation of a dynamic system, using a computational model in order to evaluate and improve the performance of a system. Still according to the author, the use of simulation models provides a way to know whether a particular set of decisions is really the best set, avoiding the traditional, expensive and time-consuming techniques such as trial and error.

Some advantages of simulation use, according to Pegden (1995) and Harrell et al. (2012) are: a) lower cost and development time when compared to the changes in the real system; b) versatility to model any system; c) ease of understanding the obtained results; d) the high level of detailing available to model the complexities of real systems; e) control of simulation time, which can be compressed or expanded; and f) bottleneck identification.

On the other hand, Harrel et al. (2012) states that the use of simulation is valid only if the following criteria are true: a) an operational decision (logical and quantitative) is being made; b) the analyzed process is well defined and repetitive; c) activities and events are interdependent and variable; d) decision-making costs are greater than the costs of model development; e) testing costs in the real system are more expensive than model developing costs.

This paper followed the simulation methodology based on Banks et al. (2001), in which six main steps are used as guidelines. According to them, the process of simulation can be divided in objective definition, data collection and analysis, model building, verification and validation, output analysis and experimentation.

The objective of a simulation model is what defines its purpose and reason to exist. There are generally four groups, in which one can establish simulation goals: efficiency analysis, capacity/bottleneck analysis, configuration comparison, and optimization.

Process mapping and numerical data collection comprise the data collection and analysis step. Process mapping aims to define the processing sites, the resources responsible for the execution of tasks, the interrelationships of the various activities in the system and which entities will be processed at any given time. On the other hand, numerical data is the real system data which will be inputted in the model in the form of task times, distances travelled, item types, and others.

To Altiok and Melamed (2007), the actual construction of the model can only begin when the problem has been fully investigated and the necessary data has been collected. Then, the modeler must define the best structure of the simulation model to represent the real system without extreme simplifications.

Following the verification and validation steps, the modeler will verify whether the model is “sufficiently correct” for further use and for comparison with real system performance data. Altiok and Melamed (2007) state that a model, as a simplified representation of reality, will never precisely represent a real situation, therefore quality of the model is relative, rather than absolute. Some statistics tools such as the One-Sample Student’s T Test (Devore, 2012) or the Two-Sample Student’s T Test (Kleijnen, 1999) are often used when it is wanted to compare solely two alternative systems.

Scenario analysis is usually conducted to experiment certain conditions. To Brauers and Weber (1988, apud Markham and Palocsay, 2006), a scenario can be defined as the future state of an organization’s environment, considering possible developments in interdependent factors. In Markham and Palocsay (2006) MS Excel is presented as an useful what-if analysis tool and examples of break-even point simulation, queues and decision trees applications are given.

To the authors above, on the other hand, there are limitations in scenario analysis. To them, this analysis does not consider explicitly the probability of occurrence of different scenarios beyond those already established by the analyst. This problem may give too much weight to unlikely scenarios during the decision process.

In order to experiment with scenarios, the model and the status quo of the system must be compared. From this, several situations may be proposed, from the simplest (such as changing the service time in a queue system), or more complex (such as infrastructural changes on the company or changes in the economic environment in which it is situated). According to Montgomery and Runger (2009) and Devore (2012), when comparing more than two alternative systems, the Bonferroni approach to the Paired T Test may be used, adding a confidence level correction when simultaneously analyzing all scenarios proposed.

4. Industry Application

The object of this study is the iron ore extraction site located in the Carajas mining complex in northern Brazil. The exploration project started in 1980 and comprises ore mining, crushing, milling, rail transportation and ship loading at the Port of Itaqui, São Luís. The iron ore is by far the most exported mineral product by the State of Pará, where the mines are located, so that, according to the DNPM (2012), the state’s production in 2011 was in the order of 110 million tons, an amount that is increasing each year.

The mining complex consists of three mines here named as MINE A, MINE B and MINE C, from which iron ore at different concentrations, and waste material (minerals, eliminated during the process, with low or no commercial value) are both extracted. The waste material is kept in deposits reserved for future use. MINE A and MINE B are the richest by iron content, but the most productive is MINE C. To meet the market’s requirements, the ore from the mines must be blended due to their difference in iron content.

