World Academy of Science, Engineering and Technology
International Journal of Geological and Environmental Engineering
Vol:14, No:11, 2020

The Benefits of End-To-End Integrated Planning from the Mine to Client Supply for Minimizing Penalties

G. Martino, F. Silva, E. Marchal

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf

***Abstract*—**The control over delivered iron ore blend characteristics is one of the most important aspects of the mining business. The iron ore price is a function of its composition, which is the outcome of the beneficiation process. So, end-to-end integrated planning of mine operations can reduce risks of penalties on the iron ore price. In a standard iron mining company, the production chain is composed of mining, ore beneficiation, and client supply. When mine planning and client supply decisions are made uncoordinated, the beneficiation plant struggles to deliver the best blend possible. Technological improvements in several fields allowed bridging the gap between departments and boosting integrated decision-making processes. Clusterization and classification algorithms over historical production data generate reasonable previsions for quality and volume of iron ore produced for each pile of run-of-mine (ROM) processed. Mathematical modeling can use those deterministic relations to propose iron ore blends that better-fit specifications within a delivery schedule. Additionally, a model capable of representing the whole production chain can clearly compare the overall impact of different decisions in the process. This study shows how flexibilization combined with a planning optimization model between the mine and the ore beneficiation processes can reduce risks of out of specification deliveries. The model capabilities are illustrated on a hypothetical iron ore mine with magnetic separation process. Finally, this study shows ways of cost reduction or profit increase by optimizing process indicators across the production chain and integrating the different plannings with the sales decisions.

***Keywords*—**Clusterization and classification algorithms, integrated planning, optimization, mathematical modeling, penalty minimization.

I. Introduction

THE iron ore global trade market is characterized by a mix of long-term contracts and spot sales, following pricing criteria that impose penalties and bonuses based on the ore's chemical composition. Due to those characteristics, it is very common to find iron mining companies that value a stable production pace and ore composition.

The first step in the iron ore production process is the extraction of minerals from the mine. This ROM is extracted simultaneously in several spots of the site, following the mine planning schedule, and it usually contains low iron content and high impurity proportion. Those materials are blended and sent to the beneficiation plant to increase its value.

G. M. is with Cassotis Consulting 220-11S R. da Paisagem, Nova Lima, MG 34006059, Brazil (phone: +55 31 98837-7817; e-mail: gma@cassotis.com).

F. S. is with Cassotis Consulting 220-11S R. da Paisagem, Nova Lima, MG 34006059, Brazil (phone: +55 31 98818-9857; e-mail: fsi@cassotis.com).

E. M. is with Cassotis Consulting 220-11S R. da Paisagem, Nova Lima, MG 34006059, Brazil (phone: +55 31 99120-8395; e-mail: ema@cassotis.com).

Beneficiation plants are mainly operated using standard parameterization independently of the ROM's characteristics being processed, or iron ore chemical targets. Some operational adjustments like grinding velocity, magnetic field intensity, or floating agent blend could be made to control some process indicators. However, adapting equipment is not a common practice because coordinating adjustments with shift changes and ROM's input queue requires close attention by management, extra costs, and especially, a change of mindset.

In addition to processing the ore, it is also the plant's responsibility to guarantee the quality and volume of the product shipped to the client. An iron ore beneficiation plant usually produces multiple qualities, in different volumes and chemical characteristics, within its process chain. These qualities are then blended to a final product and shipped to the market, hopefully within the specifications stated by the contract.

The production pace and quality of the produced iron ore in the beneficiation plant are highly dependent on the input ROM characteristics. Applying machine learning techniques to production data can generate key insights to shape mine and beneficiation plant's tactical and operational strategies. Indeed, knowing the impacts of the ROM blend into the downstream production in advance allows for predictive rather than reactive decision making.

This study shows the techno-economic impacts of a multi-period integrated mine plant model using as leverages:

- the best way of consuming the ROM piles,
- adjustments of some process variables,
- stock level management,
- the best blending strategy to ensure the quality of the delivered products,
- the contracts selection based on their profit contribution.

This paper describes the usual operation of an integrated mine plant in Section ‘Contextualization’. Section ‘Integrated planning’ is dedicated to detailing the methodology proposed to improve the plant's decision-making process. Section ‘Optimal Planning’ shows the results of applying the methods from the last section for the context of the mine. Section ‘Additional Analyses’ expand the benefits of the integrated model. Section ‘Improvements’ proposes ideas to include in the modeling of integrated mining plants. Section ‘Conclusion’ summarizes the findings of this study.

II. Contextualization

This study uses a generic iron mine with a beneficiation plant equipped with magnetic separators. The plant generates

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf

three types of iron ores sub-products, named here as Nonmagnetic (NMAG), Magnetic (MAG), and Concentrate (CON). Both NMAG and MAG are generated in the earlier stages of the beneficiation process; while CON is produced downstream by processing the fine ores of upstream (the plant's mass flow is available in Appendix A). They can be sold separately or blended in different proportions to meet different qualities specifications. The production rate and composition of each sub-product vary in function of the lithology of ROM being fed to the plant (Table I).

TABLE I
SUB-PRODUCT PRODUCTION RATE AND COMPOSITION RANGE

Sub-product	Range	Rate (t/h)	Fe (%)	SiO_2 (%)
MAG	Max	135.18	64.5	6
	Min	107.64	62.5	8.5
NMAG	Max	141.28	60	7
	Min	90.12	57	10.5
CON	Max	192.5	66.5	3.5
	Min	179	65	5.5

Let's assume that the ROM consumption is not driven by any process or delivery coordinated decision-making strategy but by other aspects, like pile formation order, or logistics considerations. It could also be that all the ROM is blended in a unique homogenization pile. In any case, we will arbitrarily consider that the weekly consumption of ROM follows the same distribution as the monthly availability of each lithology. The operational planning is divided into 21 sequential time slots, where the first 12 represent weeks (W1 to W12) and the last 9 represent months (M4 to M12). Each week has 28 shifts of 6 hours and one of those is exclusive for maintenance.

The plant supplies three clients, classified as High Quality (HQ), Medium Quality (MQ), and Low Quality (LQ), with custom products to be delivered in specific amounts every month (Table II). The sub-products stocked at the train terminal are blended and loaded to satisfy both the chemical specifications and period demand mass. The delivery of a product out of specification is avoided at all times.

TABLE II
CLIENT'S PRODUCT SPECIFICATION

Client	Min/Max demand (kt/month)	Min Fe (%)	Max SiO_2 (%)	Min/Max load (kt/train)
MQ	37.8 / 46.8	62.5	6	13.5 / 15
LQ	50.5 / 61.6	59.5	8.8	13.5 / 15
HQ	151.2 / 184.8	63.5	5.5	14 / 15

Given those guidelines and the availability of ROM described in Table III, the plant can schedule its trains to better supply its clients. However, even with flexibility in the delivery, some trains are loaded with products out of specification, as shown in Fig. 1. This behavior is very common as most mines operate near its blending capabilities when balancing the volume and quality of the clients' demands. In this specific case, at month 1, one out of the three trains delivered to client MQ (2.8% of overall supply) has exceeded the SiO_2 content by 0.22%. Also, at month 3, four out of the eleven trains delivered to HQ client (3% of overall supply) have exceeded the SiO_2 content by 0.31%.

TABLE III
ROM'S AVAILABILITY

Month	Availability (kt)
1	564
2	571
3	572
4 to 12	560

Fig. 1 Train delivery schedule and classification (white = no delivery, grey = delivered within specification, black = delivered out of specification)

The revenue of the mining company depends on the price of the iron ore product delivered to the client at the period (Table IV). Prices are based on the Value-in-use differentials assessments made by [6], that consider bonuses and penalties in function of iron and impurities content (SiO_2, Al_2O_3, and P). Notice that in this study we will be focusing on Fe and SiO_2 content. Nevertheless, the methodology can be applied to any traced compound.

TABLE IV
EXPECTED IRON ORE PRICE PER WMT[a]

Month	MQ (R$/WMT)	LQ (R$/WMT)	HQ (R$/WMT)
Month 1	258.37	200.37	384.05
Month 2	279.88	211.85	406.5
Month 3	318.73	225.48	432.18
Months 4-6	320.31	231.86	444.39
Months 7-9	320.31	231.86	444.39
Months 10-12	320.31	231.86	444.39

[a]WMT = wet metric ton.