The operation of the mining complex runs 24 hours per day, 7 days a week, and is constantly monitored from an operating room. The operations work with three shifts, from 06:00 to 15:00, from 15:00 to 24:00, and from 24:00 to 06:00. The operation control is carried out via radio, cameras and GPS trackers, with the staff in control rooms and in the mines.

4.1. The process of iron ore mining

According to the company responsible for the mining complex's exploration, around 130 trucks (over 100 are 240 tons-trucks and more than 10 are 400 tons-trucks), around 20 bulldozers and 15 loaders, plus other auxiliary equipment are available to keep the mines in operating condition (excavation site cleaning, opening and drainage). Altogether, approximately 430 mining equipment are used. The exact amount of resources was changed due to data confidentiality.

As previously mentioned, during the mining process, iron ore and waste are obtained from the mines. Although the waste material is basically removed to allow the extraction of the iron ore, part of this material has some potential economic value to the company, so that it is transported to storage banks for possible further use. All mined ore undergoes a process of initial crushing by semi-mobile crushers (SMCs) and then transported by conveyor belts to milling stations that, unfortunately, will not be addressed in this work. For this study, it was considered that the mining process is done when the ores are unloaded inside the SMCs. Figure 3 best describes the basic conceptual model used in this paper.

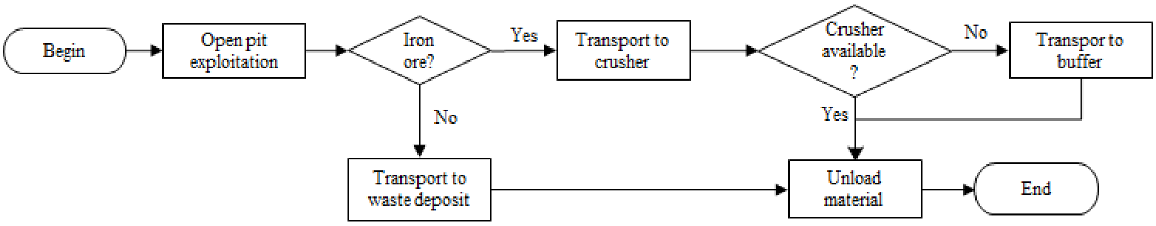

Figure 3 - Conceptual model of the ore extraction activity

Next to each SMC there is an electronic scale that reads the weight of the truck, assessing its load. Then, the iron ore is unloaded inside the SMC. On site, all routes (origin and destination), speed, type of cargo (iron ore or waste) and load weight are monitored. In an attempt to avoid trucks from staying still for a long time in the SMC's queue, there is an instruction to unload the material on a buffer next to the SMC's. A truck will unload on the buffer only when there is already one truck waiting in queue for the SMC.

MINE A is the oldest and once was the largest open mine in the world. However, currently a lot of waste is extracted from it. Recently, new studies have been conducted and it was found that there is still iron ore in deeper areas. MINE B is relatively new and is being expanded to obtain another extraction point. Waste is removed to correct soil or to reach the ore. Similarly to MINE A, MINE B has high quality ore as compared to MINE C. MINE C is currently the largest mine in Carajas producing iron ore, however its ore has lower iron content compared to MINE A and MINE B. While MINE A and MINE B have iron content between 66 and 67%, MINE C's is between 62 and 63%. Thus, its ore goes through a process called blending to achieve the minimum level of 64%, required by the market.

There are five crushers, one stationary (CRUS) and four semi-mobile (SMC1, SMC2, SMC3 and SMC4). The ore extracted from MINE A goes through the SMC2 and CRUS crushers. The ore mined at MINE B is sent to the SMC1 and SMC4 crushers. Finally, SMC3 serves the production of MINE C, however CRUS, SMC2 and SMC4 assist in the processing as well. It is important to mention that every crusher, except for CRUS, has two iron ore receptors. In other words, two trucks can unload at the same time.

Figure 4 is a satellite picture taken from the mining complex obtained by Google Maps in 2013. The red markings represent the three mines (from left to right: MINE B, MINE A, MINE C), the yellow dashed markings represent the waste storage banks, the marking in white represent the mill, and the black arrows point the position of the crushers (from left to right:

SMC4, SMC1, SMC2, CRUS, and SMC3).

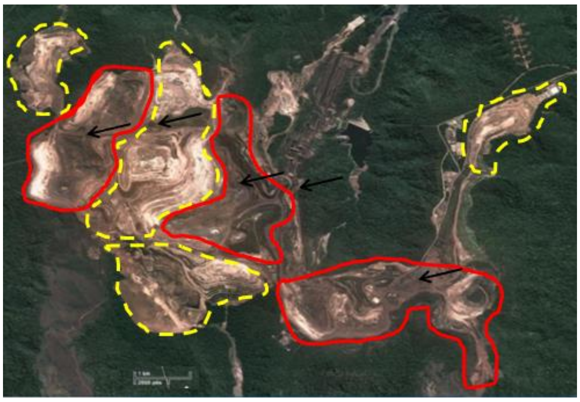

Figure 4 - Satellite picture of the Carajas mining complex (scale: 1 km).

4.2. Data collection

The data selected as the input to the model were the truck's load (in tons), the loading time, maneuver time and unloading time, all referring to the off-road trucks. The spreadsheet provided by the company, from which were obtained relevant data, was built with the electronic records of trucks, where each truck was represented by a row and the fields in each column represented the collected information.

The spreadsheet contained more than eight hundred thousand lines (the maximum allowed by a given Excel 2007 spreadsheet is 1,048,576) of records dating from January 1 to August 31. It is recorded to each truck a variety of fields such as date, departure time from the mine, truck code, origin, destination, among others.

Knowing that the spreadsheet works recording information for the trucks, it became clear that there was a deficiency of data for SMC1, which is supplied solely by loaders. There are data about trucks unloading on SMC1's buffer, but no information about the loaders, which are responsible for the crusher's supply with the buffer's iron ore.

Due to the vast amount of data, it was possible to carry out various filters to obtain the required model input. For load weight, loading and unloading time, for obvious reasons, it was made a separation between 400 ton and 240 ton trucks. For loading times it was filtered: 240 ton trucks loaded by bulldozers or loaders and 400 ton trucks loaded by bulldozers or loaders. Finally, for the maneuver time, the times were filtered for each truck (240 and 400) and destination, be it a mine, crusher/buffer or waste storage bank.

After obtaining the filtered data, it was noted the existence of severe outliers. Performing a boxplot graph analysis with Minitab 16, the adopted course of action was to select 80% of the middle data in the distribution, that is, eliminating the 10% smaller and 10% larger observations.

Even after the Boxplot treatment there was still a considerable amount of data for each group, therefore a sample of 200 observations was selected via Excel, for each filter. This was necessary because when there is gain in the number of observations, but not in variability, the standard deviations become too low, forming short confidence intervals that reject the H_0 curve fitting hypotheses. The samples were then compared to probability distributions. Results pointed Erlang and Gamma distributions for the most part, and the results were applied to the model.

4.3. The simulation model

From the information presented above, the simulation model was built using the simulation software ProModel 7. The software was chosen, among other reasons, because it is available with relative ease at major universities and because of the affinity that the authors have in its modeling interface.

The proposed model is characterized by being dynamic, stochastic and of discrete events. As for the goal, different configurations were compared, therefore characterizing a scenario analysis. The structural and logical elements of the model are presented in the next section but all real data were slightly altered due to information confidentiality

In the model, 46 locations were placed to represent the mine's excavation sites, waste storage banks, crushers and crushers' buffers and queues. Two entities were used to represent the iron ore and the waste. A path network was outlined from the mine chart and used as paths and routes to off-road trucks'. Finally, 17 resources, being 2 to represent 240-ton and 400-ton trucks, 1 to represent the loaders and 14 to represent the bulldozers, were built in the model.

Then, the logical elements built were the attributes and global variables. The attributes are those that identify the type of resource being used, the amount of load, type of material, the origin and destination of the cargo and the departure time from their origin. The global variables include the control of the crusher's queue size, the amount of ore in the storage banks and the amount of ore being processed in each crusher.

4.4. Simulation time, number of replications and warm-up time

The simulation ran for 168 hours (7 days) because it was still possible to generate and extract important result to the analysis after this not so long simulation time. Also, running the model for one week minimizes the non-inclusion of maintenance data in the simulation, which was not provided by the company. It is important to note here that due to the size and complexity of the model, each day's simulation time grows exponentially.