III. INTEGRATED PLANNING

There are several alternatives to boost the decision-making process over the end-to-end operations of a mining plant. This section is dedicated to describing the combination of techniques applied in this study: ROM clustering and classification, and mathematical programming.

A. ROM Clustering and Classification

This study proposes a combination of clustering and logistic classification techniques in order to predict the results of the beneficiation process. The clustering is first used to define groups of ROMs that yield similar composition for a given product. Then a logistic regression model is used to predict the group of a given ROM for each type of product based on its lithology.

Cluster analysis is a set of techniques to derive a partition in a set of elements so that elements in the same group are similar, and elements in different groups are heterogeneous with respect to a given set of variables. The k-means technique used in this study was first introduced in [1] and has been widely used. The procedure aims to find, in an iterative manner, k centroids representing the mean values of each

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf

cluster, and assign each element to the cluster with the nearest centroid. The notion of distance is based on the Euclidean distance in the feature space. Some examples of successfully applying this technique in geochemistry are presented in [2] and [3].

In this study, we apply the k-means technique to group piles of ROM based on the beneficiation product total Fe and SiO_2 composition and the production pace. The data are normalized before applying the algorithm that uses one hundred random initializations to avoid local minima.

For predicting the group of a given ROM for a given product a logistic regression based on the lithology proportion is used. Logistic regression is a commonly used classification technique for both binary and multinomial classification. In the binary case the following regression equation is fitted in the training process:

$$P = \frac{1}{1+e^{-(b_0+\sum_i LIT_i \times b_i)}} \tag{1}$$

where P = Value representing the probability that the pile belongs to one of the two classes. LIT_i = Value of the lithology for the pile i. b_i = Value of the weight related to the lithology i. b_0 = Bias.

Classifying an element can be done by choosing the group with the highest probability. The logistics regression technique as we use in this study was developed throughout many years in incremental steps. A detailed history can be found in [4].

The application of those techniques over the mine's orebody has produced three classifications for the mine's ROM (A, B, and C) found in Table V. This allows for the pit planning and beneficiation plant to coordinate the ROM pile formation and consumption, estimating in advance the pace and qualities generated in the iron ore treatment process.

TABLE V
SUB-PRODUCT PRODUCTION RATE AND COMPOSITION PER ROM

Sub-product	ROM	Rate (t/h)	Fe (%)	SiO_2 (%)
MAG	A	132.45	64.5	6
	B	135.18	64	6.5
	C	107.64	62.5	8.5
NMAG	A	141.28	60	7
	B	90.12	58	9.5
	C	115.92	57	10.5
CON	A	192.5	65.5	4.5
	B	181	66.5	3.5
	C	179	65	5.5

B. Mathematical Programming

Different methods and techniques exist in the field of Operations Research to enable problem-solving considering their peculiarities. For the scope of this study, it was selected to use mathematical programming. It can be defined as a method whose goal is to minimize or maximize a particular objective function, seeking an optimal solution, changing the value of defined variables within a viable set that respects a group of constraints.

Mathematical programming has been widely used to describe and solve production planning problems. Reference [5] defines production planning as the planning of the resources required to perform transformation steps, in order to satisfy the customers most efficiently or economically. In other words, the production decisions are typically taken by looking at the best trade-off between financial objectives and customer service or satisfaction objectives. In production planning and operations management, the financial objectives are usually represented by production costs – for machines, materials, manpower, startup costs, overhead costs, etc. – and inventory costs – opportunity costs of the capital tied up in the stocks, insurances, etc. –. Customer service objectives are represented by the ability to deliver the right product, in ordered quantity, at the promised date and place. Using mathematical programming, all these elements can be modeled with variables, parameters, constraints and objectives functions, allowing planners to optimize their decisions.

Although many models can be created to represent the decision-making process of the mine, this study has chosen to use a deterministic model with linear constraints (e.g.: mass balances and operating times) combined with variables that assume real (e.g., sub-product generation per period) or integer values (e.g., number of trains delivered to client). Those characteristics allow a solver to apply techniques for finding solutions, such as the Branch-and-Bound method.

The objective function is defined as the maximization of the profit subtracted by a penalty. The penalty is large enough to outweigh the profit in absolute values when there are deliveries out of specification.