After running the simulation for 5 preliminary replications, the correct number of replications necessary for the model was calculated with the sample size equation with specified error to the average and known variance (MONTGOMERY AND RUNGER, 2006).

The number of replications was based on the variability of the utilization level for the 240-ton trucks, which was verified to be the response variable that varied the most. The minimum replications number found was 9, henceforth it will be the replication number carried on throughout the paper. Table 1 shows the calculations for the minimum replications number.

Replications	First try (5 replications)	Second try (9 replications)
1	31.15	29.31
2	27.23	28.75
3	31.46	27.94
4	33.44	27.53
5	30.32	27.38
6		27.36
7		28.19
8		29.94
9		27.72
Standard Deviation	2.26	0.91
Error (5%)	1.54	1.41
n'	8.33	1.61

Table 1 - Number of replications calculation.

Lastly, the warm-up time was calculated. The warm-up time is the period of time necessary so the model can reach its steady state. According to Taylor (2010), it is when the system is free from the influences of its initial conditions. Still according to the author, some methods to find the warm-up time are: the Welch's method, the Fishman's method, the Marginal Standard Error Rule, the Conway's rule, among others. The method chosen to identify the warm-up time was Welch's method and the state variable used was the number of free units of all off-road trucks. Figure 5 presents Welch's method's plots for the moving average window of 5, 10 and 15 degrees along with the observations.

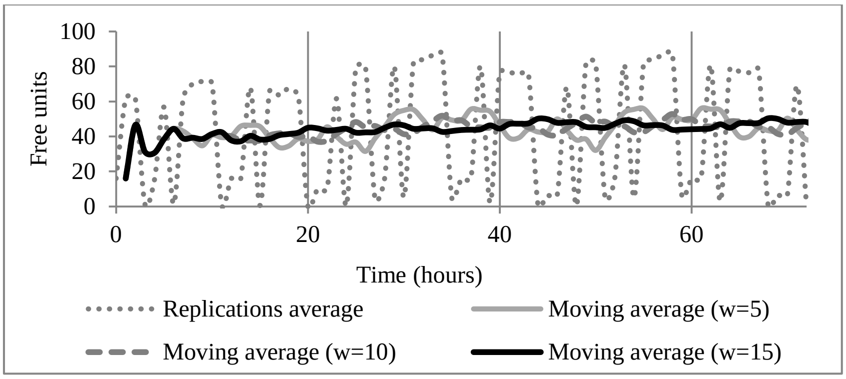

Figure 5 - Moving averages plots of the Welch's method for the first 72h

Graphically, the moving average with w=15 shows a smoother outline. It is also noticed that the state of the system becomes stationary while between 20 and 30, more specifically between the moments 23 and 25 hours. The transition point was set, then, as 24 hours.

4.5. Verification and validation

To verify the model, some of ProModel's own tools were used, such as the Trace Step and Trace Continous. These tools allow the monitoring of the simulation step by step, therefore at every occurrence of an event, the tools record and show the origin of the entity, where it was routed to and what resource was transporting it.

Another used tool was the DISPLAY statement. With this instruction it was possible to follow the occurrence of certain blocks of code, mainly in the conditional statements IF THEN.

Finally, the resources' displacement was analyzed through the model animation in order to understand if it was working appropriately. With the animation it was possible to see that the trucks and loaders were moving in an evenly distributed fashion among all the mines and crushers without overcrowding at any specific point.

Thus, the model was considered adequate and properly constructed. In other words, the logic used and all the structural elements are working properly.

To validate the model, the iron ore and waste material routing information were used. With ProModel, an external file was generated, that recorded specific information, through the use of attributes: a number corresponding to each point of origin and destination in the network. With this system, tables were set up with the percentage frequency that the resources come from one specific origin x and move to a specific destination y in each of the nine replications of the model.

The routing percentages generated with the model were compared with the percentages of actual weekly routes averages (Table 2). Thus, the One Sample Student's T Test was applied in order to check the correspondence between the average percentage of the model and the real system. Confidence intervals were built and the real system percentages were tested to see if they would fall within the range. All averages were verified to fall within the confidence intervals from Table 3 for iron ore and Table 4 for waste.