IV. OPTIMAL PLANNING

Optimal planning is found by solving the model, considering the classification of ROM and the other parameters described in the Contextualization section. This solution has found an operating planning that ensures all deliveries within clients' specifications, as shown in Fig. 2. Furthermore, it shows the possibility of increasing the deliveries of LQ and HQ contracts, by 8.11% and 0.74% respectively. The extra deliveries correspond to a 2.2% increase in profits.

Fig. 2 Train delivery schedule and classification in optimal planning (white = no delivery, grey = delivered in the specification, black = delivered out of specification)

The main driver for this solution is the better utilization of ROM. The plant has benefited from the possibility of choosing which ROM to treat each week, reducing the overall inflow mass to the plant. Fig. 3 shows the comparison of ROM type consumption proportion per period between the optimal planning and the contextualization case. Other results are available in Table VI.

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf

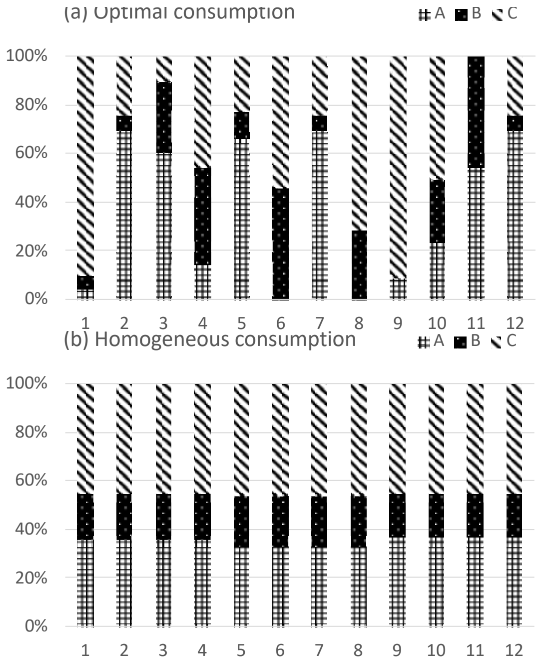

Fig. 3 Proportion of clustered ROM processed in the first 12 weeks

TABLE VI
COMPARISON BETWEEN UNOPTIMIZED AND OPTIMIZED CASES

Variable	Indexes	Unit	Unoptimized	Optimized
SiO_2 content out of specification	W1 MQ	%	0.22	0.00
	W12 HQ	%	0.31	
The proportion of trains delivered out of specification	MQ	%	2.78	0.00
	HQ	%	3.03	
ROM consumption	Month 1	kt	538.13	536.73
	Month 2	kt	536.02	534.64
	Month 3	kt	539.02	537.72
	Month 4	kt	537.89	536.38
	Month 5	kt	537.24	535.77
	Month 6	kt	537.46	535.97
	Month 7	kt	540.47	539.16
	Month 8	kt	538.68	537.28
	Month 9	kt	537.89	536.38
	Month 10	kt	538.03	536.67
	Month 11	kt	538.46	537.08
	Month 12	kt	538.56	537.11

V. Additional Analyses

The benefits of using an end-to-end integrated decision support system are expended when analyzing two scenarios: process setup definition and contracts selection.

The two analyses are performed on top of the optimized scenario presented in the previous section.

A. Process Setup Definition

All processes are composed of a group of machines in the beneficiation plant. Those machines operate using a predefined configuration, for instance, a crushing velocity in the crusher or a specific reagent consumption in froth flotation. Usually, a single configuration is used although there are a set of options, each one impacting the production in its own way.

This case introduces an alternative setup for the Process I, which is allowed for the treatment of ROM type C. This setup has a higher generation of MAG and a lower generation of NMAG, resulting in a lesser sub-product production rate in comparison with the standard setup, as seen in Fig. 4.

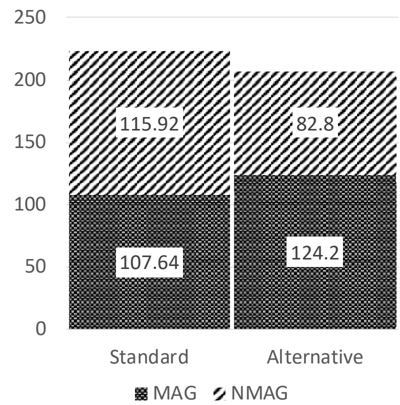

Fig. 4 Production rate (t/h) of MAG and NMAG per setup

After solving the model considering this possibility, the mine has benefited by using the alternative setup in a small proportion of the shifts (Fig. 5). The sub-product lower generation is compensated by an increase of the mean quality of the production, allowing for better utilization of lower quality sub-products. Additionally, the model was able to deliver more products to HQ which increased the profit increase of 0.22%. Extra details can be found in Table VII.