Material	Origins	Destinations				
		CRUS	SMC1	SMC2	SMC3	SMC4
Iron Ore	Mine A	22.23%	*	77.77%	*	*
	Mine B	*	10.92%	*	*	89.08%
	Mine C	41.86%	*	*	58.14%	*
		West Waste Storage Bank 2	West Waste Storage Bank	South Waste Storage Bank	Mine C Waste Storage Bank	North Waste Storage Bank
Waste	Mine A	39.44%	9.52%	51.04%	*	*
	Mine B	100.00%	*	*	*	*
	Mine C	*	*	9.72%	43.93%	46.35%

Table 2 - Real system data for weekly routing percentages

Origin	Boundaries	CRUS	SMC1	SMC2	SMC3	SMC4
Mine A	Upper	23.00%	*	78.34%	*	*
	Lower	21.66%	*	77.00%	*	*
Mine B	Upper	*	10.92%	*	*	89.83%
	Lower	*	10.17%	*	*	89.08%
Mine C	Upper	41.86%	*	*	59.94%	*
	Lower	40.06%	*	*	58.14%	*

Table 3 - Confidence intervals for the routings in the model transporting iron ore.

Origin	Boundaries	West Waste Storage Bank 2	West Waste Storage Bank	South Waste Storage Bank	Mine C Waste Storage Bank	North Waste Storage Bank
Mine A	Upper	39.77%	9.97%	51.77%	*	*
	Lower	38.63%	9.34%	50.53%	*	*
Mine B	Upper	100.00%	*	*	*	*
	Lower	100.00%	*	*	*	*
Mine C	Upper	*	*	10.46%	44.98%	46.42%
	Lower	*	*	9.54%	43.41%	45.18%

Table 4 - Confidence intervals for the routings in the model transporting iron ore with a confidence level of 96.2%.

4.6. Scenario analysis

Since the simulation model has been properly verified and validated in previous sections, the analysis proceeds to the scenarios designed to ascertain whether it is possible to obtain a better allocation option for the resources used in the Carajas mining complex.

The number of possible scenarios is limited, as described in Section 3, to the modeler's judgment. Thus, four scenarios considered most appropriate to the reality of the company were designed, in addition to the Base Scenario (validated model), and are described below:

- Scenario 1: No sharing of 240-ton trucks and loader between mines;
- Scenario 2: Sharing of 240-ton trucks and loaders by Mines A and B;
- Scenario 3: Sharing of 240-ton trucks and loaders by Mines A and C;
- Scenario 4: Sharing of 240-ton trucks and loaders by Mines B and C.

The amount of trucks and loaders was equally divided between mines. In other words, approximately 35 240-ton trucks and 5 loaders were allocated at Mines A, B and C. Thus, in the scenarios where there is sharing of resources, the mines have available the sum of resources allocated to each mine.

The same amount of resources was used in all scenarios to provide a better comparison between scenarios, so that the response variables would depend only on the differences in the allocation of these resources and not on the amount of resources used in each experiment.

The quantity of bulldozers was maintained the same in all scenarios as in the Base Scenario. Since this resource naturally isn't easily displaced, it will not be shared between mines.

To compare the scenarios, three response variables were chosen: the level of resource utilization, the average level in the crusher's buffers and weekly total production. Thus, it was sought to evaluate the scenarios not only by a possible improvement in resource utilization, but also in maintaining the level of production and inventory or raising total production and reducing inventory. For this evaluation 20 replications of the model were used in each scenario, thus obtaining larger samples that will be compared by the Bonferroni approach to the Paired T test.

With the assumption that the data followed a normal distribution, the Paired T Confidence Intervals were constructed primarily to the utilization level of 240-ton and 400-ton trucks, loaders and bulldozers, with a confidence level, based on the Bonferroni approach, per interval of 99.5% and a simultaneous confidence level of 95%. Tables Table **5**-Table **8** present the results.

Confidence Intervals	Lower	Upper	Results
(Base-1)	-6.1	-4.6	1> Base
(Base-2)	-5.7	-4.2	2> Base
(Base-3)	-9.2	-7.6	3> Base
(Base-4)	-6.7	-5.4	4> Base
(1-2)	-0.5	1.2	1=2
(1-3)	-4.2	-1.9	3>1
(1-4)	-1.5	0.1	1=4
(2-3)	-4.3	-2.5	3>2
(2-4)	-2.0	-0.2	4>2
(3-4)	1.4	3.3	3>4

Table 5 - Paired T Confidence Intervals for 240-ton trucks' utilization level scenario comparison

Confidence Intervals	Lower	Upper	Results
(Base-1)	-24.0	-21.6	1> Base
(Base-2)	-21.6	-19.8	2> Base
(Base-3)	-21.5	-18.3	3> Base
(Base-4)	-21.2	-19.5	4> Base
(1-2)	0.8	3.4	1>2
(1-3)	0.8	5.0	1>3
(1-4)	1.3	3.6	1>4
(2-3)	-0.6	2.2	2=3
(2-4)	-0.3	1.0	2=4
(3-4)	-2.2	1.4	3=4

Table 6 - Paired T Confidence Intervals for 400-ton trucks' utilization level scenario comparison

Confidence Intervals	Lower	Upper	Results
(Base-1)	-2.1	-1.8	1> Base
(Base-2)	-1.4	-1.0	2> Base
(Base-3)	-1.5	-1.3	3> Base
(Base-4)	-1.8	-1.6	4> Base
(1-2)	0.6	1.0	1>2
(1-3)	0.4	0.6	1>3
(1-4)	0.2	0.3	1>4
(2-3)	-0.5	-0.1	3>2
(2-4)	-0.7	-0.3	4>2
(3-4)	-0.3	-0.2	4>3

Table 7 - Paired T Confidence Intervals for loaders' utilization level scenario comparison

Confidence Intervals	Lower	Upper	Results
(Base-1)	-3.2	-3.0	1> Base
(Base-2)	-3.4	-3.3	2> Base
(Base-3)	-3.8	-3.6	3> Base
(Base-4)	-3.6	-3.4	4> Base
(1-2)	-0.4	-0.1	2>1
(1-3)	-0.8	-0.5	3>1
(1-4)	-0.6	-0.3	4>1
(2-3)	-0.5	-0.2	3>2
(2-4)	-0.3	-0.1	4>2
(3-4)	0.024	0.3	3>4

Table 8 - Paired T Confidence Intervals for bulldozers' utilization level scenario comparison

From the tables above it is possible to realize a satisfactory improvement in resource utilization, especially for off-road trucks. Compared to all alternatives, the Base Scenario has the lowest utilization level than any other. The highest levels of utilization happen in Scenarios 1 and 3. However with this information is not yet possible to define the best possible system. Therefore crusher's buffer size and total weekly production were evaluated by the same methodology. Tables Table 9 and Table 10 show the results.

Confidence Intervals	Lower	Upper	Results
(Base-1)	16109.7	25556.3	Base>1
(Base-2)	18630.5	31695.7	Base>2
(Base-3)	17831.4	28658.8	Base>3
(Base-4)	9503.1	21937.6	Base>4
(1-2)	-175.7	8836.0	1=2
(1-3)	-1161.2	5985.4	1=3
(1-4)	-9558.4	-666.9	4>1
(2-3)	-5810.7	1974.7	2=3
(2-4)	-12506.8	-6378.7	4>2
(3-4)	-11769.4	-3280.1	4>3

Table 9 - Paired T Confidence Intervals for average buffer size scenario comparison

Confidence Intervals	Lower	Upper	Results
(Base-1)	43298.4	82228.9	Base>1
(Base-2)	72393.1	111055.4	Base>2
(Base-3)	62168.3	112161.0	Base>3
(Base-4)	12654.8	53643.1	Base>4
(1-2)	4321.2	53600.0	1>2
(1-3)	2586.8	46215.2	1>3
(1-4)	-50584.6	-8644.8	4>1
(2-3)	-33973.8	24854.6	2=3
(2-4)	-78730.2	-38420.4	4>2
(3-4)	-82952.9	-25078.5	4>3

Table 10 - Paired T Confidence Intervals for total weekly production scenario comparison

The tests in Tables Table 9 and Table 10 show that even with the increased percentage utilization of resources, the total production was not improved at all. According to the tests, the Base Scenario has significantly higher weekly production, although generating more WIP in the process.

Moreover, Scenario 3 emerged as the leanest alternative to the system. The scenario brought a reduction of approximately 25% to the WIP level in comparison to the Base Scenario, but with a cost of 5% in total weekly production. It was found that the significant loss of production occurred at the SMC4.