Such alternative operative modes could be investigated at each step of the process, multiplying the economic benefits of this optimization.

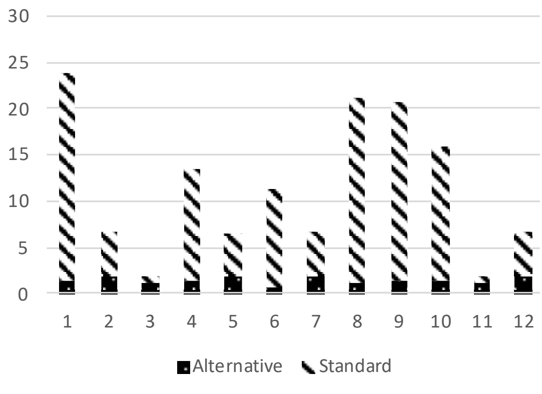

Fig. 5 Number of shifts per setup for ROM C treatment

B. Contract Selection

Salesforce teams usually have limited information regarding the operational challenges during the production while the industrial engineering team has low access to contractually defined product prices. That incoordination regarding what type of product is more suitable can be eliminated by using the model as a mediator. In this case, it is imagined that the contracts with MQ (starting at month 10, defined as MQ-B) and LQ (starting at month 7, defined as LQ-B) are in

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf

discussion to be renewed, and two new contracts (LQ-C and HQ-B) are possible to be signed. The first new contract has the same chemical specifications and prices as LQ, with a maximum demand of 100 kt from months 6 to 12. The second has the same chemical specifications and prices as HQ, with a maximum demand of 100 kt from months 6 to 12. All contracts up to debate have no minimum demand.

TABLE VII
COMPARISON WITH AND WITHOUT ALTERNATIVE SETUP

Variable	Index	Unit	Without alternative setup	With alternative setup
Blended mass loaded to contract	MQ	kt	486.00	486.00
	LQ	kt	720.00	720.00
	HQ	kt	1917.47	1921.30
NMAG C mass in stock	W1	kt	39.59	39.40
	M12	kt	138.20	50.80
Mass of ROM used	M1	kt	536.73	538.20
	M2	kt	534.64	535.99
	M3	kt	537.72	539.17
	M4	kt	536.38	537.95
	M5	kt	535.77	537.27
	M6	kt	535.97	537.49
	M7	kt	539.16	540.61
	M8	kt	537.28	538.77
	M9	kt	536.38	537.95
	M10	kt	536.67	538.09
	M11	kt	537.08	538.54
	M12	kt	537.11	538.64
Sub-product masses in product blends	CON A	kt	518.71	518.71
	CON B	kt	302.00	302.00
	CON C	kt	610.91	610.91
	MAG A	kt	356.75	356.75
	MAG B	kt	224.72	224.72
	MAG C	kt	365.84	375.41
	NMAG A	kt	380.53	380.53
	NMAG B	kt	149.81	149.81
	NMAG C	kt	214.21	208.47

TABLE VIII
COMPARISON OF DELIVERED PRODUCT MASS

Clients	Contracts	Cases	Unit	W1-M6	M7-M9	M10 - M12
MQ	1	Renewal	kt	364.50		-
		Optimized	kt	364.50		-
	1B	Renewal	kt	-	-	121.50
		Optimized	kt	-	-	0.00
LQ	2	Renewal	kt	360.00	-	-
		Optimized	kt	351.23	-	-
	2B	Renewal	kt	-	360.00	
		Optimized	kt	-	360.00	
	2C	Renewal	kt	-	-	
		Optimized	kt	-	100.00	
HQ	3	Renewal	kt	1917.47		
		Optimized	kt	1919.55		
	3B	Renewal	kt	-		
		Optimized	kt	-	0.00	74.77

Renewal = Renewal of current contracts; Optimized = optimizing the contract selection.