Thus, the results obtained with the simulation model and the scenario analysis methodology indicate that the current system generates the best results regarding the level of production, in-process inventory level and resources utilization level. The methods used here confirm the current system used by the company as the best choice in the allocation of resources in extraction and transportation of iron ore in the mining complex in Carajas.

It is necessary, however, to emphasize that there was not any attempt to optimize the number of resources used in each mine or the amount of resources shared between mines. Thus, it is possible that with the use of optimization techniques some of the scenarios would become better than the Scenario-Base, based on the criteria established in this study.

5. Conclusion

This study aimed to develop a simulation model that corresponds to the process of extraction and transportation of iron ore in the Carajas mining complex, through the methods of modeling, simulation and statistical treatments. First, a general diagnosis of the production system was done, and then a simulation model was designed, representing the real system. Scenarios were constructed to evaluate possible improvement proposals, in which the Base Scenario was verified to be the best when compared to the others, according to the chosen criteria.

On the other hand, Scenario 3 can be considered as a potential alternative, therefore it is important to assess whether it is possible to obtain a better system performance with the development of a Simulation-Optimization study. Thus, as the model has already been built, an optimization algorithm can be used with relative ease.

After the study's completion, a certain level of system unbalancing was noticed, which causes severe in-process inventory formation at certain places. Hence, a proposed future study is to evaluate the system balance through a careful sensitivity analysis, in order to construct a more efficient alternative.

References

Altiok, T. and Melamed, B, Simulation Modeling and Analysis with Arena, Elsevier, San Diego, 2007.
Banks, J, Carson, J. S. II, Nelson, B. L. and Nicol, D. M., Discrete-Event System Simulation, 3rd ed, Prentice Hall, 2001.
Beresford, A et al. (2011), Multimodal supply chains: iron ore from Australia to China, *Supply Chain Management: An International Journal*, 16**(**1), 32-42.
British Geological Survey–BGS, World Mineral Production 2006-10, British Geological Survey Nottingham, 2012.
Byrne, P. J. and Heavey, C. (2006), Simulation model of a vertically integrated supply chain: a case study, *International Journal of Industrial Engineering*, 13(2), 126-135.
Departamento Nacional de Produção Mineral-DNPM, Economia Mineral do Estado do Pará – 2011, DNPM, Belém, 2012.
Devore, J. L. Probability & Statistics for Engineering and the Sciences, 8th ed, Cengage Learning, Boston, 2012.
Harrel, C et al. Simulation using ProModel, 3rd ed, McGraw-Hill, New York, 2012
Instituto Brasileiro de Mineração-IBRAM. Informações e Análises da Economia Mineral Brasileira, 7th ed, IBRAM, Brasília, 2012.
Jayant, A et al. (2012), Simulation modeling of outbound logistics of supply chain: a case study of telecom company, *International Journal of Industrial Engineering*, 19(2).
Kleijnen, J. P. C. (1999), Validation of Models: Statistical Techniques and Data Availability, *Winter Simulation Conference*, 1, 647-654.
Markham, I. S. and Palocsay, S. W. (2006), Scenario Analysis in Spreadsheets with Excel's Scenario Tool, *INFORMS Transactions on Education*, 2, 23-31.
Martins, J et al. (2011), Setor mineral rumo a um novo marco legal, Série cadernos de altos estudos, 8, Câmara dos Deputados, Edições Câmara, Brasília.
Montgomery, D. C. and Runger, G. C. Applied statistics and probability for engineers, 4th ed, John Wiley & Sons, New York, 2006
Pegden, C. D. Introduction to Simulation using SIMAN, 2nd ed, McGraw-Hill, New York, 1995.
Plambeck, L and Gibson, P. (2010), Application of agency theory to collaborative supply chains, *Oxford Business & Economics Conference (OBEC)*, 2-12.
Taylor, S. L. Analyzing Methods of Mitigating Initialization Bias in Transportation Simulation Models, 109 p, Masters of Science Thesis in School of Civil and Environmental Engineering, Georgia Institute of Technology, 2010.
United States Geological Survey-USGS. Mineral Commodity Summaries 2013, United States Geological Survey, Reston, 2013.