The comparison of this case with the optimal planning has shown that, due to market prices, the blend of high and low-quality sub-products to produce the MQ products is diminishing the profits.

In the 7th month, the model has the first option to choose the next contracts to supply between LQ-B, LQ-C, and HQ-B. It decides to select the LQ contracts from that point on. The second decision regarding contracts occurs in the 10th month, where it now faces the decision to renew the MQ-B or to supply for HQ-B. And the model has identified that it is more profitable to supply the HQ contract. The delivered masses in both cases are detailed in Table VIII.

The drop of MQ-B and subsequent supply of LQ-B, LQ-C, and HQ-B has increased the profit by 1.88% (Table IX).

TABLE IX
COMPARISON OF MAIN INDICATORS

Variable	Index	Unit	Renewal	Optimized
Economics	Profit	MR$	877.48	893.98
Blended mass loaded to contract	MQ	kt	486.00	364.50
	LQ	kt	720	811.23
	HQ	kt	1917.47	1994.32

Renewal=Renewal of current contracts; Optimized=optimizing the contract selection

VI. IMPROVEMENTS

The introduction of product dynamic pricing to an end-to-end integrated planning is the natural next step for a support decision model. Although the shift from mixed-integer programming to non-linear programming could correspond to a simplification of the train loading (allowing for rational numbers), this implementation can better analyze the economic trade-off of delivering products out of specifications or in premium qualities following Platts.

Additionally, the list of specifications per sub-product could be extended to add more compounds (P, Al_2O_3) and physical properties (like granulometry). Therefore, the choice of compounds and physical properties to be included in the model should follow the relevance of each in the mines' decisions. Every inclusion of compounds or quality in the scope can also significantly increase the complexity of the mathematical program. The increase that list implicates in more restrictive blends which a model is more capable of dealing with.

VII. CONCLUSION

The predictability provided by combining clustering and classification technics to the throughput of a mining production plant incorporated with flexible processing ROM selection, dynamic blending recipes and determination of train loading schedule generates many possible production scenarios. Applying it as input to an end-to-end integrated planning mathematical program, as proposed in this study, has potentially increased profits and reduced penalties of a mining company.

The model used was capable to support the decision-making process throughout the iron ore chain, proposing the optimal configuration per process and contract selection.

APPENDIX

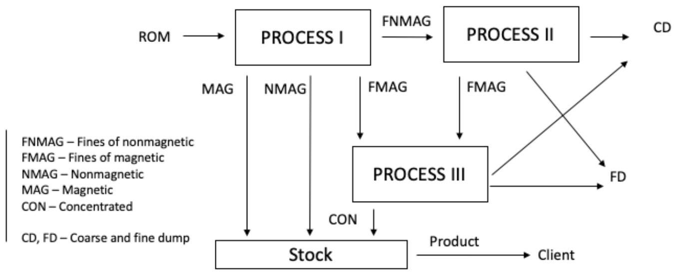

Fig. 6 Plant's mass flow

REFERENCES

[1] E.W. Forgy, "Cluster analysis of multivariate data: efficiency versus interpretability of classifications," in Biometrics, 21, 1965, pp.768-769.

[2] S.S. Ghannadpour, A. Hezarkhani, and E. Farahbakhsh. "An investigation of Pb geochemical behavior respect to those of Fe and Zn based on k-Means clustering method," in Journal of Tethys, 2013, 1(4), pp.291-302.

[3] S.A. Meshkani, B. Mehrabi, A. Yaghubpur, and Y.F. Alghalandis. "The application of geochemical pattern recognition to regional prospecting: A case study of the Sanandaj–Sirjan metallogenic zone", Iran. In the Journal of Geochemical Exploration, 2011, 108(3), pp.183-195.

[4] J.S. Cramer. "The origins of logistic regression". 2002

[5] Y. Pochet. "Mathematical Programming Models and Formulations for Deterministic Production Planning Problems". In: Jünger M., Naddef D. (eds) Computational Combinatorial Optimization. Lecture Notes in Computer Science, 2001, vol 2241. Springer, Berlin, Heidelberg.

[6] Platts, "Specifications Guide - Global Iron Ore, August 2020", 2020, S&P Global, New York

Open Science Index, Geological and Environmental Engineering Vol:14, No:11, 2020 publications.waset.org/10011564.pdf